ISSN: 2619-9491
BUSINESS AND ECONOMICS RESEARCH JOURNAL
www.berjournal.com
Business and Economics Research Journal Vol. 17, No.3, 2026 pp. 377-401 doi: 10.20409/berj.2026.503

Does Field of Study Shape the Hourly Wage Distribution? Evidence from Quantile Regression

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Abstract: *Higher education expansion in Türkiye has sharply increased the supply of bachelor's degree graduates, yet how field of study is associated with wages across the conditional wage distribution remains insufficiently examined. Using 2024 Household Labour Force Survey microdata, this study estimates weighted conditional quantile regressions for bachelor's degree wage workers. Fields are grouped using ISCED-F 2013, with Business and Law as the reference category. Results reveal substantial distributional heterogeneity in field-of-study wage associations. Science, Technology, Engineering, and Mathematics graduates show the largest and most distribution-sensitive conditional wage advantage, increasing from lower to upper conditional quantiles. Education graduates exhibit a hump-shaped profile peaking at Q75, while Health and Veterinary graduates show a declining association from Q10 to Q90. These patterns are consistent with differences in sectoral allocation, public-sector concentration, and institutionally structured wage-setting, but should be interpreted as conditional associations rather than causal returns. Humanities and Arts graduates do not display statistically significant wage associations at individual quantiles. Overall, the findings show that OLS estimates mask important distributional differences and support more systematic monitoring of field-specific labor market outcomes in higher education planning and career guidance.*

Keywords: Field of Study, Wage Structure, Quantile Regression, Higher Education, Türkiye

JEL: C21, I26, J31

Received : 30 March 2026
Revised : 16 June 2026
Accepted : 10 July 2026

Type : Research

1. Introduction

Turkish higher education has undergone a dramatic expansion over the past two decades. The Council of Higher Education (CoHE-YÖK) reports that the number of state universities grew from 53 in 2003 to 129 in 2018, and by 2024 the total number of higher education institutions (including foundation universities and vocational schools) reached 208. Total enrolment more than tripled between 2003 and 2024 (YÖK, 2024). Yet this expansion has been heavily concentrated in certain fields of study, particularly social sciences, business, and education, raising concerns about credential inflation and misalignment between university output and labor market demand (Ege & Erdil, 2023; Özoğlu et al., 2016). OECD (2023) data confirm that education and business programs account for a disproportionate share of Turkish higher education enrolment, while science, technology, engineering, and mathematics (STEM) fields remain comparatively underrepresented.

A critical policy question follows from this expansion. Are different fields of study associated with different wage outcomes, and do these associations vary across the conditional wage distribution? Standard

Cite this article as: Özkan Değirmenci, H. Ö. (2026). Does field of study shape the hourly wage distribution? Evidence from quantile regression. *Business and Economics Research Journal, 17*(3), 377-401. http://dx.doi.org/10.20409/berj.2026.503

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returns-to-education analyses focus on years of schooling or education levels, treating all bachelor's graduates as homogeneous. This approach obscures the substantial wage heterogeneity that exists within the bachelor's-degree holder population. A student choosing between engineering and humanities at a Turkish university is not simply choosing between "graduate" and "non-graduate" status. They are choosing between fields that may be associated with fundamentally different labor market outcomes. Crucially, these differences may not be constant across the wage hierarchy. A field may be associated with stronger wage positions among lower-paid graduates while offering limited upper-tail differentiation, or conversely with larger conditional wage differences only among graduates who enter high-productivity employment.

The international literature has increasingly recognized this gap. Altonji et al. (2012) demonstrate that field of study matters as much as years of schooling in explaining wage variation in the United States. Webber (2014) extends this insight by showing that field-of-study premia vary substantially across the wage distribution. That is, the returns to studying engineering relative to humanities are not constant but depend on where a graduate ends up in the wage hierarchy. Kim et al. (2015) confirm comparable patterns using longitudinal earnings data. Zhang et al. (2024), using American Community Survey data, find that internal rates of return to college degrees are systematically higher at the upper end of the earnings distribution, with engineering and computer science majors recording the highest returns among all major groups. For Türkiye, two prior studies address distributional field-of-study premia but in ways that differ from the present analysis. Çiftçi and Ulucan (2021) estimate conditional quantile regression with sample selection correction using Household Labour Force Survey (HLFS) data from 2014–2017, documenting field premia across the wage distribution but without a systematic focus on how premia vary by quantile across all fields. Di Paolo and Tansel (2025) apply unconditional quantile regression and RIF decomposition to HLFS data from 2009–2015 for male graduates, decomposing wage gaps into endowment and returns components along the distribution rather than estimating conditional field-of-study premia directly. The present study complements these studies by estimating conditional quantile-specific field-of-study premia for the full employed graduate workforce using the most recent available wave.

This study asks whether field of study is associated with wage outcomes differently across the conditional wage distribution. It is a question that standard mean-based analysis cannot answer. To address this, data are drawn from the HLFS which is a nationally representative annual survey of 598,923 individuals and a final analysis sample of 29,908 employed bachelor's degree wage workers is constructed. The weighted quantile regression is estimated at five quantiles (10th, 25th, 50th, 75th, 90th) of the log hourly wage distribution. The 22 International Standard Classification of Education: Fields of Education and Training (ISCED-F) field codes available in the survey are collapsed into eight broad groups. The central question is the following. Which fields are associated with significantly higher or lower wages than Business and Law graduates, and does this advantage or disadvantage expand, contract, or remain stable as we move from lower to upper conditional wage quantiles?

The contribution of this study is fourfold. First, it uses the recent available HLFS 2024 micro data to estimate conditional quantile-specific field-of-study wage differentials for the full employed bachelor's degree wage-worker sample in Türkiye. It extends the prior Turkish literature of Çiftçi and Ulucan (2021) and Di Paolo and Tansel (2025) with a more recent wave and a full-sample conditional quantile design. Second, by focusing on the conditional wage distribution rather than the mean, it reveals distributional patterns that standard OLS estimation conceals. Third, the findings speak directly to the higher education policy agenda of the Council of Higher Education (CoHE), which sets field-specific enrolment quotas that shape the supply of graduates across disciplines. Fourth, the study contributes a methodological template for distributional field-of-study analysis in emerging economies where survey data contain field classification, but institutional panel data are unavailable, demonstrating that HLFS-type household surveys can support richer inference than is typically exploited in the applied literature.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on returns to field of study and distributional wage analysis. Section 3 describes the data, sample construction, and econometric methodology. Section 4 presents descriptive statistics and regression results. Section 5 discusses the findings in the context of Turkish higher education policy. Section 6 concludes.

2. Literature Review

2.1. From Years of Schooling to Field of Study

The foundational human capital framework of Becker (1964) and Mincer (1974) treats education as an investment whose returns are measured by the additional wages earned relative to the years of schooling invested. This approach dominated empirical labor economics for decades and produced a rich literature on the "college wage premium", the earnings advantage of bachelor's degree holders over high school graduates.

The framework generates several testable predictions about how field-of-study wage differences vary across the wage hierarchy. Through occupational sorting, field choice constrains the set of occupations available to graduates. Fields with highly specific technical training in engineering, computing, and natural sciences channel graduates into competitive private-sector occupations where wages respond to employer demand for specialist skills; this generates conditional premia that tend to expand toward the upper tail of the wage distribution. Fields with more general training provide wider occupational access but lower field-specific returns at any given point in the distribution. Through sectoral allocation, fields differ systematically in the share of graduates employed in the public sector. In Türkiye, centralized civil service pay grids govern the wages of a large proportion of graduate workers. Fields concentrated in public-sector employment therefore face a wage-setting mechanism that compresses the upper tail: graduates receive a regulated base salary above the private-sector minimum but cannot access the high wages available in competitive private markets, and the result is a declining or hump-shaped conditional premium rather than the monotone upper-tail divergence observed for market-exposed fields. Through regulated wage-setting, certain occupations linked to specific fields operate under licensure, collective agreements, or central salary schedules that generate wage floors without commensurate ceilings; many health-related occupations in Türkiye, which are partly shaped by Ministry of Health pay scales and professional licensing arrangements, provide a direct illustration. Three mechanisms emerge from these channels: market exposure, which predicts rising conditional premia for fields concentrated in competitive private employment; public-sector compression, which predicts flat or hump-shaped profiles for fields concentrated in government employment; and regulated wage floors, which predict declining profiles for fields governed by professional wage schedules. These mechanisms are elaborated in Section 5 in connection with the empirical findings.

Empirical research across multiple countries has confirmed that the choice of field matters at least as much as the length of schooling. Altonji et al. (2012) document that the variation in mean earnings across college majors in the United States is at least as large as the earnings gap between college and high school graduates, and that this variation persists after controlling for ability and family background. Lovenheim and Smith (2023) review returns to different postsecondary investments and show that field of study, credential level, and institution type all contribute independently to earnings variation, with field of study being a particularly powerful predictor within the bachelor's degree population. Ma and Savas (2014) further show that field of study can be more consequential than institutional selectivity for earnings differences among recent college graduates, reinforcing the importance of curriculum content as a dimension of graduate wage inequality. These findings collectively motivate moving beyond the years-of-schooling framework and toward a field-specific analysis of the wage distribution.

