Wage differentials by fields of study among college graduates in Turkey: a decomposition analysis

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Abstract

Purpose – This paper analyzes the drivers of wage differences among male college graduates who hold a degree in a different field of study. We focus on Turkey, an emerging country that is characterized by a recent sustained expansion of higher education.

Design/methodology/approach – We first estimate conditional wage gaps by field of study using OLS regressions. Average differentials are subsequently decomposed into the contribution of observable characteristics (endowment) and unexplained factors (returns). Next, we shed light on wage disparities by field of study along the wage distribution using unconditional quantile regression, by decomposing the wage gaps by fields of study by applying the Recentered Influence Function regression and decomposing the contribution of explained and unexplained factors in accounting for wage gaps along the whole distribution.

Findings – The results indicate the existence of important wage differences by field of study, which are especially high for the fields of law and health. Wage differentials by college majors are mostly driven by differences in endowments (especially occupation and, to a lesser extent, employment sector). The share of wage differentials that can be attributed to differences in observable characteristics of workers with degrees in different fields of study varies along the unconditional wage distribution.

Originality/value – This is the first study analyzing wage differentials by fields of study in Turkey using average and distributional decomposition techniques.

Keywords Fields of study, Wage differentials, Decomposition, Unconditional quantile regression, Turkey

Paper type Research paper

1. Introduction

This paper investigates the determinants of both average and distributional wage gaps among university graduates across different fields of study. Using regression models and decomposition methods, we explore the extent to which individual, family, and job characteristics contribute to wage differentials across college majors. There is extensive

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evidence about wage disparities across college majors, which generally reflect differences in labor market demand and the way the labor market rewards the distinct skills and other attributes associated with degrees from different fields (see Altonji *et al.*, 2016, Patnaik *et al.*, 2021; Lovenheim and Smith, 2023 for recent overviews).

Quantifying wage differences across fields of study is important for several reasons. First, relative wage disparities among university majors are likely to influence students' choices when selecting their field of study (see Berger, 1988; Montmarquette *et al.*, 2002; Bhattacharya, 2005; Beffy *et al.*, 2012; Long *et al.*, 2015, among others). Therefore, providing evidence on earnings gaps across fields of study would be valuable for prospective university students (and their parents) when making decisions about college majors. Moreover, recent evidence suggests that prospective university students base their decisions about college majors not only on expected earnings profiles associated with different degrees from various fields. In addition to individual traits such as preferences and risk aversion (see Wiswall and Zafar, 2015; Patnaik *et al.*, 2022, among others), job-related and non-job-related features linked to different fields of study are important determinants of this choice (Ersoy and Speer, 2025). Consequently, disentangling the mechanisms behind wage differentials across fields of study is crucial for designing more effective and comprehensive information campaigns to guide future university students.

Second, providing evidence on the factors that explain wage differences across fields of study is particularly relevant for broader tertiary education policies. Such evidence can help allocate economic resources efficiently across university programs, establish admission criteria for degrees in different fields, and set tuition fees and scholarships, all with the goal of increasing (or reducing) enrollment in specific majors. In fact, wage differences across college majors often reflect mismatches between the skills acquired in certain fields of study and the demand for those skills in the labor market (Lemieux, 2014; Cassidy and Gaulke, 2024). This issue is especially relevant in the context of a sustained expansion of tertiary education, as seen in many developed and emerging countries, where the supply of university graduates from various fields plays a crucial role in shaping the skill composition of the future workforce (Altonji *et al.*, 2014). Its efficient allocation in the economy is a fundamental aspect for ensuring a sustainable pattern of economic growth and development. Understanding the determinants of wage disparities by field of study can help policymakers address skill shortages in critical sectors. This is important not only for sectors where wages may not reflect the social value of the work (e.g. teaching or nursing), but also considering the growing importance of technological change and innovation, which increases the demand for technical skills in the economy. Finally, examining the underlying factors driving wage gaps between fields can contribute to a broader understanding of the sources of income inequality and social mobility.

We consider the case of Turkey, a developing country that has been characterized by a significant expansion of tertiary education over the last decades. The high and increasing demand for university education in Turkey is mainly due to the substantially high returns to tertiary education, compared to lower levels of schooling (Patrinos *et al.*, 2021). Moreover, the Turkish case is especially relevant, since access to university is determined by a highly selective centralized university entrance examination. Its results determine the final placement of applicants across different fields, degrees, and universities (see Caner and Okten, 2010; Frisancho *et al.*, 2016). The evidence presented in this paper could be directly useful for Turkish higher education administrators, as it can serve as a foundation for optimally setting the university entrance examination cut-off points for different disciplines. More broadly, this is the first paper examining wage differences across fields of study in Middle East and North Africa (MENA) countries and, most importantly, the first providing evidence on the role of individual, family, and job characteristics in explaining these wage differentials.

For the empirical analysis, we draw on data from the Turkish Household Labor Force Survey (HLFS), covering the period 2009–2015. We retain only university graduates who are regularly employed as wage earners and focus on males to minimize potential issues related to self-selection into labor market participation and employment. We estimate wage regressions augmented with field of study indicators and a comprehensive set of individual, family, and job characteristics, which are likely to act as mediating factors in the relationship between fields of study and wages. This approach is consistent with common practices in studies using decomposition methods (e.g. Firpo *et al.*, 2018). The full model is then used to investigate the factors driving the raw wage gaps across college majors by performing the Oaxaca-Blinder decomposition for average outcomes. This allows us to disentangle wage differentials across college majors into the component explained by compositional differences in observable characteristics and the component driven by unexplained differences.

Subsequently, we decompose distributional wage differentials by fields of study using the Unconditional Quantile Regression (UQR) approach and the corresponding decomposition proposed by Firpo *et al.* (2007, 2009). This represents a key innovation in our work, as both policymakers and students are likely to be more interested in the relative returns to different college majors along the unconditional wage distribution. However, to the best of our knowledge, no existing studies have used this distributional decomposition along the unconditional wage distribution to investigate the determinants of wage differentials by fields of study.

It is important to recognize that our approach remains subject to one of the main challenges in estimating the wage effect of holding a degree in a specific major: the issue of self-selection into different disciplines based on unobservable characteristics. Given the impossibility of addressing selection issues as done in recent studies (e.g. Hastings *et al.*, 2013; Kirkebøen *et al.*, 2016), we are forced to rely on conditional correlations (as is common in related literature) and to interpret the unexplained component of wage differentials across fields as a composite effect of returns to observable characteristics and selection on unobservable characteristics. The rest of the paper proceeds as follows: in Section 2 we briefly review of the relevant literature. Section 3 describes the data and the methodology. Section 4 presents the results and Section 5 contains discussions and conclusions.

2. Brief review of the literature

There is a large and growing body of research quantifying earnings differentials among university graduates from different fields of study. Most of the existing literature focuses on the U.S. and has been recently summarized by Altonji *et al.* (2016), Patnaik *et al.* (2021), and Lovenheim and Smith (2023). Therefore, for the shake of brevity, in this section we provide a brief review of existing papers that provide evidence for other countries, especially those that are more closely related to our work.

Some authors have analyzed the heterogeneity in returns to university degrees across fields of study relative to high school graduates. For example, Bratti *et al.* (2008) used data from the British Cohort Study to examine average wage differences across broad academic disciplines. They found heterogeneous returns, with graduates in science, social sciences, and arts and humanities experiencing different outcomes. Among these, arts and humanities graduates received the lowest returns compared to individuals who obtained A-level qualifications in high school and could have pursued higher education. Similarly, using Labour Force Survey data for the UK, Walker and Zhu (2011) found positive wage returns for women, with no significant differences across broad fields of study. In contrast, for men, they identified substantial positive returns only for degrees in law, economics, and management.

