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The Effect of Education on Individual Earnings: A Statistical Analysis Using Quantile Regression and the Mincerian Model

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الملخص: تتناول هذه الدراسة أثر التعليم على الدخل الفردي في المملكة العربية السعودية باستخدام أسلوب الانحدار الكمي ودالة مينسر للأجور. وعلى خلاف أسلوب الانحدار بالمربعات الصغرى الاعتيادية(OLS) ، يتيح الانحدار الكمي فهماً أكثر دقة لكيفية تأثير التعليم في الأجور عبر مختلف مستويات توزيع الدخل. ويعتمد التحليل على بيانات مسحية شملت 804 مفردات من مناطق مختلفة في المملكة العربية السعودية، مع الأخذ في الاعتبار مجموعة من العوامل الرئيسة مثل الجنس، والحالة الاجتماعية، والخبرة العملية، وقطاع العمل .وتشير النتائج إلى أن للتعليم أثراً إيجابياً ذا دلالة إحصائية على الدخل، إلا أن حجم هذا الأثر يختلف باختلاف مستويات الدخل. ففي حين يحقق التعليم العالي عوائد ملموسة لدى أصحاب الدخول المنخفضة والمتوسطة، تتناقص هذه العوائد عند أعلى الكميات (Quantiles) من توزيع الدخل، مما يدل على أن تخصصات العلوم الصحية والهندسة وعلوم الحاسب وتقنية المعلومات، إلى جانب الخبرة العملية، تؤدي دوراً أكثر بروزاً في تحديد الأجور عند المستويات العليا من الدخل. كما تكشف النتائج عن وجود فجوات واضحة بين الجنسين، حيث يتقاضى الرجال أجوراً أعلى من النساء، ولا سيما عند مستويات الأجور المرتفعة، الأمر الذي يعزز المزايا المهنية طويلة الأجل للرجال .وتُظهر الدراسة أيضاً أن الحالة الاجتماعية تُعد متغيراً مهماً في تفسير الدخل، خاصةً لدى أصحاب الدخول المرتفعة، في حين يوفر العمل في القطاع العام قدراً أكبر من الاستقرار في الأجور عبر مختلف الكميات. كما تدعم نتائج نموذج مينسر هذه الاستنتاجات، حيث تؤكد أن كلاً من التعليم والخبرة العملية يسهمان بصورة معنوية في تحديد الدخل، غير أن تناقص العائد على الخبرة في المراحل المتقدمة من المسار الوظيفي يبرز أهمية التطوير المستمر للمهارات. وتخلص الدراسة إلى أن لهذه النتائج دلالات مهمة لصياغة سياسات التعليم، واستراتيجيات سوق العمل، وتخطيط القوى العاملة في المملكة العربية السعودية.

الكلمات المفتاحية : التعليم، الدخل، الانحدار الكمي، نموذج مينسر، عدم المساواة في الأجور، المملكة العربية السعودية.

ABSTRACT: This study examines the impact of education on individual earnings in Saudi Arabia using quantile regression and the Mincerian earnings function. Unlike traditional ordinary least square (OLS) regression, quantile regression allows for a more nuanced understanding of how education influences wages across different points of the income distribution. The analysis is based on a survey of 804 respondents, collected from various regions of Saudi Arabia, and accounts for key factors such as gender, marital status, work experience, and employment sector. The findings reveal that education has a significant positive effect on earnings, but its impact varies across income levels. While higher education substantially benefits lower- and middle-income earners, its returns diminish at the highest quantiles, suggesting that Health sciences, engineering, computers, and information technology (IT) and experience, play a more prominent role in wage determination at the upper end of the income distribution. Gender disparities are evident, with men earning significantly more than women, particularly at higher wage levels, reinforcing long-term career advantages for men. Additionally, marital status is found to be a strong predictor of income, particularly for high earners, while public sector employment provides greater wage stability across all quantiles. The Mincerian model results further support these findings, showing that both education and work experience contribute significantly to earnings. However, diminishing returns to experience at later career stages highlight the need for continuous

skill development. The study's findings have critical implications for education policies, labor market strategies, and workforce planning in Saudi Arabia.
Keywords: **Education, Earnings, Quantile Regression, Mincerian Model, Wage Inequality, Saudi Arabia .**

1. Introduction

Education plays a fundamental role in human development, shaping individuals' abilities to solve problems and adapt to an increasingly complex job market. Studies across various countries and time periods consistently demonstrate that individuals with higher education levels—particularly those holding a bachelor's degree or beyond—tend to earn higher wages, experience lower unemployment rates, and secure more prestigious positions compared to their less-educated counterparts (Holmlund & Martin, 2023; Volante et al., 2017). Human capital theory conceptualizes education as an investment, where initial costs, such as tuition and time, yield long-term financial and social benefits through increased productivity and higher lifetime earnings (Robinson & Pope 2023).

Beyond financial gains, higher education correlates with improved quality of life, including better health outcomes, lower healthcare costs, and greater civic engagement. More educated individuals are also more involved in their children's education and overall community development, reinforcing intergenerational socioeconomic mobility (Bakker & Van Vliet, 2022). Additionally, an increase in educational attainment is strongly linked to proportional income growth. However, salary variations exist within each level of education, influenced by factors such as academic performance, family background, cognitive ability, intrinsic motivation, and broader economic conditions (Pascoe et al., 2020). These interrelated elements make it challenging to isolate education's impact on earnings precisely.

Higher education also contributes to broader economic and societal progress by reducing income inequality, increasing tax contributions, and expanding employment opportunities. The human capital hypothesis supports the notion that financial investment in education enhances future productivity, reinforcing its critical role in personal and national economic growth (Nguyen, 2018; Rahman & Akhter, 2021). Therefore, ensuring access to quality education remains a key priority for fostering economic mobility and addressing social disparities.