2.2. Distributional Approaches to Wage Returns

Quantile regression, introduced by Koenker and Bassett (1978), allows the estimation of the entire conditional wage distribution rather than its mean. This is the common statistical tool for testing the distributional predictions described in Section 2.1. If market exposure, public-sector compression, and regulated wage floors operate differently across fields, then these field-specific associations will vary across the conditional wage distribution in predictable ways that a single OLS coefficient cannot capture. Buchinsky (1994) documents substantial variation in returns to education across quantiles in the United States, establishing the empirical case that wage-distribution position, not merely average wages, is shaped by educational investments. Tansel and Bodur (2012) document comparable distributional variation in returns to education in Türkiye using quantile regression, confirming that the pattern of heterogeneous wage returns observed in the United States is also present in the Turkish labor market.

Webber (2014) applies this distributional framework specifically to field-of-study analysis, producing results that are consistent with the three-channel structure described above. Premia for STEM fields expand monotonically from the bottom to the top of the conditional wage distribution, consistent with the market-exposure mechanism: STEM graduates who sort into high-productivity private-sector positions earn substantially more than comparable Business and Law graduates at the upper tail, while the advantage is smaller but still positive at the lower tail. Premia for education and humanities fields are relatively flat or declining across the distribution, consistent with the institutional-compression mechanism: the wage-setting environment for these graduates does not allow the upper-tail divergence observed for market-exposed fields. Kim et al. (2015) confirm using longitudinal data that these distributional differences compound over careers, with STEM fields generating widening conditional advantages relative to humanities and social science fields as workers accumulate experience. The implication is that a single OLS coefficient can be misleading in both directions: it understates STEM returns for workers who sort into high-productivity positions and overstates them for workers who do not.

Zhang et al. (2024) confirm the market-exposure pattern in a lifetime earnings framework: the internal rate of return to a college degree is highest for engineering and computer science graduates and is concentrated at the upper tail of the earnings distribution, consistent with competitive private-sector wage-setting rewarding technical specialization. In Türkiye, by contrast, field-specific distributional evidence is limited. Tansel and Acar (2016) apply quantile regression to the formal-informal wage gap but do not decompose returns by field of study. The combination of distributional methods with a systematic field-of-study classification has received limited attention in the Turkish context, despite the institutional features of the Turkish labor market that make such an analysis particularly informative. Section 2.3 reviews the two prior Turkish studies that do address this combination, and identifies the specific gaps that the present analysis fills.

2.3. The Turkish Higher Education and Labor Market Context

The Turkish higher education and labor market context makes a distributional approach particularly relevant. As noted in the Introduction, university expansion has reached all 81 provinces (YÖK, 2019), and prior research suggests that the spread of state universities has had labor market effects at the local level (Değirmenci, 2023). Enrolment growth has been heavily concentrated in low-cost fields. Education and Business and Law graduates together dominate the sample, accounting for more than half of employed bachelor’s degree wage workers, while STEM accounts for 13.1 percent, reflecting the pattern of expansion documented by OECD (2020, 2023) and World Bank (2007), in which administrative scalability rather than labor market demand drove program growth.

The labor market further shapes field-of-study returns in ways that make mean-based analysis insufficient. Nearly half of graduate wage workers in the sample are employed in the public sector. Given the more compressed wage structure typically associated with public-sector pay setting, sectoral composition is likely to shape field-of-study premia across the wage distribution (San & Polat, 2012). Regional wage disparities add a further dimension of heterogeneity, with earnings generally higher in more developed western regions than in eastern and southeastern regions; this pattern is part of a broader and persistent West–East divide in Turkish regional economy (Aşık et al., 2023; Çelik & Selim, 2016; Karahasan et al., 2016). Because field composition, public sector concentration, and regional location are correlated, mean wage comparisons across fields confound these structural features. Distributional methods allow field-of-study premia to be examined at different points in the wage hierarchy, net of these controls, making Türkiye a particularly relevant setting for this type of analysis.

Two prior studies estimate field-of-study wage differences in Türkiye using HLFS data and distributional methods, and both provide important reference points for the present analysis. Çiftçi and Ulucan (2021) apply conditional quantile regression with Heckman-type sample-selection correction to HLFS data pooled from 2014 to 2017, estimating separate models for male and female graduates. Their results document statistically significant wage associations for STEM, Health and Veterinary, and Education graduates relative to other fields at most quantiles, and show that these associations vary in magnitude across the conditional wage distribution. The present study extends this analysis in three respects. First, the 2024 HLFS wave is more than seven years more recent, covering a Turkish labor market that has changed substantially in its graduate supply, sectoral composition, and wage levels. Second, the full employed bachelor's degree wage-worker population is analyzed in a single pooled model that controls for gender rather than through separate male and female specifications. Third, formal inter-quantile equality tests are reported for each field group, allowing distributional shape claims to be evaluated against a statistical criterion rather than through visual comparison of point estimates.

Di Paolo and Tansel (2025) apply unconditional quantile regression and recentered influence function decomposition to HLFS data for male bachelor's degree graduates from 2009 to 2015, decomposing wage gaps at different unconditional quantiles into endowment and returns components. Their analysis shows that field-of-study endowments account for a substantial share of wage inequality among male graduates, and that occupational sorting is the primary channel through which field choice translates into earnings differences. The present study differs from Di Paolo and Tansel (2025) in two fundamental respects. First, the conditional quantile approach used here estimates the wage association for each field at a specific conditional quantile of the wage distribution, holding other worker characteristics constant; this differs from the unconditional quantile approach, which targets effects on the marginal wage distribution and is designed for aggregate wage inequality decomposition rather than conditional field-specific inference. Second, the analysis covers both male and female graduates using the 2024 wave, providing a more current and inclusive characterization of field-of-study wage associations in the Turkish labor market.

Against this institutional backdrop, three features of the Turkish labor market are particularly relevant for interpreting the empirical findings and connect directly to the mechanisms identified in Section 2.1. First, the public-sector employment share varies sharply by field: Education and Health and Veterinary graduates are employed in the public sector at rates exceeding 70 percent, while STEM graduates are employed predominantly in the private sector (Table A1). This sectoral sorting by field provides the institutional foundation for the public-sector compression mechanism. Second, healthcare and veterinary occupations are regulated professions in Türkiye, with wages partly determined by Ministry of Health civil service scales and professional licensing boards; this is the regulated wage-floor mechanism. Third, STEM graduates are concentrated in engineering, ICT, and applied science occupations where wages are determined by market competition for specialist skills. This is the market-exposure mechanism. These three mechanisms are foreshadowed here so that the discussion in Section 5 follows directly from the theoretical framing developed in this literature review.

3. Data and Methodology

3.1. Data Source

This study uses the 2024 microdata of the Household Labour Force Survey (HLFS) published by the Turkish Statistical Institute (TurkStat; Publication No. 4776). The HLFS is Türkiye's main nationally representative labor market survey and is designed as a continuous household survey covering all residential addresses in the country through a two-stage stratified cluster sampling framework. The 2024 annual file includes information on approximately 198,511 households and 598,923 individuals. The survey is sample based; therefore, all descriptive statistics and regression estimates are weighted using the sampling weight provided in the dataset, divided by 1,000 as specified in the codebook.

The use of the 2024 HLFS is appropriate for two reasons. First, it provides the most recent nationally representative microdata available for analyzing graduate wage outcomes in Türkiye. Second, the survey includes detailed information on completed education, labor market status, monthly earnings, working hours, and field of study, making it suitable for estimating wage differentials among bachelor's degree holders. It should also be noted that, beginning in 2021, HLFS statistics have been produced under the revised

International Labor Organization definitions adopted in the 19th International Conference of Labor Statisticians (ICLS). As a result, post-2021 HLFS data are not fully comparable with earlier waves, and the present study is therefore intentionally cross-sectional, focusing only on the 2024 survey year.

3.2. Sample Construction

The empirical analysis is restricted to individuals who are relevant for identifying field-of-study wage differentials among university graduates. The starting sample is limited to employed wage and salary workers, excluding employers, own-account workers, and unpaid family workers, since the wage concept used in the analysis is defined only for paid employment. The sample is then restricted to individuals whose highest completed qualification is a four-year bachelor's degree. This restriction is central to the design of the study because the objective is to compare wage outcomes across fields of study within a common level of higher education, rather than across education levels.

