

# **Analyzing Wage Differentials by Fields of Study: Evidence from Turkey**

**Antonio Di Paolo**

Department of Econometrics, University of Barcelona, Barcelona, Spain

E-mail: [antonio.dipaolo@ub.edu](mailto:antonio.dipaolo@ub.edu)

Phone: +(34) 934 03 71 50

**Aysıt Tansel**

Department of Economics, Middle East Technical University, Ankara, Turkey and

Institute for the Study of Labor (IZA) Bonn, Germany and

Economic Research Forum (ERF) Cairo, Egypt

E-mail: [atansel@metu.edu.tr](mailto:atansel@metu.edu.tr)

Phone: + (90) 312 210 2073

# Analyzing Wage Differentials by Fields of Study: Evidence from Turkey<sup>†</sup>

Antonio Di Paolo<sup>†</sup>

and

Aysit Tansel<sup>‡\*\*\*</sup>

*AQR-IREA, University of Barcelona;*

*Middle East Technical University, ERF & IZA*

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## Abstract

This paper analyzes the drivers of wage differences among college graduates who hold a degree in a different field of study. We focus on Turkey, an emerging country that is characterized by a sustained expansion of higher education. We estimate conditional wage gaps by field of study using OLS regressions. Average differentials are subsequently decomposed into the contribution of observable characteristics (endowment) and unobservable characteristics (returns). To shed light on distributional wage disparities by field of study, we provide estimates along the unconditional wage distribution by means of RIF-Regressions. Finally, we also decompose the contribution of explained and unexplained factors in accounting for wage gaps along the whole distribution. As such, this is the first work providing evidence on distributional wage differences by college major for a developing country. The results indicate the existence of important wage differences by field of study, which are partly accounted by differences in observable characteristics (especially occupation and, to a lesser extent, employment sector). These pay gaps are also heterogeneous over the unconditional distribution of wages, as is the share of wage differentials that can be attributed to differences in observable characteristics across workers with degrees in different fields of study.

**JEL Classifications:** J31, J24, I23, I26

**Keywords:** Fields of Study, Wage Differentials, Decomposition, Unconditional Wage Distribution, Turkey

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<sup>†</sup> Antonio Di Paolo, e-mail: [antonio.dipaolo@ub.edu](mailto:antonio.dipaolo@ub.edu). Address: Department of Econometrics, University of Barcelona, Avinguda Diagonal 690, 08034, Barcelona (Spain), telephone: +34934037150, fax: +34934021821.

<sup>‡</sup> Aysit Tansel (corresponding author), e-mail: [atansel@metu.edu.tr](mailto:atansel@metu.edu.tr). Address: Department of Economics Middle East Technical University, 06800 Ankara (Turkey), telephone: +903122102073, fax: +903122107964; Institute for the Study of Labor (IZA), Bonn, Germany; Economic Research Forum (ERF) Cairo, Egypt.

## 1) Introduction

What drives wage disparities among university graduates who studied different fields? There is an extensive amount of evidence documenting the general payoff to obtaining a university degree (relative to lower education levels), but also a growing number of papers highlighting the existing heterogeneity in the return to tertiary education according to the field of study (see Altonji et al., 2012 and Altonji et al., 2015 for recent overviews). However, the forces that drive wage gaps by field of study among university graduates have not been widely explored so far and the literature focused on this specific issue is still scarce.

Indeed, analyzing the factors that account for wage differences by field of study is becoming an attractive area of research, since there are several policy-relevant issues that motivate such interest. First, relative wage differences across fields of tertiary education are likely to affect the choice of university major (see Berge, 1988, Montmarquette et al., 2002, Bhattacharya, 2005, Beffy et al., 2012, Long et al., 2015, among others). Therefore, providing evidence about earnings gaps across fields and, more importantly, about the drivers of such disparities would be extremely valuable for future university students (and their parents) when deciding about their college major. Second, insights about determinants of earnings disparities across fields of study would be useful for academic policies aimed at efficiently allocating economic resources across universities and academic areas, setting tuition fees for different university programs, as well as determining the course composition of different fields of study that will prepare students for the labor market. This would be especially important in the context of a sustained expansion of tertiary education, as is occurring in many developed and emerging countries, since the supply of university graduates from different fields of study constitutes an important input into the skill composition of the future workforce (Altonji et al., 2015). Its efficient allocation in the economy represents a fundamental aspect for guaranteeing a sustainable pattern of economic growth and development.