Research in the UK has demonstrated a strong correlation between higher levels of education and a reduction in criminal behavior (Brennan et al., 2013). This finding underscores the importance of integrating educational policies with crime prevention strategies, as investments in human capital may serve as a powerful complement to traditional law enforcement measures. Policymakers can effectively reduce recidivism rates and promote societal stability by addressing the root causes of criminal behavior. One of the most impactful strategies is expanding access to high-quality education and enhancing skill development programs. Equipping individuals with educational opportunities and practical skills not only improves their employability but also fosters personal growth, reducing the likelihood of reoffending. By investing in rehabilitation-focused policies, such as vocational training and reintegration programs, governments can help formerly incarcerated individuals' transition successfully into society, ultimately contributing to lower crime rates and a more stable community (Vandala, 2019).

Numerous studies have consistently demonstrated the significant economic benefits of investing in education for individuals (Pascoe et al., 2020; Nguyen, 2018; Rahman & Akhter, 2021). As higher levels of education are strongly correlated with increased earnings, a growing body of research utilizes statistical models to quantify this impact. These models provide valuable insights into the long-term financial returns of different education levels, helping individuals make informed decisions about their academic and career paths. Estimating returns to education is particularly important for Saudi Arabia as the country strives to diversify its economy under Vision 2030, which prioritizes the development of a knowledge-based economy and reducing dependence on oil revenues. Despite substantial investments in education, there remains a shortage of detailed research examining how educational attainment translates into earnings within the Saudi labor market. Existing studies often fail to account for crucial factors such as income inequality, regional disparities, and sectoral differences in wage structures. Addressing these gaps can equip policymakers with actionable insights to align education policies with labor market demands, ensuring both equitable opportunities and sustainable economic growth (Almutairi, 2024).

This study fills a crucial empirical gap in the analysis of labor market outcomes in Saudi Arabia by estimating the private returns to education using both quantile regression (QR) and the Mincerian model. While prior research has examined the relationship between education and earnings in Saudi Arabia, most studies have relied on OLS regression, which only provides average estimates and fails to capture variations across the income distribution. By employing QR, this study offers a more comprehensive analysis of how education influences earnings at different quantiles, uncovering disparities that would be overlooked in mean-based analyses.

Unlike previous studies (Alsulami, 2018; Sfar, 2024), this research is not merely an extension but a novel contribution in several ways. First, it integrates both the Mincerian earnings function and QR to provide a more detailed estimation of returns to education across different wage levels, identifying whether education benefits low-income earners differently than high-income earners. This approach offers valuable insights into wage inequality and labor market stratification. Second, it examines the effects of study disciplines, employment sectors (public vs. private), and gender-based differences, creating a more holistic understanding of wage disparities in Saudi Arabia—an aspect often overlooked in traditional earnings function estimations.

This study focuses on the private returns to education due to their direct policy relevance, particularly in relation to individual earnings, labor market behavior, and wage-setting strategies. While broader social benefits like improved health and social mobility are important, they require complex data and are harder to quantify. In contrast, private returns can be directly measured through wage data. To examine how educational attainment affects income—and the influence of public vs. private sector employment—the study uses econometric methods, including the Mincerian model and QR. "Returns to education" here refers to the financial gains from education across labor market segments. The paper proceeds with a review of Saudi Arabia's education system, recent developments in estimating education returns and follows with methodology, data, analysis, and discussion.

1.1 The Saudi Arabian Educational System

Since its establishment, the Kingdom of Saudi Arabia has placed a strong emphasis on education, evident in the substantial allocations from the state budget. Over the years, the education sector has expanded significantly, providing free education and increasing student enrollment. However, despite this progress, challenges have emerged, particularly concerning student performance. A considerable number of students struggle with core subjects such as mathematics, English, and

Arabic, indicating deficiencies in teaching methodologies and learning outcomes (Quamar, 2020; Barry, 2021).

Education in Saudi Arabia is compulsory for children from the age of six until fourteen. However, participation in education extends beyond this legal requirement, with over 90% of students between the ages of 7 and 17 enrolled in some form of schooling. Most postsecondary students (95%) attend public institutions, while only 5% opt for private universities. Between 2013 and 2020, the percentage of tertiary students in private universities remained unchanged. Enrollment in higher education declines significantly with age, with only 12% of individuals aged 25–29 and just 1% of those aged 30–39 participating in tertiary education in 2020. Additionally, international students represent a small proportion of tertiary enrollment, with only 4% coming from abroad, while 43% of students originate from neighboring countries.

Recognizing the need for reform, the Saudi government has prioritized education as a key driver of economic sustainability. To meet the country's evolving workforce demands, the education system has been strategically aligned to produce skilled professionals in fields such as science, engineering, economics, and law. As part of this vision, the government has approved a five-year development plan exceeding $21.33 billion, aimed at fostering research, innovation, and entrepreneurship within the education sector. This initiative underscores Saudi Arabia's commitment to strengthening its education system as a foundation for long-term economic growth and diversification (Essa & Harvey, 2022).

1.2 Estimating the Returns to Education

The estimation of returns to education has been a focal point in economic and labor market research, attracting significant scholarly attention (Zheng et al., 2023; Kim, 2021; Mamun et al., 2021; Somani, 2021; McGuinness et al., 2021; Li et al., 2023). According to human capital theory, education enhances an individual's productivity, leading to increased earnings and better employment opportunities (Psacharopoulos & Patrinos, 2018). Numerous empirical studies confirm that education and labor market experience are fundamental determinants of income, reinforcing the importance of educational investments for policymakers and families alike.

A growing body of research applies statistical models to quantify the effect of education on earnings, helping individuals make informed decisions about educational attainment. Mincer (Mincer, 1974), the pioneer of human capital theory, established a linear relationship between the logarithm of earnings and years of schooling. He posited that the return to education can be estimated as the coefficient of education in a regression model of log earnings on years of schooling. This approach has become the foundation for many subsequent studies on wage determination and educational investment (Card & Krueger, 1992).