Additional restrictions are imposed to improve comparability and measurement quality. The sample includes only individuals aged 22 to 65, thereby excluding most observations that are unlikely to have completed a bachelor's degree or that are likely to be at or beyond standard retirement ages. Observations are further limited to workers reporting positive monthly wage income and positive usual weekly hours in the main job. To reduce the influence of implausible hour reports, usual weekly hours are restricted to the interval 1 to 98 hours. Individuals holding postgraduate qualifications (master's degrees, doctoral degrees, and long-cycle tertiary programs) are excluded because the survey does not allow these categories to be distinguished separately. After applying all restrictions, the final analytical sample consists of 29,908 employed bachelor's degree holders in wage employment.

3.3. Variable Definitions

The dependent variable is the logarithm of hourly wage. Hourly wages are derived from the respondent's last month's net cash wage income and usual weekly hours worked in the main job. Monthly hours are obtained by multiplying usual weekly hours by 4.33, the standard conversion factor based on 52 weeks divided by 12 months. Prior to the log transformation, the top 1 percent of the hourly wage distribution is winsorized at 743.36 TL to reduce the influence of extreme outliers on the estimates. As a robustness check, an alternative winsorization threshold of p0.5–p99.5 is applied in Appendix Table A2; the main field-of-study patterns are unchanged.

The explanatory variables include both the field-of-study indicators and a set of standard labor market controls. Age and age squared are included as proxies for labor market experience in a standard Mincerian specification. Gender is captured using the survey's sex variable. Employment sector is measured through a public-sector indicator, while formal employment status is identified through registration with the social security system. A full-time employment indicator is also included to account for systematic differences in hourly earnings associated with work intensity. Finally, the regressions control for broad regional variation through three macro-region dummies: South, Central, and East Türkiye, with West Türkiye as the omitted reference category. This regional aggregation follows the logic of earlier Turkish wage studies and is intended to capture major spatial differences in labor demand and wage-setting conditions (Özkan Değirmenci, 2026; Tansel & Acar, 2016).

3.4. Field of Study Grouping

The HLFS identifies completed field of study through a variable recording 22 detailed ISCED-F 2013 field codes. For the purposes of empirical analysis, these detailed categories are collapsed into eight broader groups. This aggregation follows two complementary sources of authority. The first is the ISCED-F 2013 classification published by UNESCO (2014), which organizes fields of education into broad groups at the first-digit level. The grouping strategy used here preserves the logic of the ISCED-F 2013 broad-field structure, with two modifications. First, the broad fields covering sciences, engineering, manufacturing, construction, and information and communication technologies are combined into a single STEM category, reflecting a common practice in the labor economics literature. Second, the broad field covering health and welfare is divided into Health and Veterinary on the one hand and Personal and Welfare Services on the other, to reflect differences in occupational structure and wage formation across these areas.

The second basis for the grouping is the empirical literature on field-of-study wage differentials. The field aggregation follows the ISCED-F 2013 broad-field structure, with a limited number of modifications informed by the field-of-study earnings literature. Webber (2014) and Kim et al. (2015) support treating STEM-related majors as a distinct high-return category, while Kim et al. (2015) and Carnevale et al. (2015) also justify keeping Health and Education separate from STEM. Altonji et al. (2012) is better read as evidence that engineering and science fields tend to earn more than humanities, social sciences, and education, rather than as a source for a single unified STEM category. The distinction between Humanities and Arts and Social Sciences is likewise consistent with prior work that reports different earnings profiles across those broad groups. Business and Law are combined primarily because ISCED-F 2013 places them in the same broad field; using them as the reference category is then an empirical modeling choice. A full mapping of all 22 ISCED-F 2013 codes to the eight broad field groups used in this analysis is provided in Table A3.

Accordingly, the eight field groups used in the analysis are STEM, Health and Veterinary, Business and Law, Social Sciences and Journalism, Humanities and Arts, Education, Applied and Technical, and Personal and Welfare Services. Among these, Business and Law is used as the omitted reference category in all regression models. This choice is both substantively and statistically convenient. It is the largest field group in the sample, accounting for 30.4 percent of unweighted observations and 31.1 percent of the weighted sample, and it occupies a broadly central position in the raw wage distribution. Using it as the benchmark therefore allows the estimated coefficients on other fields to be interpreted as wage advantages or disadvantages relative to a large and economically important category rather than a more specialized field. It should be noted that Business and Law are internally heterogeneous. Law graduates earn a substantially larger conditional wage premium than Business graduates across all quantiles (Table A4 reports results with Business alone as the reference category). Law, however, represents a relatively small subgroup within the analytical sample, while Business accounts for most of the combined category. We therefore retain the combined reference for consistency with the ISCED-F 2013 broad-field classification and with prior Turkish studies; the field patterns of other groups are substantively unchanged under the alternative specification. Table 1 reports the sample shares and mean hourly wages for each grouped field of study.

3.5. Econometric Methodology

The empirical strategy combines an ordinary least squares (OLS) benchmark with quantile regression estimates. OLS provides the average conditional association between field of study and log hourly wages, holding other covariates constant. However, because the central question of the paper concerns whether field-of-study premia differ across the wage distribution, the main analysis relies on quantile regression following Koenker and Bassett (1978). Quantile regression estimates the conditional quantile function of wages, allowing the relationship between field of study and earnings to vary between lower-paid and higher-paid workers. This makes it particularly suitable for identifying whether certain fields, such as STEM or Education, generate relatively compressed returns or increasingly large premia toward the top of the wage distribution.

Formally, for each quantile $\tau \in (0,1)$, the conditional quantile of log hourly wage is modeled as:

$$Q_\tau(lnw_i|X_i) = X_i'\beta_\tau \tag{1}$$

In the first equation, $Q_\tau(lnw_i|X_i)$ denotes the τ-th conditional quantile of the log hourly wage of individual i, $X_i$is a vector of field of study indicators and other control variables, and β_τ is the corresponding quantile specific parameter vector. The coefficients are estimated using weighted quantile regression:

$$\hat{\beta}_\tau = \arg\min_{\beta\in\mathbb{R}^k} \sum_{i=1}^{N} \omega_i\rho_\tau(lnw_i - X_i'\beta) \tag{2}$$

In the second equation, ω_i denotes the survey weight and $\rho_\tau(u) = u(\tau - 1(u < 0))$ is the standard quantile loss function. This approach makes it possible to examine how the association between field of study and wages varies across the conditional wage distribution.

Separate models are estimated at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional wage distribution. Survey probability weights are incorporated in all estimations. Robust standard errors are used for the OLS benchmark, while Poisson weighted bootstrap standard errors with 500 replications are reported for the quantile-regression estimates. The OLS model is estimated with the same set of regressors to provide a mean-based benchmark against which the quantile estimates can be compared. This comparison is important because it allows the analysis to show whether mean effects conceal substantial heterogeneity across the conditional wage distribution.

It is important to note that these quantile regression estimates refer to the conditional wage distribution. Each estimated coefficient locates the wage difference between the given field and the reference category at a specific conditional quantile, holding all other covariates constant. This differs from unconditional quantile methods such as RIF regression, which estimate effects on the marginal wage distribution. The conditional quantile approach is appropriate here because the object of interest is the field-of-study wage association at different points in the distribution of wages among workers with otherwise comparable observed characteristics.

To formally evaluate the distributional shape claims, Wald tests of cross-quantile equality are computed using simultaneous quantile regression (500 bootstrap replications), which yields a joint variance-covariance matrix across all five quantiles and allows tests of H0: $\beta Q10 = \beta Q90$ as well as joint equality across all quantiles. Results are reported in Table A5.

A note on the exclusion of occupation and industry controls is warranted. Because the sample is restricted to bachelor's degree holders, years of schooling are effectively held constant and field-of-study indicators replace educational attainment as the primary dimension of interest. Occupation and industry are treated as potentially endogenous channels through which field of study operates on wages: including them in the baseline model would partial out the channel of interest rather than control for a confounder. Nonetheless, to assess the robustness of the field coefficients to this choice, specifications that add one-digit ISCO-08 occupation and one-digit NACE Rev.2 industry fixed effects are estimated and reported in Table A6. The field-of-study coefficients are generally attenuated after adding these controls, indicating that occupation and industry account for part of the observed field-related wage differences. This pattern is consistent with occupation and industry operating partly as mediating channels rather than as simple confounders.

Although the HLFS contains additional labor market information, the baseline specification is kept parsimonious to focus on conditional field-of-study differences among bachelor's degree wage workers. The absence of tenure, firm size, marital status, and more detailed regional controls is therefore acknowledged as a limitation.

4. Results

4.1. Descriptive Statistics

Table 1 reports weighted descriptive statistics for the final analysis sample of 29,908 bachelor's degree holders in wage employment. The mean monthly wage is 40,744 TL, while the mean hourly wage is 234.9 TL. Wage dispersion within this relatively homogeneous education group is substantial. The 10th percentile of the hourly wage distribution is 87.8 TL, the median is 216.5 TL, and the 90th percentile is 394.5 TL, implying a 90–10 ratio of approximately 4.5. The standard deviation of log hourly wages is 0.619, further indicating considerable inequality even among workers who all hold the same formal level of education. This pattern provides an initial descriptive justification for the use of quantile regression, since average wage comparisons alone are unlikely to capture the full extent of within-group heterogeneity.