We consider the case of Turkey, a developing country that has been characterized by a huge 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 (see Tansel, 1994, 2001, and 2010). Indeed, during the period 2014-2016, the numbers of male (female) students within the entire higher education system rose from 2.9 (2.1) to 3.6 (3.1) million, representing substantial increases in recent years. 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 (for additional details, see Caner and Okten, 2010 and Frisanchio et al., 2016). Therefore, having a clear picture about the relative monetary rewards of holding a degree in different fields of study would be beneficial for prospective students, when carrying out the necessary investment to prepare for the university entrance examination. Moreover, the evidence we report in this paper could be useful for administrators, since it can serve as a basis to optimally set the university entrance examination cut-off points associated with different disciplines. More generally, our work represents the first contribution about the monetary value attached to different fields of tertiary education in developing countries, since to the best of our knowledge the existing literature is exclusively focused on developed countries.<sup>1</sup>

Our empirical analysis proceeds as follows: First, we run simple OLS regressions for (log) real hourly wages with a set of field of study indicators. The wage equations are estimated for male wage-earners, in order to minimize issues due to possible self-selection into labor market participation and employment. The model is initially based on a parsimonious specification that includes only controls for survey wave, current job tenure, and potential experience (previous to current employment). Next, we progressively augment the wage equation by including additional controls for family characteristics (marital status and the number of children), job characteristics (employment sector, a quadratic function of firm size and occupation), and regional fixed effects (dummies for the 26 NUTS2 regions). These estimates reveal that *ceteris paribus* differences in wages across fields of study are, to a certain extent, mediated by the conditional association between wages and other observed characteristics. Third, we investigate the factors that account for the raw wage gaps across college majors by performing the Oaxaca-Blinder decomposition for average outcomes. This methodology disentangles the observed average differences in hourly wages into the contribution of observable characteristics (endowments or explained component) and the corresponding coefficients (prices or unexplained component). A similar decomposition approach has only been applied by Grave and Goerlitz (2012) to analyze wage differences by field of

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<sup>1</sup> See Arcidiacono (2004), Hamermesh and Donald (2008), Altonji et al. (2012), Altonji et al. (2014), and Webber (2014) for the case of the US, Bratti et al. (2008), Chevalier (2011), and Walker and Zhu (2011) for the UK, Finnie and Frenette (2003) and Lemieux (2014) for Canada, Hasting et al. (2013) and Rodríguez et al. (2015) for Chile, Ballarino and Bratti (2009) and Buonanno and Pozzoli (2009) for Italy, Kelly et al. (2010) for Ireland, Livanos and Pouliakas (2011) for Greece, Grave and Goerlitz (2012) for Germany and Kirkeboen et al. (2016) for Norway.

study among university graduates in Germany. However, no other paper relies on decomposition analysis to examine the role of observed and unobserved factors in explaining wage gaps between fields of study for university graduates<sup>2</sup>. This means that we provide additional evidence about the drivers of average wage differences by field of study.

The simple regressions and the corresponding decomposition provide evidence only on the average of the wage distribution, which might hide important differentials that take place at other points of the wage distribution than the mean. Therefore, we go a step further by providing distributional wage gaps. There are a few papers that investigate wage differences by field of study along the conditional wage distribution using classical Quantile Regressions (see Hamermesh and Donald, 2008, Kelly et al., 2010, Chevalier, 2011 and Livanos and Pouliakas, 2011). In this paper, rather than considering the effect of fields of study at different points of the conditional wage distribution, we adopt the Unconditional Quantile Regression (UQR) approach proposed by Firpo et al. (2009). This approach provides the wage differential of a given field relative to the chosen base category at different points of the unconditional wage distribution. This is indeed an important piece of evidence, since not only policy-makers but also students and parents are more likely to be interested in the relative returns to different college majors on the unconditional wage distribution. Such estimates can be obtained through the Recentered Influence Function (RIF) Regression. It yields estimates of Unconditional Quantile Partial Effects of holding a degree in a given field. This novel approach has never been applied in the literature on fields of study, and thus represents an important contribution of this paper. Therefore, in a subsequent step, we decompose the gaps observed at different points of the unconditional wage distribution using the decomposition method based on RIF-Regressions (Firpo et al., 2007). The decomposition based on RIF-Regressions extends the classical Oaxaca-Blinder decomposition<sup>3</sup> by disentangling the explained and unexplained components of the wage gap by field of study at different points of the unconditional wage distribution. The evidence from this distributional decomposition is informative, since the relative role of returns and endowments in explaining wage differences across fields of study is likely to depend on the point of the wage distribution at which they are evaluated. As such, our RIF-based decomposition

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<sup>2</sup> It seems also worth mentioning that Lemieux (2014) decomposed the wage gap between high school graduates and university graduates in a given field, focusing on the role of occupation and its relationship to the field of study.