Card and Krueger (1992), expanded on Mincer's model by examining the impact of education quality on earnings across different birth cohorts. Their study confirmed that log earnings increase systematically with years of education, particularly for individuals with 15–16 years of schooling, highlighting the credential effect. They found that the returns to education were higher at this level than at lower educational stages, while the lowest percentiles of the education distribution experienced relatively low returns. Moreover, their analysis suggested that completing higher education does not yield disproportionately high returns, contradicting the assumption that more education always translates into significantly greater earnings.

Estimating returns to education remains crucial in economics, as educational choices significantly influence earnings and inform policy decisions. Education, viewed as an investment in human capital, should be assessed similarly to physical capital. While Hamdan et al. (2020) argue that higher education's role in growth may be limited, they emphasize its impact on poverty reduction, particularly in sub-Saharan Africa, where university participation is just 5%. In countries like Saudi Arabia, Algeria, and Jordan, education investment strongly correlates with GDP growth, enhancing innovation and productivity (Sfar, 2024). Recent Mincer-based studies show tertiary education now yields the highest returns, surpassing earlier emphasis on primary education (Patrinos, 2024).

1.3 External of Advantages of Education

Extensive research shows that higher education levels lead to significantly higher individual earnings. Beyond these private financial gains, education also yields broader societal benefits, known as social returns. These include improved economic development, public health, and reduced crime (Lochner & Moretti, 2004). Social returns combine private returns with external benefits from human capital investments. For instance, higher education is linked to lower crime rates due to increased earning opportunities. Rauch (1993) demonstrated that regions with higher average education levels experience greater income growth, reflecting education's spillover effects. While causality remains a challenge, later studies have used instrumental variable methods to strengthen evidence for education's impact on income (Salma, 2025). These findings underscore the importance of educational policies that promote both individual advancement and societal well-being.

2. Methods and Data

We conducted a comprehensive data collection across various regions of Saudi Arabia from March 2022 to August 2023 using structured questionnaires distributed via email and mobile applications. The initial dataset consisted of 850 responses, of which 46 were excluded due to incomplete data, resulting in a final sample of 804 participants. To enhance accessibility and minimize language barriers, the questionnaire was prepared in both English and Arabic and comprised eight key questions capturing the main variables of the study. Confidentiality and ethical considerations were strictly maintained to ensure participant anonymity and that all collected data was used exclusively for research purposes.

To minimize self-selection bias, the study employed a random sampling approach, inviting participants from diverse employment sectors and regions. The questionnaires were distributed through human resource departments within various institutions and companies, ensuring a broad and representative sample. The allocation across different Saudi states was based on population density and workforce concentration, achieving a balanced representation between the public and private sectors while reflecting the standardized wage structures within the country. The highest number of surveys was distributed in Jeddah, Riyadh, Makkah, Madinah, and the northern region due to their significant population density and economic activity. To further enhance the representativeness of the findings, we applied survey weights to the data, accurately reflecting the broader population and reducing potential biases.

Saudi Arabia has one of the highest internet penetration rates globally, reaching 99% as of 2024 (Desjardins et al., 2006). The widespread adoption of smartphones and digital services ensures that email and mobile applications serve as highly effective tools for survey distribution. Given that the vast majority of Saudi residents actively use online communication platforms, this method confirms the feasibility and reliability of our data collection approach.

The final dataset accurately reflects Saudi Arabia's employment distribution, with 70.9% of respondents working in the public sector and 29.1% in the private sector. This aligns with national labor market statistics, where approximately 84% of public sector employees are Saudi nationals, compared to only 16% in the private sector (Gulf Research Center, 2022). The preference for government jobs is driven by better benefits, job security, and long-term stability, contributing to an employment imbalance between sectors. The sample distribution closely mirrors the broader economic structure and workforce realities of the country. For data analysis, we utilized SPSS V.24, applying suitable statistical techniques to present clear, interpretable results that enhance understanding of labor market dynamics in Saudi Arabia.

To mitigate potential biases related to different career stages, we conducted a separate analysis for individuals aged 35–44, comparing their earnings determinants with the entire study sample. This approach helps isolate life-cycle effects that may influence salary progression, career development, and returns to education. Younger individuals are often in the early stages of their careers, where salary growth is affected by entry-level positions, limited work experience, and fewer opportunities for promotion. By analyzing this group separately, we aim to provide a clearer understanding of how earnings determinants evolve over time and how education, experience, gender, and employment sector influence wage outcomes at different career stages.

This study estimates the returns to education using three primary methods: Quantile Regression (QR), the Mincerian earnings function, and Ordinary Least Squares (OLS) for comparative analysis. Additionally, Analysis of Variance (ANOVA) is employed to determine the statistical significance of the regression model, assessing whether the independent variables collectively explain a meaningful proportion of variance in earnings. A significance threshold of $p < 0.05$ confirms that the likelihood of the observed relationships occurring by chance is minimal, reinforcing the model's robustness.

To detect multicollinearity among predictors, we use the Variance Inflation Factor (VIF), which quantifies the extent to which the variance of regression coefficients is inflated due to collinearity. The explanatory power of our models is assessed using the coefficient of determination (R^2), which measures the proportion of variance in earnings explained by the independent variables.

To gain a more comprehensive understanding of wage disparities across different income levels, we implement QR. Unlike OLS, which focuses on the mean effect, QR evaluates the impact of independent variables at different points in the earnings distribution, providing deeper insights into heterogeneity in returns to education. We analyze the relationship between education and earnings at specified quantiles (0.10, 0.25, 0.50, 0.75, and 0.90), allowing us to observe how the returns to education vary across low, median, and high-income earners. The goodness-of-fit for the QR model is assessed using R^2, while 2000 bootstrap replications are performed to obtain unbiased parameter estimates and reliable SE. The independent variables in this study have been carefully selected to capture key determinants of earnings, ensuring a robust analysis of the relationship between education and wages.