As shown in Table 1, the sample is 44.4 percent female with a mean age of 36.3 years. Nearly half of workers are employed in the public sector, formal employment is near-universal, and 93.6 percent work full-time, suggesting stable and formal employment relationships that strengthen cross-field comparability.

Table 1. Descriptive Statistics: Bachelor's Degree Wage Workers, HLFS 2024

Variables	Mean	Std. Dev.	p10	p50	p90
Monthly wage (TL)	40,744	27,563	17,002	40,000	60,000
Hourly wage (TL)	234.9	134.5	87.8	216.5	394.5
Log hourly wage	5.297	0.619	4.475	5.378	5.978
Age (years)	36.3	8.8	25	35	49
Female (=1)	0.444	0.497	0	0	1
Public sector (=1)	0.463	0.499	0	0	1
Formally employed (=1)	0.986	0.115	1	1	1
Full-time (=1)	0.936	0.244	1	1	1
Weekly hours	41.5	9.1	30	40	50

Note: N = 29,908. All statistics are survey-weighted.

Table 2 complements these overall descriptives by showing the distribution of workers across the eight field-of-study categories and the corresponding mean hourly wage in each group. The sample is highly concentrated in a small number of fields. Business and Law accounts for 31.1 percent of the weighted sample and Education for 22.1 percent, so that these two groups together comprise more than half of employed bachelor's degree wage workers. STEM represents 13.1 percent of the sample and Health and Veterinary 4.9 percent, while Personal and Welfare Services is very small at 2.2 percent. This composition is important because it reflects the strong concentration of tertiary expansion in non-STEM fields documented earlier in the paper.

The raw wage ranking across fields hints at substantial heterogeneity. Education graduates record the highest mean hourly wage (275.0 TL), followed by STEM graduates (271.9 TL), both well above the Business and Law mean of 210.5 TL. Personal and Welfare Services records the lowest mean wage at 197.0 TL. These unconditional differences should be interpreted cautiously, however, since they do not control for age, sector, or region. The regression analysis below isolates conditional field associations.

Table 2. Field of Study Groups: Sample Sizes and Mean Hourly Wages

Field Group	ISCED-F codes	N	Share (%)	Mean hourly wage (TL)
STEM	9–13	3,164	13.1	271.9
Health & Veterinary	17, 18	1,652	4.9	226.4
Business & Law (ref.)	7, 8	9,092	31.1	210.5
Social Sciences & Journalism	5, 6	2,983	11.3	211.4
Humanities & Arts	2–4	2,399	8.6	215.8
Education	1	7,885	22.1	275.0
Applied & Technical	14–16, 21, 22	2,083	6.7	228.6
Personal & Welfare Services	19, 20	650	2.2	197.0
Total		29,908	100.0	234.9

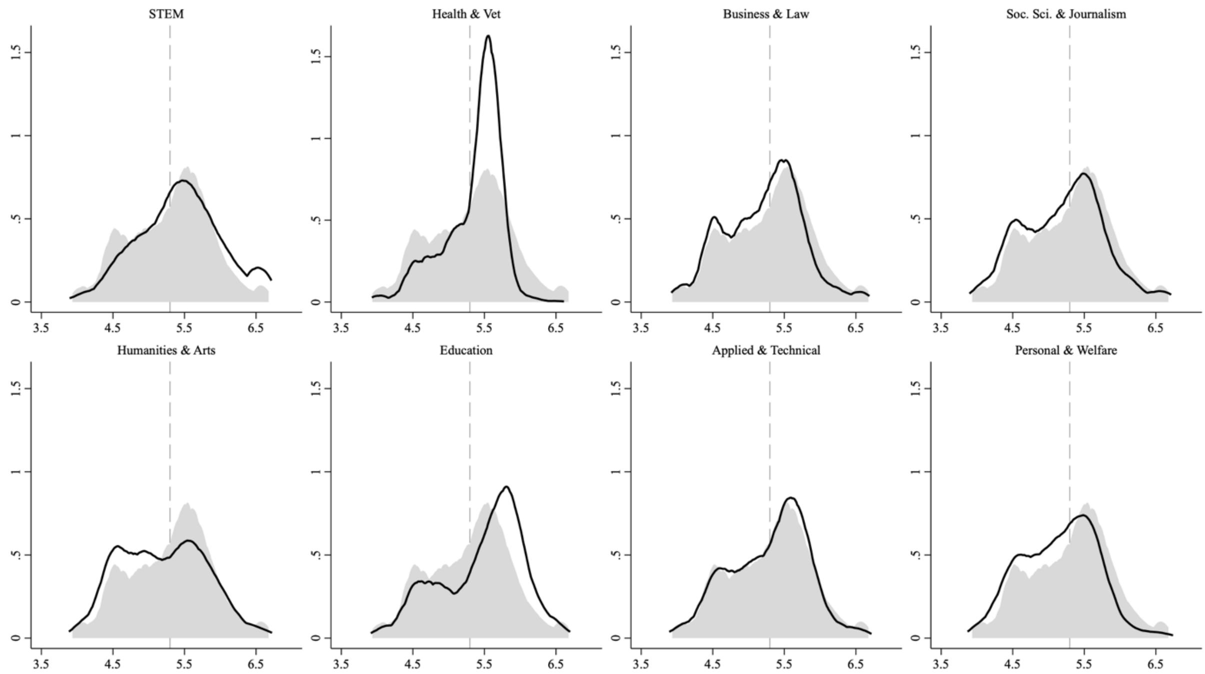
Note: N = 29,908. Unweighted sample sizes are reported; sample shares and mean hourly wages are survey-weighted. Reference category: Business & Law.

4.2. Wage Distribution by Field of Study

Figure 1 presents kernel density estimates of the log hourly wage distribution for each of the eight field-of-study groups. The figure reveals that field groups differ not only in their mean wages (as reported in Table 2) but in the shape, spread, and skewness of their entire wage distributions, providing a direct visual motivation for the quantile regression approach.

Several features emerge. The Education and STEM distributions are the most distinctly positioned, with their density mass concentrated well to the right of the overall sample mean (indicated by the vertical dashed line at 5.297 log TL per hour). The Education distribution is notably tall and narrow, reflecting the compressed wage dispersion associated with standardised public-sector pay scales. STEM, by contrast, exhibits a flatter and right-skewed distribution with a long upper tail, consistent with the concentration of high-earning engineers and ICT specialists at the top of the private-sector wage distribution. The Business and Law distribution is broad and approximately symmetric around the sample mean, reinforcing its suitability as a reference category. The Humanities and Arts and Social Sciences and Journalism distributions overlap heavily with the Business and Law distribution, providing early descriptive evidence of limited raw wage differentiation relative to the reference group. The Health and Veterinary distribution is moderately positioned, with a peak somewhat above the sample mean but without the extended upper tail characteristic of STEM. The Applied and Technical and Personal and Welfare Services groups show distributions that are compressed and positioned near or below the sample mean, respectively. Together, these distributional shapes indicate that a mean-based comparison across fields would obscure substantial within-group heterogeneity and cross-group differences in distributional form. This is precisely the type of variation that quantile regression is designed to capture.

Figure 1. Kernel Density of Log Hourly Wage by Field of Study



Note: Grey area: full sample; Black line: field group; Dashed line: sample mean. Bachelor's degree wage workers. Survey-weighted kernel densities. Source: HLFS 2024

4.3. OLS Benchmark

Table 3, Column 1 presents the OLS estimates, which provide the conditional mean wage associations for each field of study relative to the omitted reference category, Business and Law. The OLS results confirm that field of study is an important predictor of wages even after controlling for age, gender, sector, formality, full-time status, and region. STEM graduates are associated with by far the largest average conditional wage difference. The coefficient of 0.348 log points corresponds to an approximate premium of 41.6 percent [100×(exp(0.348)−1)], conditional on observed characteristics, relative to comparable Business and Law graduates. This is the strongest average field association in the model and already suggests that technical and science-oriented degrees are associated with a privileged position in the graduate wage structure.

Other fields also show positive average conditional associations. Relative to Business and Law, Applied and Technical fields are associated with a 0.117 log-point difference in hourly wages, corresponding to approximately 12.4 percent. Health and Veterinary graduates are associated with a 0.103 log-point difference, corresponding to approximately 10.9 percent, while Education graduates are associated with a 0.106 log-point difference, corresponding to approximately 11.2 percent. Social Sciences and Journalism display a comparatively modest association of 0.029 log points (approximately 2.9 percent). By contrast, Humanities and Arts and Personal and Welfare Services do not differ significantly from the reference category on average. Among the control variables, the public-sector coefficient is 0.449, corresponding to approximately 56.7 percent [100×(exp(0.449)−1)], while the formal-employment coefficient is 0.470, corresponding to approximately 60.0 percent. Female workers are associated with lower conditional hourly wages than otherwise comparable male workers, and the age and age-squared coefficients confirm the expected concave age–earnings profile.