<sup>3</sup> Moreover, the RIF-based decomposition is not path-dependent and allows for a detailed analysis of the contribution of separate covariates (and the corresponding coefficients) on the distributional wage gap.

analysis of wage gaps by field of study constitutes the last remarkable value-added of our work with respect to the existing research.

Although informative about the role of explained and unexplained factors in accounting for the wage gaps across different disciplines, it seems worth recognizing that our approach remains subject to one of the main challenges in the estimation of the wage effect of holding a degree in a given subject: the issue of self-selection into different disciplines based on unobservable characteristics. There are very few papers that explicitly deal with this issue. The endogeneity of the choice of field of study has been approached by means of structural economic models by Arcidiacono (2004) and more recently, by Kinsler and Pavan (2015). An alternative and promising approach is based on exploiting discontinuities induced by test-score based university admission,<sup>4</sup> which generates a random variation in the choice of university-subject combinations. Variants of this general strategy have been developed by Hastings et al. (2013) for Chile and by Kirkebøen et al. (2016) for Norway. In both countries, university entrance is ruled by a centralized admission process and, more importantly, it is possible to link administrative information about exam performance, college choice, and preferences with future earnings. This enables estimating the causal effect of completing the degree in a given subject, net of the effect of selection into fields and into next-best alternatives (Kirkebøen et al., 2016). Although university entrance in Turkey is managed in a similar way, combining college application data with information on post-graduate labor market outcomes is unfortunately still unfeasible for this country. Consequently, we are forced to rely on conditional correlations (as is done in the majority of related works) and to interpret the unexplained component of wage differentials across fields as the composite impact of returns to observable characteristics and selection-on-unobservable characteristics. In our view, although clearly representing a second-best solution, the results from our approach are still informative about the drivers of wage differences by the field of study, and will highlight the factors that should be better investigated in causal terms when more detailed data become available.

The rest of the paper proceeds as follows: in Section 2 we describe the data and present some descriptive statistics, in Section 3 we explain the empirical methodology that is applied in the empirical analysis, in Section 4 we present and discuss the results

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<sup>4</sup> Additionally, Ketel et al. (2016) analyzed the return to being admitted to a medical school in the Netherlands, which is based on a lottery mechanism that enables relying on randomization to remove self-selection in the choice of the field of study.

for average wage differentials (4.1) and distributional wage differentials (4.2) and finally we conclude in Section 5.

## 2) Data Description

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. Although the HLFS database is also available for previous years, 2009 is the first wave in which a question about the individual's field of study is included. The survey originally considers 20 different categories for fields of study (plus one category for military/police career studies<sup>5</sup>). We regrouped them into 15 categories due to small sample sizes in some fields in the original classification. We select only tertiary educated males who are regularly employed as wage-earners at the time of the survey.<sup>6</sup> We retain only individuals employed full-time who work no less than 30 hours and no more than 72 hours per week. Individuals who are either older than 65 or younger than 23 are excluded from the final sample, as well as those who are enrolled in education at the time of the survey. 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 in relevant variables, we end up with a pooled sample of 77,154 observations.

Our dependent variable is the log of hourly real 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 salary. In order 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. Table A1 in the Appendix displays the distribution of college major across survey waves, as well as for the pooled sample (2009-2015).<sup>7</sup> The raw data indicate that business and

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<sup>5</sup> 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.

<sup>6</sup> This restriction implies that we aim at obtaining evidence for the (male) working population, which should not be taken as representative for the whole population of individuals in the labor force because of potential self-selection into employment. For this reason, we rely only on the male subsample, since this selectivity issue should be less pronounced for males than for females even among tertiary educated individuals.

<sup>7</sup> Descriptive statistics for the variables used in the empirical analysis are reported in Table A2 in the Appendix. Notice that the information about occupation and sector has been recorded into more aggregated categories, in order to avoid small or empty cells for certain occupations/sectors (especially in those fields where the distribution of these variables is highly concentrated into specific categories).

management is the most common field of study (27%), followed by education and engineering each accounting for about 15% of the pooled sample. Further, the fields of education, arts, humanities, personal services, architecture, agriculture & veterinary, and health have all lost importance over the period 2009-2015, while the share of observations in business & management, engineering, and (to a lesser extent) manufacturing increased over time during the same period.