Monthly Wage Income: In this research, "earnings" or "wage income" refers to an individual's net income—the total amount taken home after taxes and deductions. This metric provides a clearer reflection of an individual's financial situation, purchasing power, and overall economic well-being. By focusing on net earnings, we can more accurately assess disposable income and an individual's capacity to meet living expenses, save, or invest. To allow for meaningful comparisons across different time periods, we adjust earnings for inflation using the standard deflation formula:

$$Real\ Earnings\ =\ (Nominal\ Earnings\ /\ Price\ Index)\ \times\ 100.$$

where nominal earnings represent reported monthly wages, and the price index accounts for the general price level using a base year set to 100. This inflation-adjusted measure ensures accurate cross-period earnings comparisons (Cheng et al., 2019), enabling policymakers and researchers to assess real wage growth and shifts in economic well-being.

Educational Attainment: Instead of using years of schooling, we categorize education into attainment levels: primary/secondary school (0), high school (1), vocational/technical college (2), and bachelor's degree (3). This classification aligns with research suggesting that educational attainment provides deeper insights than merely counting years of study (Card & Krueger, 1992; Horowitz, 2018). While years of education indicate time invested, attainment reflects actual qualifications and competencies acquired, which better align with labor market expectations. This approach also accounts for variations in educational quality across different regions and highlights skill acquisition over mere attendance. By prioritizing attainment, policymakers and researchers can develop more precise evaluations of human capital development and its impact on earnings.

Demographic and Employment Variables:

- **Age Groups:** Participants are categorized into five age brackets: 15–24, 25–34, 35–44, 45–54, and 55+.
- **Gender:** A dummy variable is used, where 0 represents males and 1 represents females.
- **Marital Status:** Classified as single (0), married (1), or widowed/divorced (2).
- **Field of Study:** Grouped into humanities (0), scientific disciplines (1), health sciences (2), and engineering, computers, and IT (3).
- **Employment Sector:** A dummy variable distinguishes public (0) from private sector employment (1).
- **Work Experience:** Categorized into four levels: less than 5 years, 5–9 years, 10–15 years, and more than 15 years.

These variables create a comprehensive framework for analyzing the socio-economic dynamics influencing earnings. The study's approach ensures a nuanced understanding of wage disparities, helping to inform policy interventions that promote equitable labor market outcomes.

2.1 The empirical methodology

2.1.1 The Mincer Earnings Equation

Mincer's seminal research provided motivation for the selection of variables used in the explanation. Mincer developed a simplistic model of the factors that influence a worker's income. Initially, Mincer solely included the level of education as an explanatory variable in his model, but subsequently, he broadened it to encompass age and the duration of the worker's employment. Since then, earnings functions have incorporated a significant number of additional variables

(Mincer, 1974). Examples of some of these characteristics include a person's gender, race, and whether they are members of a labour union (Horowitz, 2018; Shaimardanova, 2022).

In this study, we applied the Mincer earnings equation, which includes earnings as an independent variable and years of education, experience, and experience squared as a dependent variable. We assume that everyone in the sample works every period for the same number of hours. Formally, we consider the following basic model (Mincer, 1974):

$$Ln\, Yi = \beta_0 + \beta_1 X_i + \beta_2 E_i + \beta_3 E_i^2 + \varepsilon_i, \quad i = 1, 2, 3, \dots, n \tag{1}$$

where, $Ln\, Yi$ represents the logarithm of a monthly wage income of individual i, X_i represents the years of education, E_i is a measure of work experience and ε_i is an individual disturbance term which is normally distributed. The parameter β1 can be interpreted as the rate of return to investments in education (Fleischhauer, 2007). Work experience is included as a quadratic element to reflect the concavity of the earnings profile; hence, β2 and β3 represent the non-linear wage income linked to ongoing investment in on-the-job training post-education. This indicates that income increases rapidly for young individuals, peaks, and thereafter declines. Generally, experience and education ($E_i$and X_i) exhibit a negative correlation; that is, among individuals of the same age, those with greater years of education possess less work experience. Both explanatory variables are anticipated to exert a beneficial influence on earnings (Ramessur & Jugessur, 2024).

The Mincer model assumes a log-linear relationship between earnings, education, and experience, with constant returns across groups. It presumes accurate measurement of education and a causal link to income. A key challenge is isolating education's effect from individual ability and selection bias, as high-ability individuals often pursue more education, potentially inflating return estimates. Institutions may also admit selectively, compounding bias (Patrinos, 2024). While advanced econometric methods suggest ability has limited influence on returns, further research is needed to clarify the education-income causality.

2.1.2 Quantile Regression (QR) Models

Each of the discussed factors uniquely influences individual earnings. For instance, higher education, such as a college degree, tends to hold more value for high-income earners as their professions typically demand such qualifications. Conversely, many low-income positions do not require tertiary education (Horowitz, 2018). Standard OLS models overlook this heterogeneity, merely providing average effects across the data, which diminishes reliability (Koenker & Bassett, 1978). To tackle this, the QR method is used to see how factors like education influence different levels of earnings, such as the 25th or 75th percentiles. This helps us understand the differences in income better. For example, QR can show how an extra year of education affects wages for both low and high earners in different ways. It does this while being strong against unusual data points and not relying on standard assumptions about the leftover data (Borgen, 2016). This adaptability has enabled QR's application in areas like wage analysis, survival studies, and income disparities.