An alternative perspective is the analysis of average wage differentials among university graduates, as considered by other authors. For example, Finnie and Frenette (2003) examined earnings differences across fields of study using cross-sectional data on Canadian college and university graduates from three successive cohorts. They found substantial earnings gaps across majors, which narrowed but remained significant after controlling for occupation and industry. Specifically, they reported higher conditional earnings for graduates in health, engineering and computer science, commerce, and mathematics/physics, lower earnings for those in arts and humanities, agricultural/biological sciences, and other social sciences, while graduates in education and economics fell between these two groups. Buonanno and Pozzoli (2009) used 2004 survey data of Italian university graduates to analyze differences in employability and early career wages across fields of study. They found that graduates in sciences, engineering, and economics had better employment prospects and higher earnings, while those with degrees in humanities and certain social science fields earned lower wages than graduates in other disciplines. More recently, Tran and Van Vu (2020) analyzed wage differences across fields of study among university graduates in Vietnam using 2018 Labour Force Survey data. To our knowledge, this is the only study examining average wage differentials by field of study in a developing country. In contrast to most findings from developed countries, they reported lower wages for several technical and quantitative degrees (e.g. engineering, science, mathematics, computer science, and business and finance) compared to arts and humanities, which served as the reference category in their analysis. Conversely, male graduates in education and pedagogy, other services, health and medicine, and especially defense and security earned higher wages than their counterparts with degrees in arts and humanities.

Other studies have analyzed wage differences not only across fields of study, but also over the conditional wage distribution using quantile regression models. Specifically, Kelly *et al.* (2010) focused on Irish university graduates and found that those with degrees in Medicine and Veterinary Science, and Education, earned substantially higher wages compared to graduates in Arts and Humanities (the reference field). Lower but still positive returns were found for graduates in Social Sciences, Engineering and Architecture, Science, and Computer Science. Moreover, while the estimated wage gap decreased along the conditional wage distribution for several fields (relative to Arts and Humanities), this was not the case for Medicine and Veterinary Science. Chevalier (2011) used data from a cohort of graduates who obtained their university degrees in 2003 from British higher education institutions. He obtained significant differentials in wages by fields of study and confirmed the high return for the field of Medicine across the entire conditional wage distribution (relative to graduates in Physics), with a slightly lower return at the top of the distribution. He also reported higher returns for Education at the lower end of the distribution. Moreover, Livanos and Pouliakas (2011) analyzed distributional wage differences by field of study among Greek university graduates, relative to secondary education graduates, using Labour Force Survey data from 2002 and 2003. They also examined differences in returns to degrees across public and private sectors. Their results again highlight significant heterogeneity across fields of study and the conditional wage distribution, as well as sectoral differences.

Finally, to the best of our knowledge, only two studies have adopted a decomposition approach to investigate the underlying channels behind wage differences by college majors. First, Grave and Goerlitz (2012) focused on German university graduates and decomposed average differences in wages right after graduation and after 5/6 years using the Oaxaca-Blinder decomposition, considering broad academic disciplines. They found that observed differences in job characteristics are important drivers of wage differentials, particularly several years after graduation, while individual and academic characteristics also play a role. Furthermore, they highlighted the relevance of overeducation in explaining the average wage gap among university graduates from different fields of study. Second, Lemieux (2014) decomposed the average wage gap between high school and university graduates in Canada. The results highlight not only significant differences by college major but also the importance of occupational differences and the alignment between occupation and field of study in contributing to the return on university education.

Building on existing works, this paper contributes to the literature in several ways: first, it provides results for Turkey, expanding the limited evidence from emerging countries. Second, and most importantly, it introduces a distributional approach using a decomposition method for unconditional wage differentials by field of study, a method not previously applied. Indeed, previous studies on distributional wage differences by field of study have focused on conditional quantile regressions, and none of the existing works that adopt a decomposition approach have analyzed differences across the unconditional wage distribution.

3. Data, descriptive statistics and methods

The empirical analysis is based on annual repeated cross-sections of data from the Turkish Household Labor Force Survey (HLFS), covering the period 2009–2015, carried out by the Turkish

Statistical Institute (TURKSTAT). Although the HLFS database is also available for previous years, 2009 is the first wave including information about the field of study. The survey originally included 20 different categories for fields of study (plus one category for military/police career studies [1]). We regrouped them into 15 categories due to small sample sizes in some fields in the original classification. Details about the definition of fields of study are reported in Appendix A.

We select only tertiary educated males with age comprised between 23 and 65, who are not in education and are regularly employed as wage-earners at the time of the survey. The choice of considering only males is aimed at minimizing possible issues of endogenous self-selection of individuals into regular employment, which could be present even among tertiary educated individuals and possibly related to the field of study [2]. We retain only individuals employed full-time who work no less than 30 h and no more than 72 h per week. Observations with real monthly wages (in 2010 prices) lower than 600 Turkish Liras (TL) are discarded, which implies eliminating individuals who earn a salary lower than the minimum wage set in 2010. Migrants and Turkish returning emigrants who returned after completing tertiary education are also excluded from the analysis. After cleaning for missing values, we end up with a pooled sample of 77,154 observations.

Our dependent variable is the log of real hourly wages from the main job in terms of 2010 prices. The database contains information on monthly wages, which are net of taxes and include extra compensations, such as bonuses and premiums in addition to the salary. To construct hourly wages, we exploit the information on "typical" hours of work per week, which are converted into monthly hours of work by applying a factor of 4.3. The distribution of college majors across survey waves, as well as for the pooled sample (2009–2015) is reported in Table A1 of Appendix B. Full descriptive statistics of all the variables used in the empirical analysis are displayed in Table A2 of Appendix B.

Kernel density estimates of the (log) hourly real wage by fields of study are reported in Figure 1. To facilitate the visualization of distributional wage differences across different fields of study, we present two graphs. Figure 1a presents the results for the broad areas of humanities and social sciences. Figure 1b presents the results for hard sciences, technical disciplines, and health-related fields.

The former figure shows that the wage distribution in the fields of education and humanities are very concentrated around the mean (log) hourly wage of about 2.3 (which corresponds to an average real hourly wage of about 10 TL). Graduates in arts and, to a lesser extent, in personal services and business and management are the least paid, since they are mostly represented in the lowest tail of the hourly wage distribution. Graduates in (other) social sciences and services fall in an intermediate position, whereas graduates in law display a wage distribution that is significantly shifted towards the right tail indicating that law is a highly rewarded field (at least without conditioning for individual characteristics). Figure 1b indicates that graduates in computing, manufacturing, and engineering are more represented in the lower part of the unconditional hourly wage distribution. In contrast, those who studied for a degree in hard sciences, mathematics and statistics, architecture, and agriculture and veterinary are placed in an intermediate position and their wages are mostly concentrated around the mean. Like the case of law, the hourly wage distribution of graduates in health disciplines is significantly shifted towards the right, with an important proportion of observations concentrated at the top of the overall unconditional hourly wage distribution. The analysis of the unconditional wage distribution by field of study reveals that different degrees are unevenly rewarded in the labor market. Moreover, wage differences across fields operate not only at the average, but also along the wage distribution. In the next section we investigate the drivers of such average and distributional wage differentials by fields of study using decomposition tools. As detailed in Online Appendix C, we begin by estimating an OLS regression for (logged) real hourly wages, initially including field of study dummies and progressively incorporating various individual and job-related characteristics. The fully specified model serves as the basis for the decomposition analysis. First, we apply the Oaxaca-Blinder decomposition to examine average wage differentials, allowing us to disentangle the contributions of differences in observable endowments and their associated coefficients to the observed wage gaps across fields of study. Second, we perform a