Kernel density estimates of the (log) hourly real wage by fields of study are reported in Figure 1. In order 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 & 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 & statistics, architecture, and agriculture & veterinary are placed in an intermediate position and their wages are mostly concentrated around the mean. Similar to 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 on 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 regression and decomposition tools.



### 3) Empirical Methodology

#### 3.1) Average Wage Differentials

The starting point of our analysis of wage differentials by fields of study consists of a simple OLS regression that explains (logged) real hourly wages ( $\ln(w_i)$ ) as a function of a vector of control variables ( $X_i$ ) and a set of dummies for each field of study ( $FS_i$ ):

$$\ln(w_i) = \alpha + \beta'X_i + \sum_j \delta_j I(FS_i = j) + \varepsilon_i \quad j = 1 \dots J - 1. \quad (1)$$

Here  $\delta_j$  represent the coefficients of interest, which measure the percentage wage difference of holding a degree in field “ $j$ ” relative to the reference category (in our case, the field of “business and management”). We first present the estimates of  $\delta_j$  without conditioning for any observable characteristics, which yield unconditional wage differences across different fields of study. Second, we progressively expand the vector of covariates, moving from a regression that contains only the basic set of controls (current job tenure and previous potential experience, both in quadratic form, plus survey wave dummies), which is subsequently augmented by family characteristics, sector dummies and firm size (in quadratic form), occupation dummies and NUTS2 region dummies. This stepwise inclusion of control variables yields different estimates of the “*ceteris paribus*” wage differentials by college major, and allows to assess whether the raw wage differences observed across different fields of study are, to some extent, mediated by other observable characteristics of the individual, his job, and his region of residence, which might co-vary with both fields of study and salaries.

In order to better appreciate the contribution of observable characteristics on the observed wage disparities between individuals who graduated from different fields, we apply the Oaxaca-Blinder (OB) decomposition for average wage gaps (Oaxaca, 1973, Blinder, 1973). This well-known decomposition method disentangles average outcome differentials into the contribution of the (average) endowment of observable characteristics (i.e. the explained or composition component) and the contribution of unexplained factors (i.e. the so-called wage structure component, which is captured by differences in the estimated coefficients). To avoid choosing an arbitrary reference field, we decompose the gap between the average wages of individuals graduated in field  $j$  and the average wages in all other fields of study different from  $j$  ( $-j$ ) of their counterparts. Moreover, as suggested by Fortin (2008) and Fortin et al. (2011), we estimate the

nondiscriminatory reference wage structure from a pooled regression with all the fields together,<sup>8</sup> imposing an identification restriction that ensures that the wage advantage of one field equals the disadvantage suffered by other fields, that is:

$$\ln(w_i) = \alpha + \beta'X_i + \gamma_j I(FS_i = j) + \gamma_{-j} I(FS_i \neq j) + u_i \quad j = 1 \dots J \quad (2)$$

subject to  $\gamma_j + \gamma_{-j} = 0$

Equation (2) is estimated for each different field of study ( $j$ ) using the pooled sample, and contains indicators for being graduated in field “ $j$ ” ( $FS_i = j$ ) and for being graduated in any of the fields that is different from “ $j$ ” ( $FS_i \neq j$ ). The estimated  $\beta$  coefficient thus represents the nondiscriminatory wage structure that is used in the decomposition. From the estimates of equation (2) it is possible to decompose the raw percentage wage differentials between graduates in field “ $j$ ” and their counterparts who obtained a degree in a different field ( $-j$ ) into different components as follows:

$$\begin{aligned} \overline{\ln(w_j)} - \overline{\ln(w_{-j})} &= (\bar{X}_j - \bar{X}_{-j})\hat{\beta} + (\hat{\gamma}_j - \hat{\gamma}_{-j}) + E[u_i|FS_i = j] - E[u_i|FS_i \neq j] \\ &= (\bar{X}_j - \bar{X}_{-j})\hat{\beta} + \underbrace{[(\bar{X}_j(\hat{\beta}_j - \hat{\beta}) + (\hat{\alpha}_j - \hat{\alpha}))]}_{\hat{\gamma}_j} - \underbrace{[(\bar{X}_{-j}(\hat{\beta}_{-j} - \hat{\beta}) + (\hat{\alpha}_{-j} - \hat{\alpha}))]}_{\hat{\gamma}_{-j}} \end{aligned} \quad (3)$$