The OLS estimates serve as a benchmark rather than the main result. Because OLS identifies only the conditional mean, it cannot reveal whether a premium is concentrated among low-wage or high-wage workers. The quantile regression results address this directly.

4.4. Quantile Regression Results

Table 3 reports the weighted quantile regression estimates at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional log hourly wage distribution. These estimates reveal much richer structure than the OLS model, because they show not only whether a field commands a wage premium relative to Business and Law, but also where in the conditional wage distribution that association is concentrated. The results suggest that field-of-study effects in Türkiye are strongly distributional rather than constant, and that the same field may be associated with very different labor market outcomes at the lower and upper conditional wage quantiles. All percentage figures reported below are computed as 100×[exp(β)−1] to convert log-point coefficients into percentage wage differences relative to Business and Law graduates at the relevant conditional quantile, holding all covariates constant.

The most striking pattern concerns STEM. The estimated conditional premium rises monotonically, from 23.4 percent at the 10th conditional quantile to 31.7 percent at the 25th, 42.3 percent at the median, 46.1 percent at the 75th, and 59.7 percent at the 90th conditional quantile. Formal inter-quantile equality tests confirm this monotone increase at every step (Table A5). Each adjacent-quantile difference is statistically significant, and the Q10–Q90 Wald test gives $\chi^2 = 49.82$ ($p < 0.001$). STEM graduates do not simply earn more on average than Business and Law graduates; rather, their relative conditional advantage becomes progressively larger at higher wage quantiles. This suggests that STEM fields are associated not only with higher average pay, but also with stronger upper-tail wage differences. The OLS-implied premium of 41.6 percent therefore conceals heterogeneity. It understates the association at the top and overstates it at the bottom.

The Health and Veterinary group displays the opposite profile. Its conditional wage association is largest at the lower end, reaching 20.0 percent at the 10th conditional quantile, before declining to 14.1 percent at Q25, 12.0 percent at Q50, 10.3 percent at Q75, and 8.1 percent at Q90. The overall Q10–Q90 difference is confirmed by formal testing ($\chi^2 = 21.98$, $p < 0.001$; Table A5). The one exception to a smooth decline is the Q50–Q75 step, where the adjacent-quantile test is not significant ($\chi^2 = 0.13$, $p = 0.720$), indicating that the decline flattens in the middle of the distribution before resuming at Q90. The field remains positively associated with wages throughout the distribution, but the advantage steadily narrows as wages rise. This declining pattern is consistent with a compressed wage structure, likely reflecting the role of regulated occupations and institutionally structured pay scales in health-related employment.

Education graduates also show positive and statistically significant conditional wage associations at all estimated quantiles, but the shape differs from both STEM and Health and Veterinary. The conditional association begins at 7.0 percent at Q10, rises to 12.9 percent at Q25 and 15.7 percent at Q50, peaks at 17.2

percent at Q75, and then declines modestly to 14.9 percent at Q90. This hump-shaped profile is formally confirmed by inter-quantile tests: the joint equality test rejects equality across all quantiles ($\chi^2 = 33.61$, $p < 0.001$), and the Q10–Q90 Wald test gives $\chi^2 = 19.20$ ($p < 0.001$). The adjacent differences from Q10 to Q25, Q25 to Q50, and Q50 to Q75 are statistically significant, while the final Q75–Q90 decline is not statistically significant ($\chi^2 = 1.73$, $p = 0.189$; Table A5). The relative conditional advantage of Education graduates is strongest in the middle-to-upper-middle part of the wage distribution rather than at the very top. A plausible interpretation is that the heavy concentration of Education graduates in public-sector employment is associated with relatively stable and predictable earnings, producing moderate conditional wage differences across most of the distribution but limiting very large upside gains at the top.

Applied and Technical graduates earn positive and significant conditional wage associations throughout the distribution, 9.8 percent at Q10, 14.6 percent at Q25, 16.0 percent at Q50, 14.0 percent at Q75, and 7.0 percent at Q90. The joint equality test across all five quantiles is statistically significant ($\chi^2 = 23.30$, $p < 0.001$; Table A5), although the Q10–Q90 difference is not statistically significant ($\chi^2 = 2.18$, $p = 0.140$). The pattern is therefore better described as an inverted-U profile rather than a simple bottom-to-top shift. This is a more moderate distributional profile than the sharp upper-tail divergence observed for STEM.

The pattern for Social Sciences and Journalism is selective. Coefficients at Q10 and Q25 are statistically insignificant. The association becomes weakly positive at the median and rises to approximately 5.5–5.8 percent at Q75 and Q90. The Q10–Q90 equality test is statistically significant ($\chi^2 = 4.52$, $p = 0.034$; Table A5), indicating that the field's relative wage position improves across the conditional distribution. This suggests that conditional wage advantages for Social Sciences and Journalism graduates emerge mainly among higher-wage workers, possibly reflecting stronger dependence on post-graduation occupational sorting.

The Humanities and Arts field stands out for a different reason. No individual quantile coefficient is statistically significant. The point estimates range from negative at the lower quantiles to near zero or slightly positive at the upper quantiles. However, the Q10–Q90 inter-quantile difference is statistically significant ($\chi^2 = 17.43$, $p < 0.001$; Table A5), indicating a distributional shift from a negative association at the bottom to a near-zero or positive association at the top. This means that while Humanities and Arts graduates do not display a clear conditional premium at any individual quantile in Table 3, their relative position is not entirely flat across the conditional distribution.

Personal and Welfare Services shows no consistent premium across the distribution. With a sample share of only 2.2 percent, estimates for this group should be interpreted with caution. The formal tests do not reject equality across quantiles for this field, and neither the Q10–Q90 test nor the joint equality test is statistically significant.

Table 3. OLS and Quantile Regression Results: Log Hourly Wage

Variable	OLS	Q10	Q25	Q50	Q75	Q90
STEM	0.348***	0.210***	0.275***	0.353***	0.379***	0.468***
	(0.014)	(0.015)	(0.011)	(0.014)	(0.017)	(0.027)
Health & Veterinary	0.103***	0.182***	0.132***	0.113***	0.098***	0.078***
	(0.012)	(0.018)	(0.012)	(0.013)	(0.014)	(0.015)
Social Sciences & Journalism	0.029**	-0.004	-0.007	0.027**	0.054***	0.057***
	(0.013)	(0.012)	(0.010)	(0.010)	(0.013)	(0.018)
Humanities & Arts	-0.022	-0.021	-0.003	0.001	0.007	0.019
	(0.014)	(0.016)	(0.012)	(0.014)	(0.014)	(0.017)
Education	0.106***	0.068***	0.121***	0.146***	0.159***	0.139***
	(0.009)	(0.013)	(0.009)	(0.009)	(0.008)	(0.012)
Applied & Technical	0.117***	0.094***	0.136***	0.149***	0.131***	0.068***
	(0.014)	(0.013)	(0.015)	(0.012)	(0.009)	(0.019)

Table 3. OLS and Quantile Regression Results: Log Hourly Wage (Continue)

Variable	OLS	Q10	Q25	Q50	Q75	Q90
Personal & Welfare Services	-0.021	0.005	-0.015	0.000	0.001	-0.036*
	(0.022)	(0.027)	(0.024)	(0.021)	(0.022)	(0.020)
Age	0.063***	0.033***	0.036***	0.055***	0.066***	0.071***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Age squared	-0.0006***	-0.0003***	-0.0003***	-0.0005***	-0.0007***	-0.0007***
	(3.69e-05)	(4.98e-05)	(4.00e-05)	(3.86e-05)	(3.56e-05)	(5.45e-05)
Female	-0.075***	-0.063***	-0.054***	-0.064***	-0.061***	-0.054***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.006)	(0.009)
Public sector	0.449***	0.646***	0.692***	0.523***	0.302***	0.116***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.012)
Formal employment	0.470***	0.419***	0.473***	0.575***	0.559***	0.387***
	(0.037)	(0.020)	(0.030)	(0.036)	(0.050)	(0.062)
Full-time	-0.342***	0.005	-0.343***	-0.409***	-0.453***	-0.463***
	(0.017)	(0.028)	(0.028)	(0.015)	(0.014)	(0.013)
Observations	29,908	29,908	29,908	29,908	29,908	29,908
Pseudo / R^2	0.329	0.214	0.270	0.235	0.170	0.147
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: N = 29,908 for all models. Standard errors are reported in parentheses. The OLS column reports robust standard errors; quantile-regression columns report Poisson weighted bootstrap standard errors based on 500 replications. Survey probability weights applied. Reference categories: Business & Law (field), West Türkiye (region), Male, Private sector, Informal, Part-time.
*** p<0.01, ** p<0.05, * p<0.10. Pseudo R^2 reported for quantile regressions.