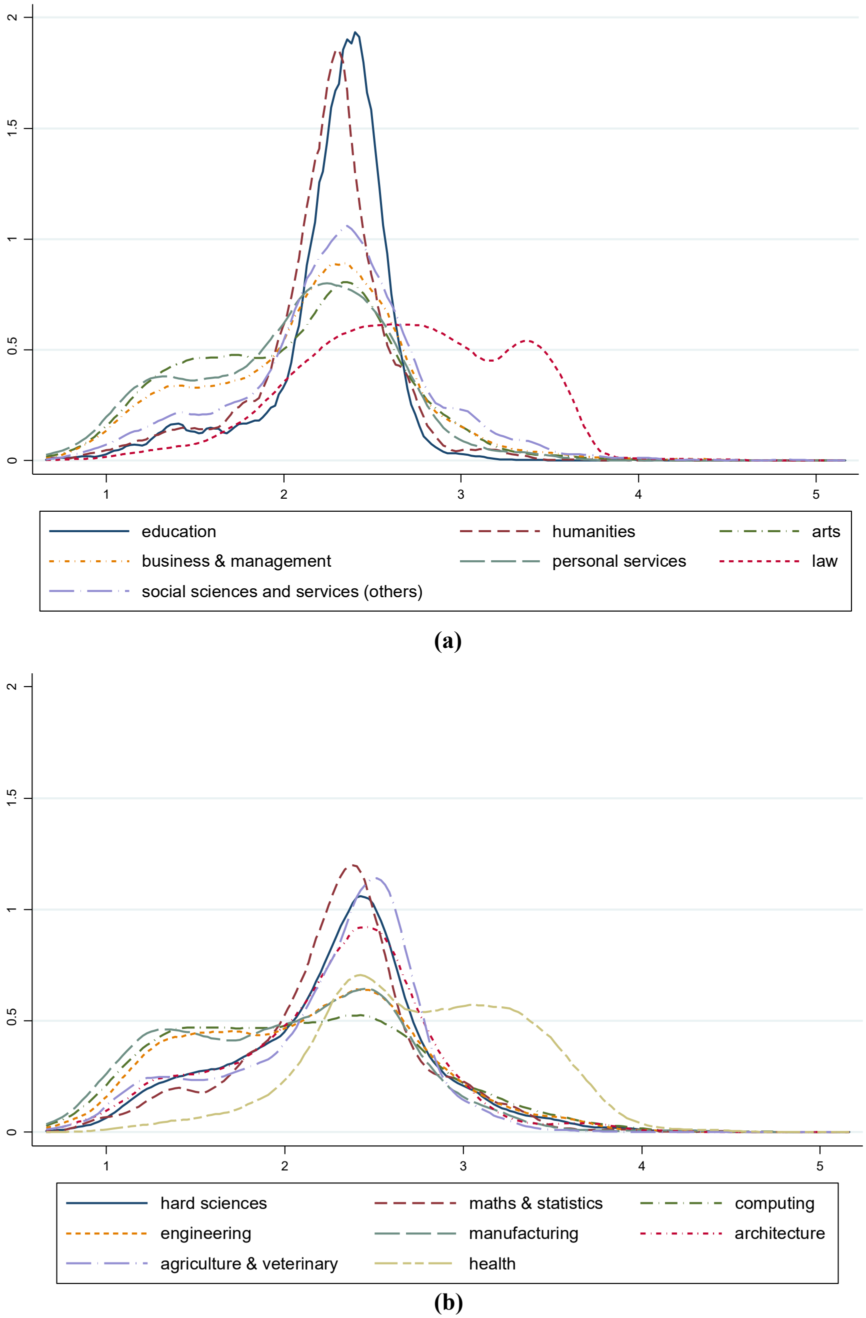

Figure 1. Kernel densities of (log) hourly wage. Source: Figure created by authors

distributional decomposition using the Unconditional Quantile Regression approach proposed by Firpo *et al.* (2007), which allows examining the contribution of differences in observable characteristics and their associated coefficients along the unconditional wage distribution.

4. Results

The main results from the OLS estimation of Equation (1) are reported in Table 1 (complete results are displayed in Table A3 of Appendix B). The estimates in column (1) are obtained

Table 1. Selected OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Education	0.129***	0.103***	0.093***	0.086***	0.013**	0.020***
	(0.005)	*(0.004)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.005)*
Arts	−0.079***	−0.034**	−0.036**	−0.016	−0.038***	−0.047***
	(0.017)	*(0.015)*	*(0.014)*	*(0.014)*	*(0.013)*	*(0.013)*
Humanities	0.085***	−0.011*	−0.008	0.038***	−0.038***	−0.036***
	(0.007)	*(0.006)*	*(0.006)*	*(0.007)*	*(0.007)*	*(0.007)*
Business and management	*Reference category*					
Law	0.550***	0.503***	0.498***	0.445***	0.310***	0.309***
	(0.018)	*(0.017)*	*(0.017)*	*(0.015)*	*(0.013)*	*(0.013)*
Personal services	−0.088***	−0.105***	−0.099***	−0.065***	−0.008	0.002
	(0.014)	*(0.012)*	*(0.012)*	*(0.011)*	*(0.010)*	*(0.010)*
Social sciences and services (others)	0.129***	0.064***	0.067***	0.059***	0.032***	0.029***
	(0.007)	*(0.006)*	*(0.006)*	*(0.006)*	*(0.005)*	*(0.005)*
Hard sciences	0.137***	0.132***	0.131***	0.130***	0.041***	0.045***
	(0.010)	*(0.009)*	*(0.009)*	*(0.009)*	*(0.008)*	*(0.008)*
Maths and statistics	0.120***	0.132***	0.119***	0.068***	−0.006	−0.009
	(0.014)	*(0.013)*	*(0.013)*	*(0.012)*	*(0.012)*	*(0.012)*
Computing	−0.121***	0.058***	0.058***	0.053***	0.017	0.008
	(0.020)	*(0.019)*	*(0.019)*	*(0.017)*	*(0.015)*	*(0.014)*
Engineering	−0.052***	0.007	0.007	0.051***	0.062***	0.067***
	(0.007)	*(0.006)*	*(0.006)*	*(0.006)*	*(0.006)*	*(0.006)*
Manufacturing	−0.141***	−0.075***	−0.077***	−0.005	−0.028**	−0.011
	(0.017)	*(0.015)*	*(0.015)*	*(0.014)*	*(0.012)*	*(0.012)*
Architecture	0.073***	0.082***	0.087***	0.094***	0.034***	0.044***
	(0.010)	*(0.010)*	*(0.009)*	*(0.009)*	*(0.008)*	*(0.008)*
Agriculture and veterinary	0.110***	0.071***	0.070***	0.075***	−0.001	0.023***
	(0.010)	*(0.008)*	*(0.008)*	*(0.008)*	*(0.007)*	*(0.007)*
Health	0.646***	0.580***	0.574***	0.531***	0.405***	0.410***
	(0.010)	*(0.009)*	*(0.009)*	*(0.012)*	*(0.011)*	*(0.011)*
Basic controls	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Family characteristics	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Sector dummies and firm size (sq.)	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
Occupation dummies	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Nuts2 regions dummies	*No*	*No*	*No*	*No*	*No*	*Yes*
Adjusted R-squared	0.091	0.263	0.283	0.361	0.472	0.489
Number of observations	77,154	77,154	77,154	77,154	77,154	77,154

Note(s): Robust standard errors in parenthesis, *** significant at 1%, ** significant at 5%, *** significant at 10%. Regression in column (2) contains controls for wave dummies, previous potential experience (quadratic) and current job tenure (quadratic). Regression in column (3) includes dummies for marital status and the number of children as additional controls. Regression in column (4) includes dummies for sector and quadratic firm size. Regression in column (5) includes dummies for occupation. Regression in column (6) includes dummies for nuts2 regions
Source(s): Table created by authors

without conditioning on observable characteristics and express percentage differences in real hourly wages relative to graduates in business and management [3], which is the reference and the most common field of study. Graduates in manufacturing (−14.1%), computing (−12.1%) and, to a lesser extent, in personal services (−8.8%), arts (−7.9%), and engineering (−5.2%) obtain a lower average remuneration than graduates in business and management. All the other fields are better paid than the reference group. The unconditional wage differential is especially pronounced for health (+64.6%) and law (+55%), which are followed by hard sciences (+13.7%), social sciences and education (+12.9%), mathematics and statistics (+12%), agriculture and veterinary (+11%), humanities (+8.5%), and architecture (+7.3%).