The term  $(\bar{X}_j - \bar{X}_{-j})\hat{\beta}$  represents the composition effect (i.e. average wage differences due to differences in observable characteristics), whereas the term  $(\hat{\gamma}_j - \hat{\gamma}_{-j}) = (\bar{X}_j(\hat{\beta}_j - \hat{\beta}) + (\hat{\alpha}_j - \hat{\alpha})) - (\bar{X}_{-j}(\hat{\beta}_{-j} - \hat{\beta}) + (\hat{\alpha}_{-j} - \hat{\alpha}))$  corresponds to the part of the mean differential that can be attributed to different remuneration of observable characteristics across fields of study.<sup>9</sup>

### 3.2) *Distributional Wage Differentials*

It seems worth noting that both the regression analysis and the OB decomposition provide evidence about average wage differences across college majors. However, as

<sup>8</sup> Notice that the OB decomposition (as well as the distributional analysis that follows) is carried out using the full set of control variables included in the vector  $X$ .

<sup>9</sup> Notice that the term  $E[u_i|FS_i = j] - E[u_i|FS_i \neq j]$  is assumed to be zero, which corresponds to the standard OLS hypothesis of orthogonality between the error term and the regressors (in this case, the dummies for field of study). Moreover, it seems worth commenting that the OB decomposition can be further divided into the contribution of each specific covariate, which can be eventually also aggregated into subgroups (as explained later). However, the presence of categorical variables makes the results of the detailed decomposition dependent on the choice of the reference category. This issue can be avoided by “normalizing” the effects of discrete covariates as explained in Jann (2008).

commented in the introduction (and confirmed by the graphical analysis of the wage distribution by field of study), focusing on average gaps could hide important disparities that could occur in other parts of the wage distribution than the mean. To evaluate distributional wage disparities across fields of study, we estimate the Unconditional Quantile Regression (UQR) proposed by Firpo et al. (2009). The UQR method is based on the statistical concept of Influence Function (IF), which represents the influence of an individual observation on a distributional statistic of interest (e.g. the quantile). By adding back the statistic to the corresponding IF, it is possible to obtain the Recentered Influence Function (RIF) for each quantile of the outcome. Specifically, the RIF for the  $\tau$ th quantile ( $q_\tau$ ) of logged hourly wages corresponds to,

$$RIF(\ln(w_i), q_\tau) = q_\tau + IF(\ln(w_i), q_\tau) = q_\tau + \frac{\tau - I(\ln(w_i) \leq q_\tau)}{f_{\ln(w)}(q_\tau)} \quad (4)$$

where  $I(\cdot)$  is an indicator function and  $f_{\ln(w)}(q_\tau)$  is the density of the marginal (unconditional) distribution of the outcome ( $\ln(w)$ ) evaluated at  $q_\tau$ . The estimated counterpart of the RIF is simply obtained by replacing the unknown components by their sample estimators, such as,

$$\widehat{RIF}(\ln(w_i), \hat{q}_\tau) = \hat{q}_\tau + \widehat{IF}(\ln(w_i), \hat{q}_\tau) = \hat{q}_\tau + \frac{\tau - I(\ln(w_i) \leq \hat{q}_\tau)}{\hat{f}_{\ln(w)}(\hat{q}_\tau)} \quad (5)$$

Where  $\hat{f}_{\ln(w)}(\hat{q}_\tau)$  corresponds to a kernel density estimator of the unconditional density function of the outcome. The RIF for a given quantile can be taken as a linear approximation of the nonlinear function of the quantile, and captures the change of the (unconditional) quantile of the outcome in response to a change in the underlying distribution of the covariates (Firpo et al., 2009). In fact, it can be shown that the expected value of the RIF can be modelled to be a linear function of explanatory variables, as in a standard linear regression. Therefore, it is possible to analyze wage disparities by field of study along the (unconditional) wage distribution by specifying the following linear UQR for selected quantiles of the unconditional distribution of real hourly wages ( $\hat{q}_\tau$ ):

$$E[\widehat{RIF}(\ln(w_i), \hat{q}_\tau) | X_i, FS_i] = \hat{\alpha}_\tau + \hat{\beta}_\tau' X_i + \sum_j \hat{\delta}_{j\tau} I(FS_i = j) \quad j = 1 \dots J - 1. \quad (6)$$

The estimates of  $\hat{\delta}_{j\tau}$  from equation (6) represents the marginal impact of a small change in the probability of holding a degree in field “j” (relative to the reference field) on the unconditional  $\tau$ -quantile of logged hourly wages.