5. Discussion

The distributional results reveal that conditional field-of-study wage associations in Türkiye are shaped by a common underlying logic. Competitive private-sector wage-setting is associated with stronger upper-tail wage differences for fields that feed into market-exposed employment, while institutional wage-setting appears to compress or stabilize associations for fields dominated by public-sector employment. The STEM conditional wage association is the clearest illustration of the first mechanism, rising from 23.4 percent at the 10th conditional quantile to 59.7 percent at the 90th conditional quantile (Table 3), with every adjacent-quantile step confirmed as statistically different (Table A5). Subsample analysis reveals that the STEM association is concentrated in private-sector employment, where the Q50 coefficient reaches 0.442, approximately 55.6 percent, compared with 0.127, approximately 13.5 percent, in the public sector (Table A7), consistent with the market-exposure mechanism. The overall public-sector share of STEM graduates is only 19.9 percent (Table A1), further supporting the interpretation that STEM wage advantages are linked to competitive private-sector wage-setting. This pattern is consistent with the international literature. Webber (2014) documents comparable patterns for science and engineering majors in the United States, and Zhang et al. (2024) confirm that returns to college degrees are systematically higher at the upper end of the earnings distribution for technical fields. Di Paolo and Tansel (2025) and Çiftçi and Ulucan (2021) provide the closest Turkish benchmarks, both finding that occupational sorting, in which STEM graduates disproportionately enter high-productivity occupational categories, is a primary channel through which field-of-study wage associations emerge.

The second mechanism, institutional compression, is consistent with the patterns for Health and Veterinary and Education graduates. Health and Veterinary conditional wage associations decline from 20.0 percent at the 10th conditional quantile to 8.1 percent at the 90th (Q10–Q90 Wald test: $\chi^2 = 21.98$, $p < 0.001$; Table A5), a pattern compatible with a wage-floor-without-ceiling structure associated with civil service scales, professional licensing boards, and collective agreements negotiated through the Ministry of Health. Notably, subsample analysis shows that the Health and Veterinary wage association is concentrated in the public sector: the field shows a positive and declining association within the public sector, from Q10 = 0.245 to Q90 = 0.028, but is largely insignificant in the private sector (Table A7). The weighted public-sector share of Health and Veterinary graduates is 76.0 percent (Table A1), the highest of any field group. Kleiner and Krueger (2013) and Kleiner and Soltas (2023) document an analogous floor-without-ceiling mechanism in the United States for regulated professions, and Kelly et al. (2010) find a comparable declining pattern for Medicine and Veterinary Science graduates in Ireland. Education conditional associations display a broadly hump-shaped profile, with 7.0 percent at the 10th conditional quantile, 17.2 percent at Q75, and 14.9 percent at Q90. The joint equality test rejects equality across quantiles, although the final Q75–Q90 decline is not statistically significant (Table A5). This pattern is compatible with the Ministry of National Education's centralized pay grids, which are associated with a relative wage floor at lower quantiles and limited upper-tail differentiation. The public-sector share of Education graduates is 71.9 percent (Table A1). Maczulskij and Pehkonen (2011) document a comparable pattern for public-sector workers in Finland, and Tansel and Acar (2016) confirm that the formal wage association in Türkiye decreases from lower to upper quantiles. For Humanities and Arts graduates, no individual quantile coefficient is statistically significant, yet the Q10–Q90 inter-quantile difference is significant ($\chi^2 = 17.43$, $p < 0.001$; Table A5), pointing to a distributional shift from a relatively disadvantaged position at the bottom to approximate parity with Business and Law graduates at the top, consistent with Altonji et al. (2012) and Webber (2014).

6. Conclusions

This study contributes to the literature on returns to higher education by providing a distributional analysis of field-of-study wage associations for bachelor's degree holders in Türkiye, using the 2024 HLFS microdata. Drawing on a sample of 29,908 employed bachelor's degree wage workers and applying weighted quantile regression at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional log hourly wage distribution, this study demonstrates that field-of-study associations are not uniform across the wage distribution. This pattern would be obscured by standard OLS analysis, which identifies only the conditional mean association.

Four main conclusions emerge. First, STEM graduates are associated with the largest and most distribution-sensitive conditional wage difference, rising monotonically from 23.4 percent at the 10th conditional quantile to 59.7 percent at the 90th, with every step confirmed by formal inter-quantile tests (Table A5) and with the conditional advantage more than doubling from the bottom to the top of the distribution. Second, conditional field-of-study wage associations are structurally shaped by sector of employment: Health and Veterinary associations are concentrated at the lower conditional quantiles (20.0 percent at Q10 declining to 8.1 percent at Q90; Q10–Q90 test: $\chi^2 = 21.98$, $p < 0.001$), and subsample analysis confirms this advantage is a predominantly public-sector phenomenon (Table A7). Education associations display a broadly hump-shaped profile, peaking at 17.2 percent at Q75 before declining to 14.9 percent at Q90. The joint equality test rejects equality across quantiles, although the final decline from Q75 to Q90 is not statistically significant (Table A5). Third, while no individual Humanities and Arts quantile coefficient is statistically significant, a significant distributional shift from negative at Q10 to near-zero positive at Q90 is confirmed ($\chi^2 = 17.43$, $p < 0.001$; Table A5), pointing to a relative disadvantage at the bottom of the wage hierarchy rather than a uniformly flat profile. Fourth, Social Sciences and Journalism graduates display an emerging conditional association that is statistically insignificant at Q10 and Q25 but rises to 5.5–5.9 percent at Q75 and Q90 ($\chi^2 = 4.52$, $p = 0.034$ for Q10 = Q90; Table A5), suggesting that associations for this field are concentrated among higher-wage workers who sort into more productive occupations.

These findings carry implications for higher education monitoring in Türkiye. CoHE sets field-specific enrolment quotas that determine the supply of graduates across disciplines. The estimated conditional wage associations provide evidence on which field groups are currently linked to higher wage outcomes, and where in the wage distribution those advantages are concentrated. It should be noted, however, that these estimates describe current conditional associations and do not forecast what would happen to wages if enrolment were expanded in any given field. Expanding STEM capacity, for example, could attenuate the current STEM wage premium through general equilibrium effects as graduate supply increases, so the current premium is not a direct basis for quota rebalancing. What the findings do support is more systematic monitoring of field-specific labor market outcomes alongside enrolment planning. The near-absence of a conditional Humanities and Arts wage association across the entire distribution, and not merely at the mean, provides one input into curriculum review in these fields, though curriculum reform decisions appropriately rest on broader considerations than wage associations alone.

For students and career counsellors, the findings underscore that field choice is associated with different wage profiles that are not fully visible from mean-based statistics. The distributional evidence suggests that STEM is associated with stronger upper-tail wage differences, while Health and Education are associated with more favorable positions at lower and middle conditional quantiles. These patterns can inform career guidance, but they should not be interpreted as deterministic outcomes for individual students, since realized wages also depend on occupation, sector, region, ability, preferences, and labor market conditions.

Several limitations should be noted. First, the cross-sectional design precludes causal inference. Selection into field of study on unobserved ability, family background, university quality, and career preferences is likely to bias the estimated associations; the direction of the bias depends on the field, and the estimated associations should be read as conditional correlations rather than causal returns to field choice. Second, the exclusion of postgraduate degree holders, which was necessitated by the structure of the HLFS education variable, may introduce selection bias. If STEM graduates continue to postgraduate education at higher rates and if postgraduate-qualified STEM workers earn more than bachelor-qualified STEM workers, the estimated STEM association would be biased downward, since the higher-earning postgraduate STEM graduates are excluded from the sample. The direction of this bias is less clear for Education and Health graduates, where postgraduate continuation rates are also non-trivial, but wage compression is more pronounced. Overall, the estimated STEM association in this study may represent a lower bound on the true field-of-study wage difference for STEM graduates in the total graduate workforce. Third, the analysis is restricted to wage and salary workers and therefore cannot speak to self-employment or entrepreneurial returns to field of study, which may be particularly relevant for applied and technical fields. The robustness of the main findings to the treatment of part-time workers is confirmed in Table A8, which replicates the quantile regression estimates for the subsample of full-time workers only (n = 27,749) and shows substantively unchanged field-of-study patterns. Fourth, although the HLFS contains additional labor market and demographic information, the baseline specification is kept parsimonious to focus on conditional field-of-study differences among bachelor's degree wage workers. The absence of tenure, firm size, marital status, and more detailed regional controls is therefore another limitation of the analysis, and future work could examine whether the estimated field associations change after incorporating these additional controls. Future research using panel data or credible sources of exogenous variation in field choice would strengthen the causal interpretation of these associations. An extension examining the interaction between field of study and regional labor-market conditions would also be valuable, given the large regional wage disparities documented in the descriptive analysis. Similarly, replicating the analysis across HLFS waves from 2021 onward would allow distributional field-of-study associations to be tracked over time as Turkish higher education and labor-market structures continue to evolve.