In Column (2) we control for the survey wave, current job tenure, and previous potential experience, where the latter two variables enter in a quadratic form. In this way we account for the fact that graduates in different fields of study may have different career profiles in terms of tenure and work experience, as well as for the changing distribution of university graduates across fields of study over time. Indeed, some of the negative differentials relative to graduates in business and management either change sign (i.e. computing), disappear (i.e. engineering), or are mitigated (as for manufacturing and arts). The positive differential observed in favor of graduates in education, law, social sciences, agriculture and veterinary, and health is lower when controlling for the basic set of covariates, and reverts sign for the field of humanities. Accounting for marital status and the number of children has virtually no effect on the coefficients associated with different fields of study (see in Column (3)). This suggests that family characteristics do not drive wage disparities between individuals who graduated in different disciplines.

Column (4) displays the wage differentials also conditioning on two important features of the job, namely employment sector (grouped into 10 categories) and firm size (in quadratic form). Wage differentials are generally reduced after controlling for sector and firm size. More remarkably, graduates in arts do not earn significantly less than graduates in business and management who work in the same sector and in firms of similar size. Graduates from the fields of humanities and engineering are slightly better remunerated than the reference group when sector and firm size are controlled for (+3.8% and +5.1%, respectively). Moreover, the negative differential experienced by graduates in manufacturing disappears when compared to the reference group with similar personal characteristics, who work in the same sector and in firms of the same size. The premium for the fields of architecture, and agriculture and veterinary is somewhat higher when employment sector and the firm size are included as regressors. Nevertheless, the high differential in favor of law and health disciplines is only marginally reduced after controlling for employment sector and firm size. Overall, health and law appear to be, by far, the college majors that are better rewarded in the Turkish labor market, even controlling for several individual and family characteristics.

Conditioning on occupation in Column (5) generally compresses wage differentials across fields of study by a substantial amount, as is usually reported in the literature (Altonji *et al.*, 2014). The sign and the significance of the wage differentials generally remain stable after accounting for occupation dummies, with some exceptions. The negative gap suffered by graduates in arts (relative to business and management) emerges again when comparing individuals who also hold similar occupations. Graduates in humanities and manufacturing are instead penalized when occupation is controlled for, whereas the wage differential for the fields of personal services (negative), mathematics and statistics, computing, and agriculture and veterinary (all positive) vanish when they are estimated conditional on occupational categories. Notably, graduates in law and health are still better remunerated and, respectively, obtain an average hourly wage higher by 31 and 40.5% than the reference category even controlling for occupation. The estimates are mostly unaffected by the further inclusion of fixed effects for 26 NUTS2 regions of Turkey as shown in Column (6). This suggests that local differences in the labor market do not significantly affect wage disparities between tertiary educated workers with different college majors. The exceptions are manufacturing, for which the negative differential disappears after conditioning on regions, and agriculture and veterinary, which is slightly more rewarded than business and management.

It is also worth noting that some of our findings differ from patterns observed in developed economies. For example, graduates in education generally earn relatively low wages, whereas they perform well in the Turkish labor market. This may be linked to their preference for public sector employment, where salaries tend to be higher (on average [4]), especially in regulated occupations. Indeed, this is in line with the findings and the interpretation reported by Kelly *et al.* (2010) for the case of Ireland, and is consistent with the results obtained by Tran and Van Vu (2020) for Vietnam.

To better appreciate the role of observable characteristics and the associated coefficients in accounting for the observed average wage gaps, we report the results from the Oaxaca-Blinder decomposition shown in Equation (3). The basic results are displayed in Table 2 and graphically illustrated in Figure 2. The detailed results that report the contribution of each group of variables (and their returns) are shown in Table A4 of Appendix B. It can be appreciated that the average wage gap in favor of graduates in education (relative to other disciplines) is entirely explained by the endowment of observable characteristics — mostly occupation. The lower average wages observed for graduates in arts are similarly explained by the contribution of observed characteristics (especially sector and firm size) and their returns.

Table 2. Oaxaca-Blinder decomposition

Field of study	% Wage difference	Explained	Unexplained
Education	0.058	0.066	−0.009
z-stat	*15.38*	*17.25*	*−2.10*
Arts	−0.162	−0.081	−0.081
z-stat	*−9.69*	*−6.84*	*−6.54*
Humanities	0.004	0.071	−0.066
z-stat	*0.79*	*15.08*	*−11.84*
Business and management	−0.110	−0.057	−0.052
z-stat	*−24.66*	*−16.94*	*−14.49*
Law	0.475	0.199	0.276
z-stat	*26.28*	*17.91*	*21.78*
Personal services	−0.172	−0.151	−0.022
z-stat	*−12.36*	*−14.99*	*−2.16*
Social sciences and services (others)	0.053	0.057	−0.004
z-stat	*8.55*	*12.57*	*−0.75*
Hard sciences	0.058	0.059	−0.001
z-stat	*5.97*	*8.99*	*−0.07*
Maths and statistics	0.040	0.079	−0.039
z-stat	*2.89*	*9.12*	*−3.41*
Computing	−0.205	−0.175	−0.030
z-stat	*−10.21*	*−14.11*	*−2.10*
Engineering	−0.155	−0.197	0.041
z-stat	*−24.43*	*−43.27*	*8.31*
Manufacturing	−0.226	−0.174	−0.052
z-stat	*−13.21*	*−15.17*	*−4.55*
Architecture	−0.008	−0.014	0.006
z-stat	*−0.86*	*−1.96*	*0.75*
Agriculture and veterinary	0.030	0.058	−0.028
z-stat	*3.37*	*8.62*	*−4.13*
Health	0.595	0.211	0.384
z-stat	*65.37*	*25.88*	*35.81*

Note(s): *z*-statistics based on robust standard errors. The results are obtained from the twofold decomposition, based on the pooled estimation with the corresponding field of study dummies. All regressions contain controls for wave dummies, previous potential experience, current job tenure and firm size (all quadratic), dummies for marital status, number of children, and dummies for occupation, sector and nuts2 regions
Source(s): Table created by authors

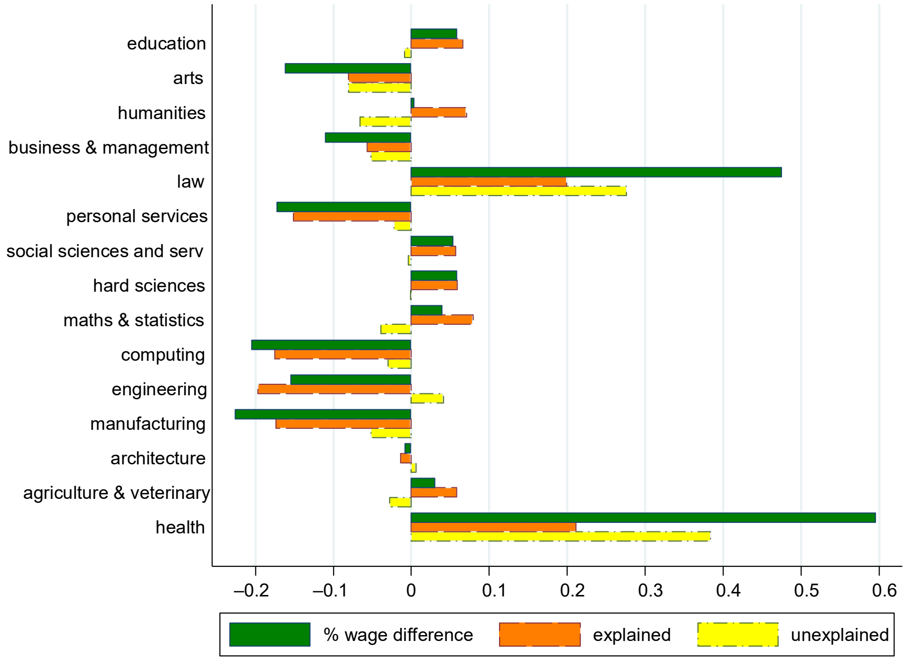

Figure 2. Oaxaca-Blinder decomposition. Source: Figure created by authors

Wages of graduates in humanities are around the overall average and, for this field, the modest contribution of explained and unexplained factors operate in opposite directions.