QR is introduced as a relatively new methodology that is more appropriate when assumptions of normality and homoscedasticity are violated. QR is recommended as a good alternative when exploring relationships between variables along the entire distribution, rather than just focusing on average performance. QR has advantages in documenting student growth percentiles and has gained popularity in educational statistics (Chen & Chalhoub, 2014). QR complements the estimation of conditional mean models by providing insights into conditional quantiles, detecting differences in the effect of a regressor across quantiles, and identifying statistical relationships between variables that mean regression models may not capture (Fitzenberger & Wilke, 2015). Mathematically, QR is modeled as:

$$Y_t = a + \beta_{\theta 1}X_{1t} + \beta_{\theta 2}X_{2t} + \cdots + \beta_{\theta k}X_{kt} + \mu_{\theta t} = X_t'.\beta_\theta + \mu_{\theta t}, \qquad t = 1, 2, \ldots, n \qquad (2)$$

being:

$$Quant_\theta(Y_t|X_t) = X_t'.\beta_\theta$$

Where $Quant_\theta(Y_t|X_t)$ represents the θ^{th} quantile of Y_t conditional on the explanatory variables X_t. Parameters are estimated by minimizing the weighted sum of absolute residuals, expressed as:

$$Q(\beta_\theta) = \sum_{t:Y_t \geq X_t'.\beta} \theta |\, Y_t - X_t'\,\beta_\theta \,| + \sum_{t:Y_t \geq X_t'.\beta} (1-\theta) |\, Y_t - X_t'\,\beta_\theta \,| \qquad (3)$$

This technique, proposed by Koenker and Bassett (Koenker & Bassett, 1978), enables robust parameter estimation unaffected by abnormal errors or outliers. Applying to individual earnings, the QR model evaluates income based on characteristics like education, age, gender, marital status, field of study, and employment sector. It offers a more nuanced understanding of how returns to education and other factors vary across income levels, bridging critical gaps in labor economics research (Koenker, 2005).

QR models linear relationships at various quantiles and assumes low multicollinearity among independent predictors. While powerful for revealing variable effects across different outcome segments, QR has limitations such as sensitivity to small samples, computational demands, and less intuitive interpretation than OLS. It also assumes equal variance across quantiles, which may require adjustments (Chen & Chalhoub, 2014).

To evaluate model fit, Koenker and Machado (1999) introduced the R(p), an R^2 analog for QR that reflects the variation explained at each quantile, unlike traditional R^2, which captures variance at the mean. This approach supports diagnostics and interpretation (Staffa et al., 2019).
In this study, the dependent variable Y_t (monthly wage) is modeled against predictors such as age, experience, gender, marital status, education, discipline, and employment sector, as detailed in the Methods and Data Section. QR enables exploration of how these factors influence earnings across the income distribution, offering richer insights into wage disparities.

3. Results and Discussion

The dataset consists of 804 valid responses, yielding an effective response rate of 96%, ensuring data reliability for further analysis. Below are key insights derived from the summary statistics of categorical variables and wage income by socio-demographic characteristics:

Table 1: Summary statistics of categorical variables and wage income by sociodemographic variables

				Income	
Variables	Frequency	Percentage	mean	Median	IQR
Age(years)					
15-24	61	7.6	9604.13	7500	6600
25-34	227	28.2	10857.74	8000	9000
35-44	285	35.4	15515.22	14500	12000
45-54	166	20.6	18447.78	18500	12600
55+	65	8.1	22151.25	25000	10200
Gender					

Female	121	85.0	13381.58	11000	8000
Male	683	15.0	15266.47	15000	15000
Marital Status					
Single	178	22.1	10009.50	8000	7000
Married	611	76.0	16496.09	15600	15300
Widow/ divorce	15	1.9	8882.83	6500	11000
Education					
Primary/ Secondary	29	3.6	9615.27	9500	5300
Higher school	42	5.2	13317.52	11000	14000
Vocational/Technical College	45	5.6	12961.62	13000	6000
Bachelor	688	85.6	15356.76	15000	15700
Discipline or area of study					
Humanities disciplines	176	21.9	16897.16	16500	9000
Scientific disciplines	471	58.6	13529.40	12500	12000
Health sciences	44	5.5	23522.18	26000	12000
Engineering, computers, and information technology (IT).	42	5.2	18781.96	20500	18000
Others	71	8.8	11719.29	10000	9000
Sector of employee					
Private	234	29.1	12039.68	8600	11500
Public	570	70.9	16084.72	15000	15050
Work experience (Years)					
<5	248	30.8	12386.70	8500	11900
5-9	184	22.9	10613.86	6800	9400
10-14	225	28.0	17691.88	15000	12000
15+	147	18.3	20434.93	18500	9500

Note: Wage income measured in Saudi riyal (SR). IQR: Inter Quartile range.

Table 1 summarizes income distribution across sociodemographic factors, revealing significant wage disparities by age, gender, education, field of study, employment sector, and experience. A clear life-cycle pattern emerges: younger workers (15–24) earn the least (Mean: 9,604 SAR), while older workers (55+) earn the most (Mean: 22,151 SAR), though variability within age groups suggests differing career paths.

Men consistently earn more than women (Mean: 15,266 SAR vs. 13,381 SAR), with wider income ranges reflecting unequal access to advancement and leadership roles. Married individuals report higher wages (Mean: 16,496 SAR) than singles or widowed/divorced, possibly due to career stability or dual-income advantages.

Education strongly influences income. Bachelor's degree holders earn the highest (Mean: 15,356 SAR), while those with lower education earn less, confirming the value of tertiary education. Field of study also matters: Health science graduates lead in earnings (Mean: 23,522 SAR), followed by engineering and IT. Humanities graduates outperform science majors, potentially due to roles in government or corporate sectors.

Public sector workers earn more on average (Mean: 16,084 SAR) and enjoy greater stability than private sector employees, whose wages are more variable. Experience remains the most reliable predictor of earnings, with those over 15 years earning the most (Mean: 20,434 SAR).

In sum, wage disparities persist across demographic and professional lines, with higher earnings linked to age, gender, marital status, education, sector, and experience. The findings underscore the need for policies addressing wage gaps and promoting inclusive workforce development.