Given the linear approximation of the conditional expectation of the RIF and the theoretical property stating that the average  $\overline{RIF}(\ln(w_j), \hat{q}_\tau)$  is equal to the corresponding marginal quantile of the distribution of the outcome ( $\hat{q}_{j\tau}$ ), it is possible to generalize the standard OB decomposition of average outcomes to a distributional decomposition applied to the unconditional distribution of the outcome (see Firpo et al., 2007 and Fortin et al., 2011 for technical details). Put in other words, it is possible to examine the contribution of the endowment of observable characteristics and the returns to these characteristics in explaining the estimated unconditional wage gap across fields of study, applying the outcome decomposition for average outcomes described by equation (3) to the RIF, that is:

$$\hat{q}_{j\tau} - \hat{q}_{-j\tau} = \overline{RIF}(\ln(w_j), \hat{q}_\tau) - \overline{RIF}(\ln(w_{-j}), \hat{q}_\tau) = (\bar{X}_j - \bar{X}_{-j})\hat{\beta}_\tau + \left[ (\bar{X}_j(\hat{\beta}_{j\tau} - \hat{\beta}_\tau) + (\hat{\alpha}_{j\tau} - \hat{\alpha}_\tau)) - (\bar{X}_{-j}(\hat{\beta}_{-j\tau} - \hat{\beta}_\tau) + (\hat{\alpha}_{-j\tau} - \hat{\alpha}_\tau)) \right] \quad (7)$$

Here  $\hat{\beta}_\tau$  corresponds to the nondiscriminatory wage structure (estimated from a pooled RIF regression) at quantile  $\tau$  estimated in a similar fashion as equation (2) using the estimated RIF for individuals graduated in field “j” and in fields different than “j” as dependent variable. Similar to equation (3), the term  $(\bar{X}_j - \bar{X}_{-j})\hat{\beta}_\tau$  represents the composition effect and the term  $(\bar{X}_j(\hat{\beta}_{j\tau} - \hat{\beta}_\tau) + (\hat{\alpha}_{j\tau} - \hat{\alpha}_\tau)) - (\bar{X}_{-j}(\hat{\beta}_{-j\tau} - \hat{\beta}_\tau) + (\hat{\alpha}_{-j\tau} - \hat{\alpha}_\tau))$  captures the unexplained component of the percentage wage differential evaluated at the  $\tau$ -quantile of the unconditional distribution of (logged) wages.

## 4) Estimation Results

### 4.1) Average Wage Differentials

The main results from the OLS estimation of equation (1) are reported in Table 2 (complete results are displayed in Table A3 in the Appendix). The estimates in column (1) are obtained without conditioning on observable characteristics and express percentage differences in real hourly wages relative to graduates in business &

management,<sup>10</sup> 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 & statistics (+12%), agriculture & veterinary (+11%), humanities (+8.5%), and architecture (+7.3%). Thus, manufacturing is the lowest and health is the highest paid field of study compared to business & management.

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 & 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 & veterinary, and health is lower when controlling for the basic set of covariates, and reverts sign for the field of humanities.

Accounting for family characteristics, namely 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 structure and cohabitation do not drive wage disparities between individuals graduated in different disciplines. The results indicate that graduates in education, law, social sciences & services, mathematics & statistics, computing, architecture, agriculture & veterinary, and health all earn more than graduates in business & management with the same amount of work experience and similar family characteristics. The field of personal services gets the lowest remuneration (-10% compared to the reference group). Graduates in arts, personal services, and manufacturing earn less than the reference group. Surprisingly, having a degree in the field of engineering is not associated with higher wages relative to business & management. Health and law appear to be, by far, the college majors that are better

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<sup>10</sup> The average of (log) real hourly wages for graduates in business & 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.

rewarded in the Turkish labor market, even controlling for several individual and family characteristics.

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 & 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 & veterinary is somewhat higher when employment sector and the firm size are included as regressors. The high differential in favor of law and health disciplines is only marginally reduced after controlling for sector and firm size.

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., 2015, p. 35). 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 & 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 & statistics, computing, and agriculture & 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 & veterinary, which is slightly more rewarded than business & management.