Declarations and Disclosures

Ethical Responsibilities of Authors: The author of this article confirms that her work complies with the principles of research and publication ethics.

Conflicts of Interest: No potential conflict of interest was reported by the author.

Funding: The author received no financial support for the preparation and/or publication of this article.

Author Contributions: The author confirms sole responsibility for conceptualization and design, data collection, analysis of data and interpretation of results, writing the first draft of the manuscript, and review and editing.

Plagiarism Checking: This article was screened for potential plagiarism using a plagiarism screening program.

Acknowledgements

The author thanks the Turkish Statistical Institute (TurkStat) for making the 2024 Household Labour Force Survey micro data available upon application.

Data Availability Statement

The HLFS 2024 micro data are available to researchers upon application to TurkStat at https://www.tuik.gov.tr/Kurumsal/Mikro_Veri. The Stata do-file used for all analyses is available from the corresponding author upon reasonable request.

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Appendix

Table A1. Weighted Public-Sector Shares by Field

Field group	Weighted % public
STEM	19.9%
Health & Veterinary	76.0%
Business & Law	40.2%
Social Sciences & Journalism	35.8%
Humanities & Arts	47.2%
Education	71.9%
Applied & Technical	37.9%
Personal & Welfare Services	42.4%

Table A2. Robustness: Alternative Winsorization (p0.5-p99.5)

	(1)	(2)	(3)	(4)	(5)	(6)
		QUARTILES				
Variables	OLS	Q10	Q25	Q50	Q75	Q90
STEM (Eng, ICT, Maths, Sciences)	0.353***	0.215***	0.278***	0.353***	0.380***	0.466***
	(0.0141)	(0.0168)	(0.0151)	(0.0165)	(0.0168)	(0.0284)
Health & Veterinary	0.106***	0.177***	0.134***	0.113***	0.0981***	0.0787***
	(0.0124)	(0.0203)	(0.0142)	(0.0138)	(0.0149)	(0.0166)
Social Sciences & Journalism	0.0292**	-0.00806	-0.00499	0.0265*	0.0539***	0.0543**
	(0.0134)	(0.0126)	(0.0154)	(0.0141)	(0.0151)	(0.0227)
Humanities & Arts	-0.0207	-0.0206	-0.00260	0.000566	0.00666	0.0173
	(0.0141)	(0.0216)	(0.0168)	(0.0150)	(0.0190)	(0.0207)
Education	0.106***	0.0688***	0.123***	0.146***	0.158***	0.141***
	(0.00934)	(0.0163)	(0.0110)	(0.00953)	(0.00890)	(0.0131)
Applied & Technical	0.118***	0.0936***	0.139***	0.149***	0.131***	0.0657***
	(0.0142)	(0.0166)	(0.0167)	(0.0137)	(0.00838)	(0.0200)
Personal & Welfare Services	-0.0194	0.00603	-0.00947	-0.000170	0.000524	-0.0354*
	(0.0222)	(0.0241)	(0.0281)	(0.0230)	(0.0254)	(0.0207)
Constant	3.484***	3.092***	3.559***	3.579***	3.809***	4.245***
	(0.0716)	(0.0881)	(0.0914)	(0.0736)	(0.0962)	(0.0875)
Observations	29,908	29,908	29,908	29,908	29,908	29,908
R-squared	0.325					

Table A3. Detailed ISCED-F 2013 Codes, Grouped Field Codes, and Frequencies

Detailed ISCED-F code	Grouped field code	Number of Observations
1	6	7885
2	5	560
3	5	1202
4	5	637
5	4	2819
6	4	164
7	3	8668
8	3	424
9	1	197
10	1	538
11	1	267
12	1	76
13	1	2086
14	7	330
15	7	777
16	7	626
17	2	28
18	2	1624
19	8	202
20	8	448
21	7	54
22	7	296

Table A4. Sensitivity: Business and Law as Separate Categories

	(1)	(2)	(3)	(4)	(5)	(6)
		QUARTILES				
Variables	OLS	Q10	Q25	Q50	Q75	Q90
STEM (Eng, ICT, Maths, Sciences)	0.361***	0.220***	0.284***	0.368***	0.395***	0.491***
	(0.0138)	(0.0149)	(0.0150)	(0.0165)	(0.0168)	(0.0279)
Health & Veterinary	0.118***	0.188***	0.137***	0.128***	0.119***	0.113***
	(0.0123)	(0.0190)	(0.0145)	(0.0141)	(0.0153)	(0.0136)
Law (ISCEDF13==8)	0.214***	0.173***	0.199***	0.228***	0.322***	0.338***
	(0.0293)	(0.0300)	(0.0414)	(0.0232)	(0.0310)	(0.0661)
Social Sciences & Journalism	0.0416***	0.00267	0.00344	0.0420***	0.0707***	0.0835***
	(0.0132)	(0.0106)	(0.0150)	(0.0136)	(0.0143)	(0.0225)
Humanities & Arts	-0.00830	-0.0124	0.00479	0.0146	0.0219	0.0503**
	(0.0139)	(0.0170)	(0.0162)	(0.0150)	(0.0197)	(0.0195)
Education	0.119***	0.0737***	0.128***	0.161***	0.174***	0.171***
	(0.00925)	(0.0164)	(0.0106)	(0.00966)	(0.00851)	(0.0121)
Applied & Technical	0.130***	0.0999***	0.145***	0.163***	0.146***	0.0947***
	(0.0140)	(0.0146)	(0.0160)	(0.0131)	(0.00808)	(0.0201)
Personal & Welfare Services	-0.00740	0.0128	-0.000947	0.0141	0.0128	-0.00180
	(0.0221)	(0.0225)	(0.0232)	(0.0223)	(0.0281)	(0.0122)
Constant	3.478***	3.187***	3.521***	3.558***	3.695***	4.163***
	(0.0696)	(0.0749)	(0.0751)	(0.0723)	(0.0836)	(0.0858)
Observations	29,908	29,908	29,908	29,908	29,908	29,908
R-squared	0.331					

Table A5. Formal Cross-Quantile Equality Tests

Field group	Hypothesis	Chi-squared	p-value	Sig.
FIELD_APPLIED	All quantiles equal	23.302	0.0001	***
FIELD_APPLIED	Q10 = Q90	2.179	0.1399	
FIELD_EDUC	All quantiles equal	33.612	0.0000	***
FIELD_EDUC	Q10 = Q25	14.839	0.0001	***
FIELD_EDUC	Q10 = Q90	19.204	0.0000	***
FIELD_EDUC	Q25 = Q50	7.624	0.0058	***
FIELD_EDUC	Q50 = Q75	8.811	0.003	***
FIELD_EDUC	Q75 = Q90	1.728	0.1887	
FIELD_HEALTH	All quantiles equal	25.702	0.0000	***
FIELD_HEALTH	Q10 = Q25	6.974	0.0083	***
FIELD_HEALTH	Q10 = Q90	21.982	0.0000	***
FIELD_HEALTH	Q25 = Q50	11.193	0.0008	***
FIELD_HEALTH	Q50 = Q75	.129	0.7196	
FIELD_HEALTH	Q75 = Q90	5.725	0.0167	**
FIELD_HUMARTS	All quantiles equal	18.888	0.0008	***
FIELD_HUMARTS	Q10 = Q90	17.434	0.0000	***
FIELD_SOCSCI	All quantiles equal	12.595	0.0134	**
FIELD_SOCSCI	Q10 = Q90	4.517	0.0336	**
FIELD_STEM	All quantiles equal	69.526	0.0000	***
FIELD_STEM	Q10 = Q25	12.211	0.0005	***
FIELD_STEM	Q10 = Q90	49.817	0.0000	***
FIELD_STEM	Q25 = Q50	35.325	0.0000	***
FIELD_STEM	Q50 = Q75	8.571	0.0034	***
FIELD_STEM	Q75 = Q90	4.8	0.0285	**
FIELD_WELFARE	All quantiles equal	1.161	0.8845	
FIELD_WELFARE	Q10 = Q90	.119	0.7305	

Wald tests based on simultaneous quantile regression (sqreg, 500 bootstrap replications). H0 for Q10 = Q90: the field-of-study coefficient at Q10 equals the coefficient at Q90. H0 for all-quantiles tests: coefficients are equal across all five quantiles (Q10, Q25, Q50, Q75, Q90). H0 for adjacent tests: coefficients at adjacent quantiles are equal. Reference category: Business and Law graduates. * p<0.10 ** p<0.05 *** p<0.01