The field of business and management is less rewarded than others, which is almost equally explained by a less favorable endowment of observable characteristics (principally occupation) and lower returns. In contrast, for law majors, both the endowment of observable characteristics and the associated returns contribute to their positive and substantial wage advantage, with the latter component playing a slightly more prominent role. For this field, the higher coefficients associated with sector and occupation, and to a lesser extent their more favorable composition in terms of these features of the job, represent the main driver of the high and positive wage gap relative to other fields.

The lower average remuneration of graduates in personal services is almost entirely explained by observable characteristics, whereby the effect of occupation prevails over the other covariates. Observables are also responsible for the higher average wages in both social sciences and hard sciences. For mathematics and statistics, the distribution of endowments positively affects average hourly wages, but the returns to endowments operate in the opposite direction. Average hourly pay is lower for graduates in computing, engineering, or manufacturing than for graduates of other fields, and the observable characteristics seem to account for almost their entire wage gaps. More specifically, lower work experience/job tenure are the main conditioning factors behind the negative wage differential experienced by graduates in computing. This result reflects that, relative to other fields, graduates in computing are likely to belong to younger cohorts, who are at the beginning of their career. For engineering, occupation is the most important observed factor that accounts for the negative gap, followed by sector/firm size and work experience. These three sets of observable characteristics are also the main driver of the wage penalty experienced by graduates in manufacturing, with a similar weight. Therefore, the low performance of graduates in engineering and manufacturing is possibly capturing a situation of qualification and skills mismatch at the beginning of the career of graduates in these two fields, relative to their counterparts. The wage rate for graduates in architecture does not significantly differ from those in other fields, and the slightly higher wages for agriculture and veterinary are driven by the net effect of a better distribution of observed characteristics and lower associated returns. Finally, graduates from health majors enjoy significantly higher wages, driven by both favorable endowments and higher coefficients. Notably, unexplained factors play a more substantial role than the explained ones in this positive wage differential. As in the case of law, the higher return to occupation (but not to employment sector and firm size) is the main factor behind the premium for graduates in health disciplines.

The decomposition results of wage gaps at different quantiles of the unconditional wage distribution are reported in Table 3 and graphically displayed in Figure 3, [5]. Detailed RIF-decomposition results are shown in Table A5 of Appendix B. Graduates in education obtain a positive and substantial return at the bottom deciles of the wage distribution, which are accounted by a more favorable distribution of observed characteristics, but also by a positive contribution of unexplained factors. Observable and unobservable components have a similar weight in explaining wage differences for the field of education at different quantiles of the wage distribution and follow the overall decreasing tendency of the wage gap relative to other fields. The positive contribution of observable characteristics detected at lower quantiles is mostly driven by occupation, which exerts a positive effect over the entire distribution. However, it is offset by the negative impact of sector and firm size above the median. The lower returns to work experience and occupation appear to be the main drivers of the decreasing contribution of unexplained factors, which is especially pronounced at the bottom quantile of the wage distribution. For the field of arts, the endowment of observable characteristics plays an important role in accounting for the negative wage gap detected at the bottom of the distribution. The negative contribution of the estimated coefficients is also very pronounced at the second and third quantile, being mostly driven by the return to family characteristics. Observable characteristics account for most of the positive wage gap observed for humanities at the bottom quantile of the wage distribution, but their relevance declines and even becomes negative at top quantiles, where graduates in this field earn less than others.

Like the case of education, although occupational selection represents a favorable endowment for graduates in humanities, differences in sector and firm size penalize them at the top of the distribution. Also, the lower returns to work experience and occupation substantially contribute to the sharp decrease of the role of unexplained factors in accounting for the wage gap at the bottom quantiles. As for business and management, the negative wage gap that graduates in this field experience relative to their counterparts generally tends to vanish along the unconditional wage distribution (except for the last quantile) and seems to be mostly driven by the unfavorable distribution of endowments at lower quantiles. More specifically, occupational selection tends to penalize low-paid graduates in this field. Occupation exerts a negative contribution to wages of graduates in business and management also at the top of the distribution, but its effect is compensated by the positive impact of sector and firm size. For law, returns and endowments operate in opposite directions at different quantiles of the wage distribution, since the effect of explained factors decreases along the quantiles and the contribution of unexplained elements increases and accounts for most of the remarkably positive wage gap graduates in this field enjoy at the top of the wage distribution. Among the observables, employment sector and firm size are especially beneficial for bottom deciles, while occupation shows a relatively stable positive contribution over the entire wage distribution.

Regarding the unexplained factors, it seems worth highlighting the changing contribution of the return to work experience, which exerts a negative impact at the bottom of the distribution and reverts sign at the median. Moreover, the coefficients of occupational categories have a positive impact at the center of the unconditional distribution and contribute to the high wage gap for law majors. The negative wage gap for personal service is largely explained by the unfavorable endowment of observable characteristics, except for the left cue of the wage distribution where the contribution of unexplained factors slightly mitigates the distribution of observables. Detailed decomposition results show that occupational choices are

Table 3. RIF-Regression decomposition

	q1	q2	q3	q4	q5	q6	q7	q8	q9
	Education								
% wage difference	0.483	0.406	0.214	0.133	0.055	0.009	−0.037	−0.130	−0.286
z-stat	*30.93*	*62.04*	*45.91*	*36.61*	*17.33*	*2.78*	*−12.01*	*−37.79*	*−52.27*
Explained	0.287	0.219	0.186	0.134	0.088	0.048	−0.004	−0.055	−0.156
z-stat	*27.95*	*26.57*	*31.16*	*30.46*	*23.42*	*12.80*	*−1.14*	*−12.92*	*−21.84*
Unexplained	0.196	0.187	0.028	−0.002	−0.033	−0.039	−0.033	−0.075	−0.130
z-stat	*10.69*	*22.66*	*4.69*	*−0.34*	*−7.77*	*−9.08*	*−7.41*	*−15.08*	*−16.50*
	Arts								
% wage difference	−0.138	−0.293	−0.317	−0.229	−0.133	−0.088	−0.079	−0.082	−0.082
z-stat	*−5.73*	*−10.37*	*−9.85*	*−6.49*	*−5.93*	*−5.33*	*−5.40*	*−5.12*	*−2.97*
Explained	−0.138	−0.237	−0.143	−0.092	−0.067	−0.051	−0.040	−0.027	0.007
z-stat	*−6.59*	*−8.44*	*−8.85*	*−8.39*	*−8.11*	*−6.97*	*−5.70*	*−3.30*	*0.54*
Unexplained	0.000	−0.056	−0.174	−0.137	−0.066	−0.037	−0.040	−0.055	−0.089
z-stat	*0.01*	*−2.07*	*−6.81*	*−4.70*	*−3.53*	*−2.59*	*−2.96*	*−3.63*	*−3.35*
	Humanities								
% wage difference	0.398	0.260	0.094	0.030	−0.022	−0.062	−0.103	−0.135	−0.204
z-stat	*21.84*	*28.49*	*15.19*	*6.08*	*−4.94*	*−14.29*	*−21.65*	*−20.89*	*−21.70*
Explained	0.259	0.347	0.208	0.107	0.047	−0.006	−0.041	−0.077	−0.139
z-stat	*27.58*	*31.61*	*28.60*	*20.36*	*11.06*	*−1.56*	*−10.99*	*−17.71*	*−19.04*
Unexplained	0.139	−0.088	−0.114	−0.076	−0.069	−0.057	−0.063	−0.058	−0.065
z-stat	*7.64*	*−8.10*	*−15.50*	*−13.61*	*−14.13*	*−11.97*	*−12.10*	*−8.08*	*−5.86*
	Business and management								
% wage difference	−0.128	−0.194	−0.155	−0.115	−0.084	−0.067	−0.036	−0.054	−0.133
z-stat	*−14.67*	*−18.07*	*−20.06*	*−23.48*	*−19.56*	*−17.06*	*−8.85*	*−12.05*	*−18.91*
Explained	−0.108	−0.132	−0.088	−0.060	−0.041	−0.027	−0.016	−0.009	−0.034
z-stat	*−17.17*	*−16.85*	*−18.04*	*−18.88*	*−15.28*	*−10.86*	*−6.54*	*−3.28*	*−6.83*
Unexplained	−0.020	−0.062	−0.067	−0.055	−0.043	−0.041	−0.020	−0.044	−0.099
z-stat	*−2.23*	*−6.49*	*−10.33*	*−13.07*	*−11.58*	*−11.51*	*−5.36*	*−10.25*	*−13.41*
	Law								
% wage difference	0.554	0.407	0.322	0.345	0.425	0.499	0.563	0.688	0.665
z-stat	*16.32*	*18.35*	*12.62*	*13.46*	*16.06*	*21.56*	*18.88*	*24.32*	*54.16*
Explained	0.281	0.420	0.250	0.176	0.148	0.147	0.155	0.168	0.160