We also repeated the OLS estimation for the full specification of the wage equation splitting the sample into three age groups namely 23-30, 31-40, and 41-65. These results are reported in Table A3 in the Appendix. This exercise provides a picture of the relative pay differentials across disciplines at different stages of the career. There are remarkable differences over the life-cycle for humanistic disciplines. Namely, the premium associated with education is mostly captured by young workers, who earn 13.2% more than their counterparts of the same age cohort who graduated in business & management, while the oldest group of workers in this field suffers an earnings penalty. A similar pattern is observed for arts, since young graduates in this field are better paid than the reference field, while the opposite is true for the older cohorts. The premium for graduates in social sciences and architecture vanishes in advanced stages of the working career. On the contrary, the premium for the fields of law, computing, manufacturing, health, and to a lesser extent, hard sciences is higher for the more senior groups of workers.

In order 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 block of variables (and their returns) are shown in Table A4 in the Appendix. 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 and their return (both with a negative sign). 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 & management is less rewarded than others, which is almost equally explained by a less favorable endowment of observable characteristics and lower returns. In contrast, for law (which is a highly paid field) the unobservable components are slightly more relevant than the observables in explaining the higher average hourly wage. 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, for computing lower work experience/job tenure are the main conditioning factors behind the negative wage differential they suffer. 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. The wage rate for graduates in architecture does not significantly differ from those in other fields, and the slightly higher wages for agriculture & veterinary are driven by the net effect of a better distribution of observed characteristics and lower associated returns. Finally, the field of health is clearly better rewarded, whereby the unexplained factors are more important than the explained. 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.

#### ***4.2) Differences along the Wage Distribution***

Selected coefficients from RIF-Regressions estimated at different deciles of the unconditional wage distribution are displayed in Table 3 (complete results are not shown but are available upon request). These represent the estimates of equation (6), which are obtained using the full set of control variables. We also report the result from the OLS regression to allow for comparison. The same evidence can be graphically appreciated in Figure 3. Overall, the results highlight substantial heterogeneity in wage differentials by field of study along the distribution of real hourly wages. Relative to business & management, graduates in education are better remunerated at the bottom of the unconditional wage distribution, but the effect decreases monotonically with the quantiles and becomes negative after the median. A similar pattern is observed for humanities. In contrast, the high average reward to a degree in law that is detected by OLS is mostly operating in the upper part of the wage distribution, since for lower deciles the positive gap relative to the reference field is significantly less pronounced (but still positive). Social science degrees yield a payoff relative to business & management only at the



bottom of the wage distribution, while no important differences are detected above the median.

Interestingly, the wage premium in hard sciences is higher at lower quantiles, but remains significant over the whole distribution. Graduates in mathematics & statistics are instead slightly less rewarded than those in business & management only in the middle of the distribution. As for graduates in computing, we observe lower wages at the left tail of the distribution, but the sign of the gap is reversed above the median. Indeed, this substantial heterogeneity was not captured by the average differential estimated by OLS, which is virtually zero. Similarly, also for the field of manufacturing there is a negative gap relative to business & management in the lower decile of the wage distribution, which reverts to positive around the center. However, no significant differences are detected at higher deciles. The returns to engineering increase along the unconditional wage distribution, while the estimated differential decreases slightly for architecture. In any case, both fields are better remunerated than business & management along the whole unconditional distribution of hourly wages. Hourly pay gaps between agriculture & veterinary and the reference field follow an inverted U-shaped pattern (being negative at the lowest and highest deciles, respectively). Finally, similar to the case of law, the positive wage gap in favor of health is especially high at the top of the unconditional wage distribution, but is also relevant even at its left cue.

The decomposition results of wage gaps at different deciles of the unconditional wage distribution are reported in Table 4 and graphically displayed in Figure 4. Detailed RIF-decomposition results are shown in Table A6 in the Appendix. It appears that observable and unobservable components have a similar weight in explaining wage differences for the field of education at different points 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 deciles is mostly driven by occupation, which exerts a positive effect over the entire distribution, but is indeed compensated 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 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, but tends to decrease along it. 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 (which is also relevant at the top of the distribution). Observable characteristics account for most of the positive wage gap observed for humanities at the bottom of the wage distribution, but their relevance declines and even becomes negative at top quantiles (where graduates in this field earn less than their counterparts). Similar to the case of education, although occupational selection represents a favorable endowment for graduates in humanities, differences in employment 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 unobservables in accounting for the wage gap at bottom deciles.