Table A6. Robustness: Occupation and Industry Controls

Panel A. OLS, Q10 and Q25

Variable	Baseline OLS	OLS + Occ + Ind	Baseline Q10	Q10 + Occ + Ind	Baseline Q25	Q25 + Occ + Ind
STEM (Eng, ICT, Maths, Sciences)	0.348***	0.216***	0.210***	0.147***	0.275***	0.137***
	(0.0137)	(0.0137)	(0.0168)	(0.0137)	(0.0151)	(0.0152)
Health & Veterinary	0.103***	0.0300**	0.182***	0.0836***	0.132***	0.0139
	(0.0122)	(0.0127)	(0.0209)	(0.0172)	(0.0140)	(0.0146)
Social Sciences & Journalism	0.0287**	0.0107	-0.00419	-0.00955	-0.00667	-0.0118
	(0.0131)	(0.0118)	(0.0125)	(0.0118)	(0.0145)	(0.0126)
Humanities & Arts	-0.0217	-0.0554***	-0.0207	-0.0461**	-0.00281	-0.0446***
	(0.0138)	(0.0137)	(0.0201)	(0.0233)	(0.0156)	(0.0137)
Education	0.106***	0.0468***	0.0679***	0.0237	0.121***	0.0234**
	(0.00918)	(0.00961)	(0.0166)	(0.0146)	(0.0109)	(0.0105)
Applied & Technical	0.117***	0.0344**	0.0939***	0.0266	0.136***	0.0396**
	(0.0140)	(0.0141)	(0.0147)	(0.0253)	(0.0170)	(0.0155)
Personal & Welfare Services	-0.0206	-0.0302	0.00477	0.0104	-0.0145	-0.0299
	(0.0221)	(0.0212)	(0.0218)	(0.0253)	(0.0280)	(0.0187)
Constant	3.535***	4.056***	3.225***	3.280***	3.669***	3.898***
	(0.0689)	(0.0797)	(0.0780)	(0.121)	(0.0789)	(0.0863)
Observations	29,908	29,908	29,908	29,908	29,908	29,908
R-squared	0.329	0.421				
Occ FE	No	Yes	No	Yes	No	Yes
Ind FE	No	Yes	No	Yes	No	Yes

Panel A. Q50, Q75 and Q90

Variable	Baseline Q50	Q50 + Occ + Ind	Baseline Q75	Q75 + Occ + Ind	Baseline Q90	Q90 + Occ + Ind
STEM (Eng, ICT, Maths, Sciences)	0.353***	0.170***	0.379***	0.233***	0.468***	0.271***
	(0.0165)	(0.0140)	(0.0168)	(0.0183)	(0.0286)	(0.0196)
Health & Veterinary	0.113***	-0.000660	0.0983***	0.00317	0.0775***	-0.0158
	(0.0138)	(0.0134)	(0.0151)	(0.0149)	(0.0162)	(0.0136)
Social Sciences & Journalism	0.0265*	0.0111	0.0538***	0.0111	0.0565**	0.0170
	(0.0141)	(0.0112)	(0.0153)	(0.0121)	(0.0231)	(0.0136)
Humanities & Arts	0.000566	-0.0574***	0.00702	-0.0412**	0.0188	0.00154
	(0.0150)	(0.0111)	(0.0191)	(0.0189)	(0.0195)	(0.0210)
Education	0.146***	0.0479***	0.159***	0.0716***	0.139***	0.0809***
	(0.00953)	(0.00853)	(0.00891)	(0.00986)	(0.0130)	(0.0106)
Applied & Technical	0.149***	0.0348***	0.131***	0.0494***	0.0679***	0.0406***
	(0.0137)	(0.0132)	(0.00844)	(0.0138)	(0.0198)	(0.0132)
Personal & Welfare Services	-0.000170	-5.59e-05	0.000515	-0.0324*	-0.0357**	-0.0716**
	(0.0230)	(0.0216)	(0.0253)	(0.0192)	(0.0170)	(0.0347)
Constant	3.579***	4.256***	3.802***	4.589***	4.236***	5.009***
	(0.0736)	(0.0821)	(0.0958)	(0.116)	(0.0834)	(0.112)
Observations	29,908	29,908	29,908	29,908	29,908	29,908
R-squared						
Occ FE	No	Yes	No	Yes	No	Yes
Ind FE	No	Yes	No	Yes	No	Yes

Table A7. Quantile Regression by Sector of Employment

Panel A. Public sector

Variable	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
STEM (Eng, ICT, Maths, Sciences)	0.141***	0.114***	0.127***	0.132***	0.137***
	(0.0448)	(0.0146)	(0.0145)	(0.0177)	(0.0212)
Health & Veterinary	0.245***	0.144***	0.0935***	0.0543***	0.0276**
	(0.0183)	(0.0124)	(0.0102)	(0.0102)	(0.0121)
Social Sciences & Journalism	-0.00256	-0.0110	0.0105	0.0124	0.0408**
	(0.0236)	(0.0139)	(0.0131)	(0.0128)	(0.0200)
Humanities & Arts	-0.0380	-0.00881	0.0572***	0.0817***	0.112***
	(0.0309)	(0.0213)	(0.0136)	(0.0151)	(0.0193)
Education	0.139***	0.173***	0.190***	0.201***	0.193***
	(0.0190)	(0.0120)	(0.00870)	(0.00786)	(0.0105)
Applied & Technical	0.162***	0.149***	0.140***	0.134***	0.123***
	(0.0211)	(0.0153)	(0.0103)	(0.0125)	(0.0131)
Personal & Welfare Services	-0.0368	-0.0362	-0.00319	-0.0124	-0.0206**
	(0.0667)	(0.0304)	(0.0196)	(0.0127)	(0.00943)
Constant	3.070***	3.945	4.519	4.690	4.729***
	(0.115)	(0)	(0)	(0)	(0.0669)
Observations	17,011	17,011	17,011	17,011	17,011

Panel B. Private sector

Variable	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
STEM (Eng, ICT, Maths, Sciences)	0.202***	0.371***	0.442***	0.444***	0.462***
	(0.0204)	(0.0210)	(0.0191)	(0.0245)	(0.0257)
Health & Veterinary	0.0266	0.0671***	0.0529	-0.0283	-0.0877
	(0.0322)	(0.0207)	(0.0565)	(0.0256)	(0.0935)
Social Sciences & Journalism	-0.0378***	-0.0134	0.0607**	0.0403	0.0503
	(0.0114)	(0.0157)	(0.0257)	(0.0278)	(0.0422)
Humanities & Arts	-0.00761	-0.0213	-0.0504**	-0.111***	-0.123**
	(0.0179)	(0.0135)	(0.0224)	(0.0305)	(0.0622)
Education	-0.000879	0.0111	-0.0360*	-0.0931***	-0.108***
	(0.0198)	(0.0115)	(0.0212)	(0.0229)	(0.0346)
Applied & Technical	0.0413**	0.106***	0.168***	0.109***	0.0517
	(0.0194)	(0.0263)	(0.0258)	(0.0279)	(0.0347)
Personal & Welfare Services	-0.0170	0.0122	0.0132	-0.0186	-0.0664
	(0.0297)	(0.0260)	(0.0384)	(0.0566)	(0.0413)
Constant	3.574***	3.515***	3.563***	3.544***	3.697***
	(0.0967)	(0.0724)	(0.135)	(0.140)	(0.168)
Observations	12,897	12,897	12,897	12,897	12,897

Table A8. Robustness: Full-Time Workers Only

	(1)	(2)	(3)	(4)	(5)	(6)
		QUARTILES				
Variables	OLS	Q10	Q25	Q50	Q75	Q90
STEM (Eng, ICT, Maths, Sciences)	0.351***	0.204***	0.283***	0.361***	0.387***	0.474***
	(0.0138)	(0.0177)	(0.0159)	(0.0167)	(0.0197)	(0.0275)
Health & Veterinary	0.104***	0.173***	0.132***	0.117***	0.103***	0.0796***
	(0.0122)	(0.0206)	(0.0139)	(0.0145)	(0.0152)	(0.0176)
Social Sciences & Journalism	0.0331**	-0.00783	-0.00114	0.0308**	0.0578***	0.0594***
	(0.0131)	(0.0126)	(0.0126)	(0.0139)	(0.0158)	(0.0211)
Humanities & Arts	-0.0279**	-0.00965	-0.00727	-0.00479	-0.00712	0.0132
	(0.0138)	(0.0180)	(0.0151)	(0.0154)	(0.0190)	(0.0241)
Education	0.0948***	0.0430**	0.104***	0.141***	0.164***	0.153***
	(0.00912)	(0.0167)	(0.0108)	(0.0100)	(0.00932)	(0.0131)
Applied & Technical	0.121***	0.0965***	0.143***	0.156***	0.135***	0.0693***
	(0.0139)	(0.0177)	(0.0179)	(0.0136)	(0.00855)	(0.0187)
Personal & Welfare Services	-0.0124	-0.000	0.00114	0.00692	0.00338	-0.0216
	(0.0222)	(0.0291)	(0.0221)	(0.0214)	(0.0267)	(0.0289)
Constant	3.193***	3.338***	3.409***	3.210***	3.221***	3.595***
	(0.0653)	(0.0832)	(0.0605)	(0.0694)	(0.0910)	(0.188)
Observations	27,749	27,749	27,749	27,749	27,749	27,749
R-squared	0.308					

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