Table 2: The result of Mincerian income function

Model	Gender	Variable	Bootstrap[a] for Coefficients			VIF	95% Confidence Interval	
			Coeff.	t- value	SE		Lower	Upper
Total Sample	1	Edu	0.153**	46.55	0.003	1.04	0.147	0.160
		Exp	0.051**	59.07	0.001	12.23	0.049	0.053
		$(Exp)^2$	-0.001**	-25.65	0.000	12.35	-0.001	-0.001
		constant	8.39	746.47	0.12		8.369	8.415
		R^2	0.45					
		F-value	53.38**					
Male	2	Edu	0.147**	41.595	0.003	1.030	0.140	0.154
		Exp	0.047**	50.052	0.001	12.21	0.045	0.049
		$(Exp)^2$	0.000	-18.613	0.000	12.29	-0.001	0.000
		constant	8.47**	966.28	0.012		8.43	8.47
		R^2	0.45					
		F-value	45.24**					
Female	3	Edu	.168**	18.798	0.009	1.128	0.150	0.188
		Exp	.145**	56.258	0.003	17.06	0.140	0.150
		$(Exp)^2$	-.004**	-46.841	0.000	17.56	-0.004	-0.004
		constant	7.68**	261.76	0.030		7.62	7.74
		R^2	0.55					
		F-value	16.28**					

Dependent variable: ln (Wage income measured in Saudi riyal (SR), a: Bootstrap results are based on 2000 bootstrap samples, Notes: The P-value is considered statistically significant at p < 0. 05. Significance is indicated by bold coefficients and ** p < 0.01, * p < 0.05.

Table 2 shows the results of the Mincerian earnings function, analyzing how education and work experience influence income, with separate estimates for the total sample, males, and females to explore gender-based differences.

Education significantly increases income across all groups. In the total sample, each additional year of education raises earnings by about 15.3%. Women see slightly higher returns (0.168) than men (0.147), likely due to labor market selection effects, although structural barriers still contribute to the gender wage gap.

Work experience also positively affects wages, especially for women (0.145) compared to men (0.047), possibly reflecting the impact of career interruptions like maternity leave. The negative coefficients for squared experience indicate diminishing returns over time, with faster wage growth early in one's career.

Despite higher returns to education and experience for women, men still enjoy higher base wages (8.47 vs. 7.68), highlighting persistent structural inequalities, occupational segregation, and negotiation disparities. Education and experience drive wage growth for both genders, but men maintain an advantage in initial earnings and advancement.

The model explains 45% of earnings variation in the total sample ($R^2 = 0.45$), with a better fit for women ($R^2 = 0.55$). All coefficients are statistically significant ($p < 0.05$). Education shows low multicollinearity (VIF ≈ 1.03–1.23), while expectedly, experience and its square exhibit higher VIFs due to correlation.

Overall, the findings confirm that education and experience are critical to earnings, but women face lower starting wages despite higher returns. The concave earnings-experience relationship and persistent gender disparities point to the need for targeted policies promoting wage equity and female career advancement.

Table 3: Regression coefficients for the discipline Of study

Model	Bootstrap* for Coefficients			VIF	95% Confidence Interval	
	Coeff. (B)	t- value	SE		Lower	Upper
Humanities	5177.86**	39.51	123.46	2.81	4937.15	5418.04
Science	1810.11**	15.27	111.20	3.29	1593.41	2026.75
Health sciences	11802.88**	66.78	156.82	1.56	11478.16	12088.18
Engineering, computers, and IT	7062.67**	39.47	171.89	1.54	6730.64	7403.40
Constant	11719.29**	105.66	101.17		11523.13	11916.88
R^2	0.32					
F-value	18.56**					

Dependent Variable: Wage income measured in Saudi riyal (SR).

Predictors: (Constant), Humanities, Science, Health sciences, Engineering, computers, and information technology (IT)

Notes: The P-value is considered statistically significant at $p < 0.05$. Significance is indicated by bold coefficients and ** $p < 0.01$, * $p < 0.05$.

*Bootstrap results are based on 2000 bootstrap samples

Table 3 presents OLS regression results on how academic discipline affects earnings, revealing significant wage differences across fields of study in Saudi Arabia. Health sciences graduates earn the highest premium—11,802.88 SAR above the baseline (p = 0.000, CI: 11,478.16–12,088.18), reflecting strong demand for healthcare skills. Similarly, engineering, computers, and IT graduates receive a premium of 7,062.67 SAR (p = 0.000, CI: 6,730.64–7,403.40), indicating the high value of STEM qualifications.

Humanities graduates earn 5,177.86 SAR more than the baseline (p = 0.000), while science graduates see a more modest gain of 1,810.11 SAR (p = 0.000), suggesting lower returns for non-applied disciplines. VIF values confirm that most fields contribute independently to wage estimation, with only moderate multicollinearity noted in the science category (VIF = 3.29).

An R^2 of **0.32** indicates that academic discipline explains 32% of wage variation, with other factors (e.g., gender, experience) also playing a role. The significant ANOVA F-statistic (18.56, p = 0.000) supports the model's explanatory power. Bootstrap sampling (2,000 replications) strengthens estimate reliability, and higher SEs in health and STEM fields suggest greater income dispersion. All 95% confidence intervals exclude zero, confirming statistical significance.

Overall, the findings show that academic discipline significantly affects earnings in Saudi Arabia, especially in health sciences and STEM. These results align with labor market trends and support economic diversification goals. To improve employability and income potential, education policy should prioritize skill alignment, career guidance, and targeted training initiatives.

3.1 The QR Results

3.1.1 QR Results of the Total Sample

The OLS method estimates average effects, but quantile regression (QR) provides a fuller view of the conditional earnings distribution. QR results reveal substantial income variations tied to education levels.