(*continued*)

Table 3. Continued

	q1	q2	q3	q4	q5	q6	q7	q8	q9
z-stat	*14.77*	*15.76*	*16.64*	*17.11*	*18.53*	*20.26*	*20.83*	*20.30*	*12.00*
Unexplained	0.273	−0.013	0.072	0.170	0.277	0.352	0.408	0.521	0.505
z-stat	*9.05*	*−0.55*	*3.41*	*8.09*	*12.22*	*17.60*	*15.37*	*20.10*	*30.98*
	Personal services								
% wage difference	−0.163	−0.258	−0.222	−0.159	−0.138	−0.124	−0.108	−0.115	−0.181
z-stat	*−7.12*	*−7.07*	*−6.99*	*−8.62*	*−8.96*	*−9.05*	*−8.05*	*−9.00*	*−13.44*
Explained	−0.261	−0.293	−0.180	−0.126	−0.099	−0.085	−0.079	−0.091	−0.148
z-stat	*−14.14*	*−11.81*	*−12.59*	*−13.63*	*−13.66*	*−13.09*	*−12.49*	*−12.77*	*−13.28*
Unexplained	0.098	0.035	−0.042	−0.032	−0.039	−0.038	−0.030	−0.025	−0.033
z-stat	*4.42*	*1.19*	*−1.72*	*−2.27*	*−3.13*	*−3.30*	*−2.49*	*−2.03*	*−2.28*
	Social sciences and services (others)								
% wage difference	0.169	0.171	0.059	0.030	0.007	0.005	0.006	0.032	0.025
z-stat	*8.95*	*14.77*	*8.40*	*5.06*	*1.36*	*0.98*	*1.08*	*4.65*	*1.89*
Explained	0.101	0.141	0.062	0.032	0.023	0.025	0.037	0.046	0.048
z-stat	*13.47*	*14.24*	*10.32*	*7.61*	*7.00*	*7.78*	*11.40*	*12.38*	*7.77*
Unexplained	0.068	0.030	−0.002	−0.001	−0.016	−0.020	−0.030	−0.014	−0.024
z-stat	*3.96*	*2.92*	*−0.38*	*−0.28*	*−3.37*	*−4.17*	*−5.80*	*−2.17*	*−1.95*
	Hard sciences								
% wage difference	0.077	0.043	0.036	0.052	0.070	0.067	0.049	0.051	0.088
z-stat	*3.65*	*1.95*	*2.24*	*4.71*	*8.04*	*8.61*	*6.18*	*5.09*	*4.26*
Explained	0.050	0.066	0.058	0.056	0.052	0.051	0.048	0.055	0.094
z-stat	*4.66*	*4.33*	*6.53*	*9.18*	*11.21*	*12.29*	*11.39*	*11.18*	*11.26*
Unexplained	0.028	−0.023	−0.023	−0.004	0.018	0.016	0.002	−0.004	−0.006
z-stat	*1.44*	*−1.24*	*−1.77*	*−0.42*	*2.49*	*2.36*	*0.25*	*−0.40*	*−0.32*
	Maths and statistics								
% wage difference	0.204	0.131	0.058	0.044	0.013	0.006	−0.011	−0.032	0.002
z-stat	*4.23*	*4.61*	*3.25*	*3.29*	*1.18*	*0.55*	*−0.97*	*−2.16*	*0.05*
Explained	0.170	0.258	0.167	0.108	0.072	0.047	0.018	−0.013	−0.042
z-stat	*12.56*	*13.86*	*15.11*	*13.93*	*11.59*	*7.99*	*2.96*	*−1.73*	*−3.22*
Unexplained	0.034	−0.127	−0.108	−0.064	−0.059	−0.041	−0.029	−0.018	0.043
z-stat	*0.75*	*−4.82*	*−6.71*	*−5.32*	*−5.66*	*−4.27*	*−2.88*	*−1.39*	*1.46*

(*continued*)

Table 3. Continued

	q1	q2	q3	q4	q5	q6	q7	q8	q9
	Computing								
% wage difference	−0.235	−0.437	−0.484	−0.408	−0.278	−0.180	−0.091	−0.019	0.071
z-stat	*−11.00*	*−18.68*	*−17.90*	*−12.91*	*−8.57*	*−6.71*	*−3.39*	*−0.80*	*1.73*
Explained	−0.321	−0.512	−0.305	−0.194	−0.131	−0.096	−0.070	−0.037	0.006
z-stat	*−15.36*	*−19.33*	*−20.37*	*−18.95*	*−15.51*	*−12.06*	*−8.64*	*−3.85*	*0.38*
Unexplained	0.087	0.075	−0.180	−0.214	−0.147	−0.084	−0.021	0.018	0.065
z-stat	*3.62*	*2.91*	*−8.12*	*−8.04*	*−5.23*	*−3.72*	*−0.91*	*0.92*	*1.75*
	Engineering								
% wage difference	−0.221	−0.416	−0.409	−0.288	−0.156	−0.082	−0.018	0.020	0.059
z-stat	*−24.43*	*−41.46*	*−40.63*	*−26.09*	*−16.82*	*−11.40*	*−2.72*	*2.79*	*5.33*
Explained	−0.388	−0.481	−0.296	−0.235	−0.174	−0.116	−0.082	−0.053	−0.032
z-stat	*−37.76*	*−50.53*	*−50.71*	*−46.39*	*−41.82*	*−33.80*	*−25.12*	*−14.49*	*−5.27*
Unexplained	0.167	0.065	−0.112	−0.052	0.018	0.034	0.064	0.072	0.090
z-stat	*13.49*	*6.22*	*−13.69*	*−5.79*	*2.28*	*5.36*	*10.59*	*10.78*	*8.12*
	Manufacturing								
% wage difference	−0.280	−0.439	−0.467	−0.350	−0.235	−0.127	−0.059	−0.062	−0.078
z-stat	*−14.55*	*−18.61*	*−14.79*	*−11.08*	*−9.29*	*−5.23*	*−3.63*	*−3.94*	*−3.48*
Explained	−0.322	−0.503	−0.293	−0.178	−0.122	−0.091	−0.059	−0.042	−0.022
z-stat	*−16.21*	*−19.60*	*−19.78*	*−17.87*	*−15.59*	*−12.70*	*−8.66*	*−5.30*	*−1.80*
Unexplained	0.042	0.064	−0.174	−0.172	−0.113	−0.036	0.001	−0.020	−0.056
z-stat	*1.96*	*2.73*	*−7.00*	*−6.68*	*−5.43*	*−1.76*	*0.04*	*−1.41*	*−2.59*
	Architecture								
% wage difference	−0.029	−0.040	−0.051	−0.008	0.006	0.035	0.049	0.037	−0.005
z-stat	*−1.34*	*−1.69*	*−2.90*	*−0.69*	*0.53*	*3.89*	*5.72*	*4.02*	*−0.36*
Explained	−0.028	−0.100	−0.072	−0.038	−0.018	0.003	0.019	0.039	0.049
z-stat	*−2.06*	*−5.61*	*−7.14*	*−5.79*	*−3.41*	*0.59*	*4.06*	*7.21*	*5.41*
Unexplained	−0.001	0.060	0.020	0.030	0.023	0.033	0.030	−0.003	−0.054
z-stat	*−0.05*	*2.87*	*1.38*	*2.97*	*2.60*	*4.11*	*3.88*	*−0.29*	*−3.95*
	Agriculture and veterinary								
% wage difference	0.013	0.072	0.067	0.086	0.093	0.092	0.061	0.047	−0.050
z-stat	*0.53*	*2.98*	*4.64*	*8.35*	*11.24*	*13.32*	*9.00*	*6.58*	*−5.41*
Explained	0.073	0.111	0.061	0.046	0.043	0.046	0.051	0.061	0.066

(*continued*)

Table 3. Continued

	q1	q2	q3	q4	q5	q6	q7	q8	q9
z-stat	*6.31*	*6.92*	*6.74*	*7.46*	*9.10*	*10.77*	*11.77*	*12.56*	*8.09*
Unexplained	−0.060	−0.039	0.006	0.040	0.050	0.046	0.011	−0.014	−0.116
z-stat	*−2.83*	*−2.04*	*0.51*	*4.74*	*7.13*	*7.55*	*1.72*	*−1.92*	*−10.31*
	Health								
% wage difference	0.730	0.554	0.406	0.420	0.501	0.617	0.710	0.758	0.791
z-stat	*48.88*	*54.83*	*41.93*	*29.48*	*32.65*	*44.44*	*59.27*	*68.44*	*65.56*
Explained	0.303	0.387	0.259	0.230	0.207	0.165	0.127	0.102	0.107
z-stat	*17.96*	*19.51*	*19.95*	*21.85*	*21.78*	*19.45*	*16.56*	*13.28*	*10.31*
Unexplained	0.427	0.167	0.147	0.190	0.294	0.452	0.583	0.657	0.685
z-stat	*19.60*	*7.99*	*9.71*	*11.49*	*17.72*	*30.58*	*45.61*	*54.94*	*47.36*

Note(s): *z*-statistics based on robust standard errors. The results are obtained from the twofold RIF decomposition, based on the pooled estimation with the corresponding field of study dummies. All regressions contain controls for wave dummies, previous potential experience, current job tenure and firm size (all quadratic), dummies for marital status, number of children, and dummies for occupation, sector and nuts2 regions
Source(s): Table created by authors

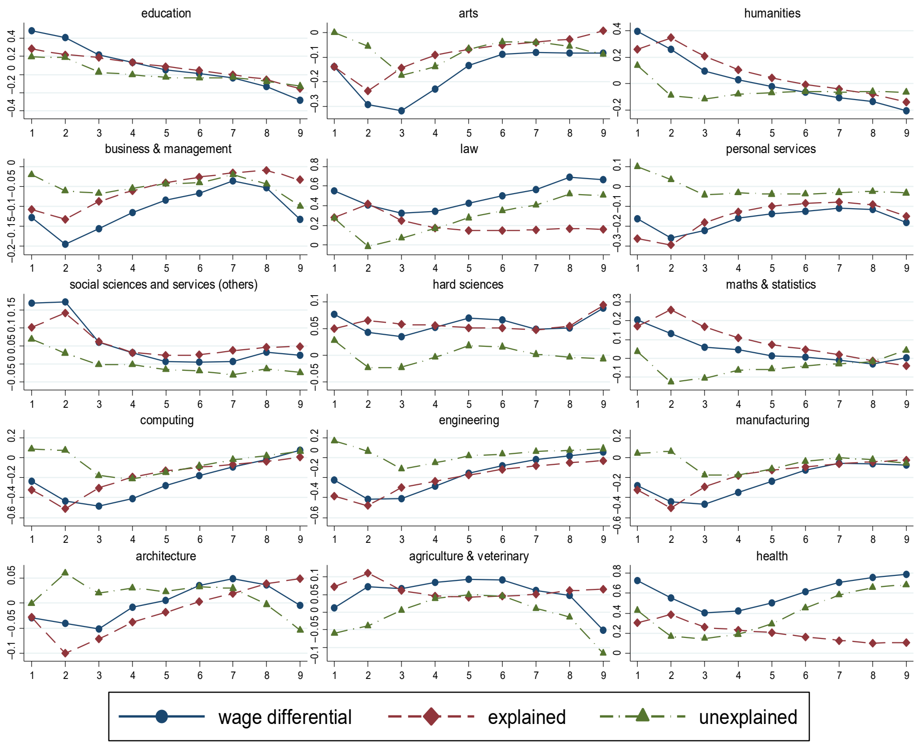

Figure 3. RIF-Regression decomposition. Source: Figure created by authors

the most important drivers of the negative effect of endowments for personal services, being the contribution of this element that is especially relevant at the bottom and the top of the unconditional distribution of wages. Graduates in social sciences experience a positive wage gap at the bottom of the wage distribution, which is mostly accounted by the positive contribution of observable characteristics (specifically, work experience, sector and firm size). The importance of observables for this field decreases along the wage distribution and is somewhat compensated by the slightly negative impact of the estimated coefficients that is detected after the median.

The modest wage disparities between hard sciences and other fields, which tend to be relatively constant over the entire wage distribution, seem to be mostly explained by the effect of covariates, among which occupational selection plays the most important role. Graduates in mathematics and statistics are better paid than their counterparts at the bottom of the wage distribution, but this positive differential vanishes at its median. However, it seems interesting to highlight that the positive (but decreasing) contribution of observables is somewhat compensated by the estimated return, which tends to be lower for graduates in this field. More specifically, occupation appears to be the most important factor behind explained differences, whereas the returns to family characteristics and sector/firm size display the most relevant contribution in accounting for the unexplained wage gap. Graduates in computing are instead penalized with respect to graduates in other fields, especially below the median of the unconditional wage distribution. The negative differential detected at lower quantiles is mainly driven by observable factors, whereas the corresponding coefficients play a most important role at the center of the distribution. A similar pattern is detected for the fields of engineering and manufacturing, which are less rewarded than other fields at the bottom of the distribution. However, this negative wage gap disappears when moving to higher quantiles (and even reverts sign in the case of engineering). Indeed, for both fields the important negative differential detected in the first half of the wage distribution is mostly explained by differences in observable characteristics. Specifically, employment sector/firm size and, to a lesser extent, work experience and occupation are the main observable factors behind these wage disparities. Graduates in engineering and manufacturing obtain higher rewards to observable characteristics at the bottom quantiles of the wage distribution, but the estimated coefficients tend to penalize them around the central quantiles. Unexplained components have a positive contribution for graduates in the former field above the median. Moreover, it seems interesting to highlight the negative contribution of the coefficients associated with work experience for the first two quantiles, which then reverts sign and tends to compensate the lower returns to observables for these two technical fields of study. The field of architecture is slightly less paid than others at the bottom of the wage distribution, while this wage gap tends to revert above the median. In this case, explained and unexplained components tend to operate in opposite directions along the unconditional wage distribution, since the endowment of observable characteristics (mainly sector/firm size) tend to penalize graduates in this field until the median, this differential being somewhat compensated by slightly higher returns to characteristics (mostly sector/firm size and occupation). For agriculture and veterinary, the inverted U-shaped contribution of unexplained characteristics is what drives the same pattern observed for the overall wage gap. Indeed, graduates in this field tend to be better paid than others around the center of the wage distribution. The endowment of observable characteristics is generally favorable for them. However, the contribution of the estimated coefficients tends to be negative at the two extremes of the wage distribution and positive in the middle. We detected a positive impact of the coefficients associated with family characteristics along the entire wage distribution, as well as of sector/firm size until the median, but these are compensated by the lower return to work experience for graduates in agriculture and veterinary relative to their counterparts. Finally, the positive wage gap in health disciplines is the result of the net effect of the contrasting contribution of characteristics (with a decreasing weight along the wage distribution) and coefficients (with an increasing weight at higher quantiles), which is indeed a similar pattern observed for the case of law. Indeed, the high wage gap in favor of health majors in top deciles is mostly driven by unexplained elements. Moreover, among the observable characteristics, occupational/sectoral choices and, to a lesser extent, differences in work experience represent the main factors behind the significant wage premium experienced by graduates in health disciplines at the bottom of the distribution.