Table 4: The result of parameter estimates by different quantiles

Parameter		q=0.10	q=0.25	q=0.50	q=0.75	q=0.90
Gender		275.00	1555.00*	2400.00*	3444.44**	4000.00**
[95% Conf. Interval]	Lower Bound	-864.08	198.50	320.74	1597.03	2391.07
	Upper Bound	1414.08	2911.50	4479.26	5291.86	5608.93
Marital status		825.00	500.00	-200.00	6833.33**	7966.67**
[95% Conf. Interval]	Lower Bound	-201.38	-722.29	-2073.55	5168.70	6516.92
	Upper Bound	1851.38	1722.29	1673.55	8497.97	9416.41
Education		1450.00**	1132.50*	1850.00*	2981.48**	511.11
[95% Conf. Interval]	Lower Bound	554.74	66.36	215.80	1529.50	-753.43
	Upper Bound	2345.26	2198.64	3484.20	4433.46	1775.65
Discipline or area of study		725.00*	555.00	1100.0*	1444.44***	666.67
[95% Conf. Interval]	Lower Bound	149.00	-130.94	48.58	510.27	-146.92
	Upper Bound	1301.00	1240.94	2151.42	2378.62	1480.25
Experience		2175.0**	3377.50**	3200.0**	2166.67**	1666.67**
[95% Conf. Interval]	Lower Bound	1742.67	2862.65	2410.83	1465.49	1056.01
	Upper Bound	2607.33	3892.35	3989.17	2867.84	2277.32
Employed sector		2000.00**	1800.00**	2600.00**	2666.67**	2200.00**
[95% Conf. Interval]	Lower Bound	1011.37	622.67	795.36	1063.26	803.58
	Upper Bound	2988.63	2977.33	4404.64	4270.08	3596.42
Intercept		-7575.00**	-6440.00**	-5150.00	-12833.33**	-1666.67
[95% Conf. Interval]	Lower Bound	-11564.2	-11190.8	-12431.88	-19303.25	-7301.37
	Upper Bound	-3585.78	-1689.34	2131.88	-6363.41	3968.04

Notes: The P-value is presented between parenthesis; the coefficients are considered statistically significant at $p < 0.05$.
Significance is indicated by bold coefficients and ** $p < 0.01$, * $p < 0.05$.

Table 4 presents estimates at the 10th, 25th, 50th, 75th, and 90th percentiles, illustrating how education and other factors impact earnings across income levels.

Gender wage gaps widen at higher percentiles. At Q = 0.10, the gender effect is statistically insignificant (275 SAR, p = 0.636), indicating minimal disparity. However, at Q = 0.75 and Q = 0.90, the male premium rises significantly to 3444.44 SAR and 4000 SAR ($p < 0.001$), showing men earn much more at higher income levels. Gender becomes significant from Q = 0.25 ($p < 0.05$), underscoring increasing inequality with rising wages.

Marital status has a nonlinear effect. It is insignificant at lower quantiles but offers substantial premiums at Q = 0.75 (6833.33 SAR, $p < 0.001$) and Q = 0.90 (7966.67 SAR, $p < 0.001$). This suggests high earners benefit more from marriage, possibly due to greater financial stability, employer perceptions, or labor specialization, especially in leadership roles.

Education's impact peaks at the median (Q = 0.50, 1850 SAR, p = 0.027) and Q = 0.75 (2981.48 SAR, p < 0.001), but weakens at Q = 0.90 (511.11 SAR, p = 0.428). This reflects diminishing returns to education at high income levels, where experience, specialization, and networking outweigh formal education in influencing earnings—aligning with human capital theory.

Field of study significantly affects earnings at Q = 0.10, Q = 0.50, and Q = 0.75, with the strongest effect at Q = 0.75 (1444.44 SAR, p = 0.002). Its influence is limited at Q = 0.25 and Q = 0.90, suggesting mid-career professionals benefit more from discipline choice, while higher earnings depend on other factors like industry demand and experience.

Work experience consistently boosts earnings across all quantiles (p < 0.001), with effects ranging from 2175 SAR (Q = 0.10) to 3377.50 SAR (Q = 0.25) and 1666.67 SAR (Q = 0.90). These results confirm that skill accumulation, tenure, and negotiation power significantly enhance income, especially in sectors that reward long-term experience.

Public sector employment consistently offers higher earnings, especially at the median (Q = 0.50, 2600 SAR, p = 0.005). This advantage stems from standardized pay, benefits, and job security, making public jobs attractive across all income levels.

Overall, the QR analysis shows that gender disparities intensify at higher wages, education yields strongest returns for middle earners, and marital status impacts high-income groups most. Experience remains the most reliable income driver across all levels, and public sector jobs offer broad financial stability. These findings call for targeted policies to reduce wage inequality and promote skill development for long-term income growth.

3.1.2 QR Results when Excluding Younger Individuals Aged (35–44)

Table 5. Parameter estimates by different quantiles:

Parameter		q=0.10	q=0.25	q=0.50	q=0.75	q=0.90
Gender		1233.33	2375.00**	4483.33**	5000.00**	5457.14**
[95% Conf. Interval]	Lower Bound	-78.21	642.03	2017.45	2984.35	3597.93
	Upper Bound	2544.87	4107.97	6949.21	7015.65	7316.36
Marital status		933.33	1725.00*	1383.33	7500.00**	8500.00**
[95% Conf. Interval]	Lower Bound	-129.23	321.01	-614.44	5866.99	6993.73
	Upper Bound	1995.90	3128.99	3381.10	9133.01	10006.27
Education		2016.67**	2650.00**	3716.67**	1250.00	-457.14
[95% Conf. Interval]	Lower Bound	946.41	1235.85	1704.44	-394.83	-1974.32
	Upper Bound	3086.92	4064.15	5728.90	2894.83	1060.03
Discipline or area of study		1066.67**	1575.00**	3133.33**	1000.00	42.86
[95% Conf. Interval]	Lower Bound	371.65	656.66	1826.60	-68.14	-942.39
	Upper Bound	1761.69	2493.34	4440.07	2068.14	1028.10
Experience		2366.67**	3400.00**	3066.67**	2500.00**	1028.57**
[95% Conf. Interval]	Lower Bound	1912.477	2799.86	2212.71	1801.96	384.71
	Upper Bound	2820.86	4000.14	3920.62	3198.04	1672.43