5. Discussion and conclusions

This paper reports evidence on the pay disparities among tertiary educated male workers who hold a degree in different fields of study. We focus our analysis on Turkey, a developing country that has been characterized by a sustained expansion of higher education during the last decades. We detected significant heterogeneity in wage rates across college majors, which are especially pronounced for the fields of law and health. Indeed, graduates in these two disciplines are by far the better paid tertiary educated (male) workers in the Turkish labor market, which is in line with the evidence reported in some previous works. Observable characteristics matter in explaining wage differences by field of study, since conditioning for characteristics alters the magnitude and, in some cases, also the sign of the estimated differentials. Consistent with previous evidence in the literature, occupational selection represents the most important driver of pay gaps, but also employment sector, firm size and work experience operate as conditioning factors of the wages of Turkish male university graduates. On the contrary, other observable factors appear to be less relevant, such as family characteristics (possibly because we focused on males) or geographical location (except for the field of agriculture and veterinary).

To investigate the extent to which the observed wage gaps are driven by differences in observable characteristics and/or by differences in the return associated to those characteristics, we performed the Oaxaca-Blinder decomposition for average wage differentials. The results indicate that differences in the endowments (i.e. the explained component) account for a substantial share of the wage gaps, and even explain almost the entire wage gap in some cases. The decomposition analysis confirms the prominent role of observed occupational differences as the main driver of wage gaps across fields of study. Moreover, the overall effect of the return to characteristics (i.e. the unexplained component) is negligible and even not significant for several fields of study, such as social science and services, hard sciences and architecture (while marginally significant for education and personal services).

An important finding to highlight is the relatively low wage performance of graduates from certain STEM fields, particularly computing, engineering, and manufacturing, which is primarily driven by differences in observable characteristics. In the case of computing graduates, this outcome is likely influenced by their concentration in younger cohorts, who are still in the early stages of their careers. However, for engineering and manufacturing graduates, our results suggest that qualification or skills mismatches in their early jobs may be a more plausible explanation. The misalignment between field of study and occupational placement also appears to underlie the negative wage returns observed for graduates in business and management, as well as personal services. Moreover, it is noteworthy that the contribution of unexplained factors is particularly high for the two highest-paid fields, law and health. In fact, for these fields, the unexplained elements exceed the positive contribution of observable characteristics, which are mainly driven by higher coefficient of occupational categories (and sector/firm size for law majors).

Important wage disparities between individuals who obtained degrees in a different field of study could occur at other points of the wage distribution than at the mean. Therefore, we decomposed wage differences across the unconditional wage distribution using the RIF-Regression decomposition method. The distributional decomposition confirms that the endowment of observable characteristics represents the main driver of wage differentials. In general, occupation and, to a lesser extent, sectoral differences are confirmed to be the most important observed driver of distributional wage gaps. However, their contribution to wage differentials tends to decrease when moving to the upper part of the unconditional wage distribution and even changes sign after the median (changing from positive to negative for education, humanities, and mathematics and statistics, and from negative to positive for architecture). More specifically, the relevance of explained differences in accounting for the negative return to majors in computing, engineering and manufacturing in the left tail of the wage distribution confirms our interpretation of average wage differentials (i.e. combination of possible mismatch at early stages of the career).

On the contrary, the positive contribution of explained factors at the bottom of the distribution for other fields such as education, humanities and social sciences and services is possibly capturing wage and entry regulation in specific sectors (especially for public jobs), which offer stable but capped wages. This is also true for the fields of law and health, the top paid college majors, who receive a positive return even at the left tail of the wage distribution. Moreover, for these two fields, unexplained elements instead appear very relevant for the fields of law and health, and account for an increasingly important part of the positive wage gap experienced by graduates in these two fields in the upper part of the unconditional wage distribution. Overall, the evidence reported for graduates in law and health is possibly due to the importance of self-selection of high wage potential individuals into these two fields, together with high chances of obtaining top job placements that are well aligned with their qualification and skills, and their capacity to obtain higher rewards from these prestigious positions due to their unobservable traits. Indeed, the fields of law and health are among the ones with the highest cut-off score requirements for the university admission test.

While we acknowledge that the inability to control for self-selection into fields of study represents a limitation of our work, the evidence presented in this paper offers various policy implications. First, the government and higher education administrators could consider adjusting university entrance cut-off scores for different majors based on wage differentials. This would ensure that fields with high returns, such as law and health, remain both selective and accessible, potentially in combination with monetary incentives (e.g. scholarships or reduced tuition fees). Such policy changes will ultimately impact the labor market by influencing the composition of the future workforce and the country's economic growth. Therefore, it is essential to exercise caution to avoid an oversupply in these fields, as this could erode wage premiums over time. Second, since sectoral employment and occupational selection significantly influence wage disparities by field of study, policies that promote greater mobility across occupations and sectors (e.g. cross-sector internships, interdisciplinary programs, etc.) may also enable graduates to diversify their career opportunities and mitigate potential issues of underemployment or qualification and skills mismatch. Additionally, promoting the acquisition of transferable skills within the academic curricula and providing career counseling for early graduates can further support this goal. Achieving these objectives is particularly important for graduates in STEM and technical fields, especially in emerging economies such as Turkey. This is also relevant for other MENA countries and developing economies experiencing significant expansion in higher education alongside rapid technological progress. Ensuring their placement in jobs that align with their qualifications and skills is crucial for maintaining an adequate supply of STEM graduates in the labor market, helping the country fully leverage scientific advancements and technological changes while fostering a sustainable pattern of economic growth and development.

Notes

1. We excluded individuals who graduated in this field, since they are mostly in the army or police forces and their labor market outcomes are hardly comparable with the results of their counterparts in other fields of study.
2. Indeed, as highlighted in previous studies (e.g. Tekgüç *et al.*, 2017; Aldan, 2021), Turkey has low female labor market participation, even among university graduates, albeit to a lesser extent than in the overall female population.
3. The average of (log) hourly real wages for graduates in business and management is equal to 2.15 (i.e. hourly wage in 2010 prices equal to 9.97 TL), which is around 8.1% lower than the overall average.
4. In our sample, real hourly wages are equal to 12.2 TL for individuals employed in the public sector and 9.2 TL for their counterparts working in the private sector.

5. In the working paper version of this work, we also analyze the main results from the RIF-regressions (see Di Paolo and Tansel, 2017).

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Supplementary material

The supplementary material for this article can be found online.

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