Employed sector		2300.00**	1075.00	1833.33	4000.00**	4928.57**
[95% Conf. Interval]	Lower Bound	1254.37	-306.62	-132.60	2393.01	3446.30
	Upper Bound	3345.63	2456.62	3799.27	5606.99	6410.84
Intercept		-11516.67**	-15100.00**	-18433.33**	-10750.00**	-242.86
[95% Conf. Interval]	Lower Bound	-16142.38	-21212.07	-27130.34	-17859.07	-6800.19
	Upper Bound	-6890.95	-8987.93	-9736.33	-3640.93	6314.48

Notes: The P-value is presented between parenthesis; the coefficients are considered statistically significant at $p < 0.05$.
Significance is indicated by bold coefficients and ** $p < 0.01$, * $p < 0.05$.

Table 5 displays quantile regression results after excluding individuals aged 35–44 to minimize life-cycle bias and better assess how education, gender, marital status, experience, and employment sector affect earnings among older workers. The adjusted analysis shows more pronounced gender disparities, shifting education returns, and stronger wage advantages for experienced public-sector employees.

In the full sample, gender differences were negligible at lower quantiles but became notable from Q = 0.50 upward. In contrast, the adjusted sample reveals an earlier and widening gender wage gap starting at Q = 0.25. Older men earn significantly more than women, reflecting persistent gender disparities linked to structural barriers like occupational segregation and career interruptions. These findings emphasize the need for policies such as wage transparency, mentorship, and flexible work arrangements to support women in later career stages.

Education shows stronger positive effects at Q = 0.10, 0.25, and 0.50 in the adjusted sample, confirming its importance for older, lower-income earners. However, at Q = 0.90, education's impact fades, indicating that experience, specialization, and sectoral roles outweigh formal qualifications at the top of the earnings distribution. This highlights the growing importance of skill development and executive training over academic credentials for high-income workers.

Experience remains a strong earnings determinant across all quantiles, with slightly greater effects at lower quantiles in the adjusted sample. This suggests that older low-income earners benefit more from accumulated experience. At higher quantiles, diminishing returns imply that leadership, networking, and specialized expertise are more crucial than tenure.

Marital status becomes significant earlier (from Q = 0.25) in the adjusted sample and remains influential at higher quantiles, indicating income benefits for married individuals—possibly due to financial stability, dual incomes, or employer preferences.

Public sector employment offers notable wage premiums at Q = 0.75 and 0.90, reflecting the advantages of senior government roles, including structured promotions and long-term benefits. By focusing on older workers, these findings capture deeper labor market trends—highlighting rising gender disparities, the sustained value of education for lower earners, and the increasing influence of marital status and public employment for high-income individuals. Targeted interventions—like career development support, incentives for lifelong learning, and gender-equitable workplace policies—are essential to reduce wage inequality and foster a more inclusive Saudi labor market.

4. Conclusion

This study provides a comprehensive analysis of the impact of education on earnings in Saudi Arabia, utilizing quantile regression and the Mincerian earnings function to assess wage disparities across different income levels. The findings highlight that education significantly influences earnings, with higher returns observed at lower and middle quantiles, while at upper quantiles, experience, specialization, and sectoral employment become more critical. The results also reveal a widening gender wage gap, especially at higher income levels, where men experience greater wage advantages due to accumulated experience and career progression, reinforcing the need for gender-equitable workplace policies. Work experience remains the most consistent predictor of wage growth, with its effect being particularly strong for older workers, emphasizing the importance of career stability and professional development. Furthermore, marital status and public sector employment significantly impact earnings, with married individuals and government employees earning higher and more stable wages. The Mincerian model confirms that education and experience positively correlate with earnings, although women experience higher returns to education, yet face lower baseline wages due to structural labor market challenges. The study underscores the importance of education, experience, and employment policies in shaping wage outcomes, advocating for targeted policy interventions such as skill development programs, gender wage equity initiatives, and public sector workforce retention strategies to create a more inclusive and equitable labor market.

5. Limitations and future research

This study offers important insights into the returns to education in Saudi Arabia but has some limitations. The sample mainly includes employed individuals, potentially excluding those in informal sectors or unemployed, which may overestimate education's impact on earnings. Endogeneity remains a concern, as unobserved factors like ability and background could bias results. Future research could use instrumental variable regression to address this. Self-reported data may also contain measurement errors, and the lack of distinction between gross and net earnings limits the analysis of wage disparities. Notably, experienced workers receive higher returns to education across all quantiles, unlike entry-level employees—challenging life-cycle labor supply theory. Future studies should explore sectoral differences, skill mismatches, and occupational mobility. While this study emphasizes private monetary returns, broader social benefits—like productivity spillovers and improved public health—warrant further investigation through longitudinal and comprehensive datasets.

Declarations

Ethics approval and consent to participate

This study is based on anonymized secondary data derived from questionnaire responses that were distributed via email to participants. As the data were anonymized and no direct interaction with participants occurred, formal ethics approval and informed consent were not required. The research was conducted in full compliance with relevant ethical guidelines and standards.

Competing interests

No potential conflict of interest was reported by the authors.

Authors' contributions

Hamid H. Hussien led the study design, conducted statistical analysis, supervised the research, drafted the manuscript, and contributed to revisions. **Mohamed Albahloul Musrati** assisted with study design, data organization, exploratory analysis, and manuscript review and manuscript editing.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. All relevant summary statistics and methodological details are included in the manuscript.

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