In the case of business & management, the negative wage gap that graduates in this field experience relative to their counterparts generally tends to vanish along the unconditional wage distribution (with the exception of the last quantile) and seems to be mostly driven by the unfavorable distribution of endowments at lower deciles. More specifically, occupational selection tends to penalize low-paid graduates in this field. Occupation seems to exert a negative effect on wages of graduates in business & 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 points 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, return to occupational categories has a positive impact at the center of the unconditional distribution and contributes to the high wage gap experienced by graduates in law. The negative wage gap for personal service is largely explained by the unfavorable endowment of observable characteristics, with the exception of the left tail of the wage distribution where the contribution of unexplained factors slightly mitigates the distribution of observables. Detailed decomposition results show that occupational choices are 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 (i.e. work experience and sector/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 distribution, seem to be mostly explained by the effect of covariates, among which occupational selection plays the most important role. Graduates in mathematics & 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, but 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, being 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 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 to 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 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 & veterinary, the inverted U-shaped contribution of unexplained characteristics is what drives the same pattern observed for the overall wage gap. Indeed, they tend to be better paid than other fields around the center of the wage distribution and the endowment of observable characteristics is generally favorable for them but the contribution of the estimated coefficients tend to be negative at the two extremes of the distribution and positive in the middle. We detected a positive impact of the coefficients associated with family characteristics along the whole 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 & veterinary relative to their counterparts from other fields. 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. Moreover, among the observable characteristics, selection into occupation and employment sector and, to a lesser extent, differences in work experience represent the main factors behind the significant wage premium experienced by graduates in health disciplines.

## **5) Conclusions**

This paper reports evidence on the pay disparities among tertiary educated 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. Observable characteristics matter in explaining wage differences by field of study, since conditioning for characteristics alters the magnitude and in some case 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 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 (with the exception of the field of agriculture & veterinary).

With the aim of appreciating 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. Indeed, 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). It seems also worth noting that, in some cases, explained and unexplained components contribute to the wage gaps in opposite directions. Finally, the contribution of unexplained elements turns out to be especially high and actually higher than the contribution of observables for the two top paid fields of study, law, and health. This finding is possibly due to the importance of self-selection of high wage potential individuals into these two fields, which are among the ones with the highest cut-off score requirements for the university admission test, but also to labor market regulations that cover most of the jobs/sectors where graduates in law and health are usually employed.

As long as important wage disparities between individuals who obtained a degree in a different field of study could occur at other points of the distribution than the mean, we investigated distributional wage gaps along the unconditional distribution of hourly wages. Recentered Influence Function (RIF) Regressions estimates indicate that wage disparities by college major generally vary over the wage distribution, making the distributional analysis particularly relevant to analyze pay gaps by field of study. Indeed, wage differences (relative to the reference category) display a decreasing pattern for the fields of education, humanities, personal services, social services, mathematics & statistics and architecture (except for the last quantile), moving from positive to negative differentials. In contrast, pay disparities tend to increase along the wage distribution for law, health, computing, and engineering (moving from negative to positive for the latter two), and display an inverted U-shaped pattern for graduates in arts, manufacturing, and agriculture & veterinary.

We finally decomposed distributional wage differentials, in order to understand whether the contributions of explained and unexplained factors also change at different points of the unconditional distribution of hourly wages. The distributional decomposition confirms that the endowment of observable characteristics represents the main driver of wage differentials, but their contribution to the observed wage gaps 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 & statistics, and from negative to positive for architecture). Unexplained elements instead appear very relevant for the fields of law and health, the top paid college majors, and actually 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 results point out that selection into occupation and, to a lesser extent, into economic sectors represents the main mechanism behind observed wage differences between individuals who obtained a university degree in a different field of study. As long as these two selection mechanisms are likely to be determined by both observable and unobservable individual characteristics (possibly correlated with wage potential), and in this work we are unable to disentangle between the two, additional research is needed to better understand the real contribution of occupation and employment sector to the wage return attributed to different fields of study. Related to this, although the contribution of unexplained factors is generally lower than the contribution of observables, understanding the extent to which endogenous self-selection of individuals into different fields of study represents the main driver of wage differences represents a challenge for future research, which will be possible when more detailed (administrative) data also becomes available in the case of Turkey. Indeed, it is quite likely that selection into the fields of law and health, based on unobserved traits that correlate with earnings potential, would account for most of the high wage premium attached to these fields at the top of the distribution (which is mostly left unexplained).

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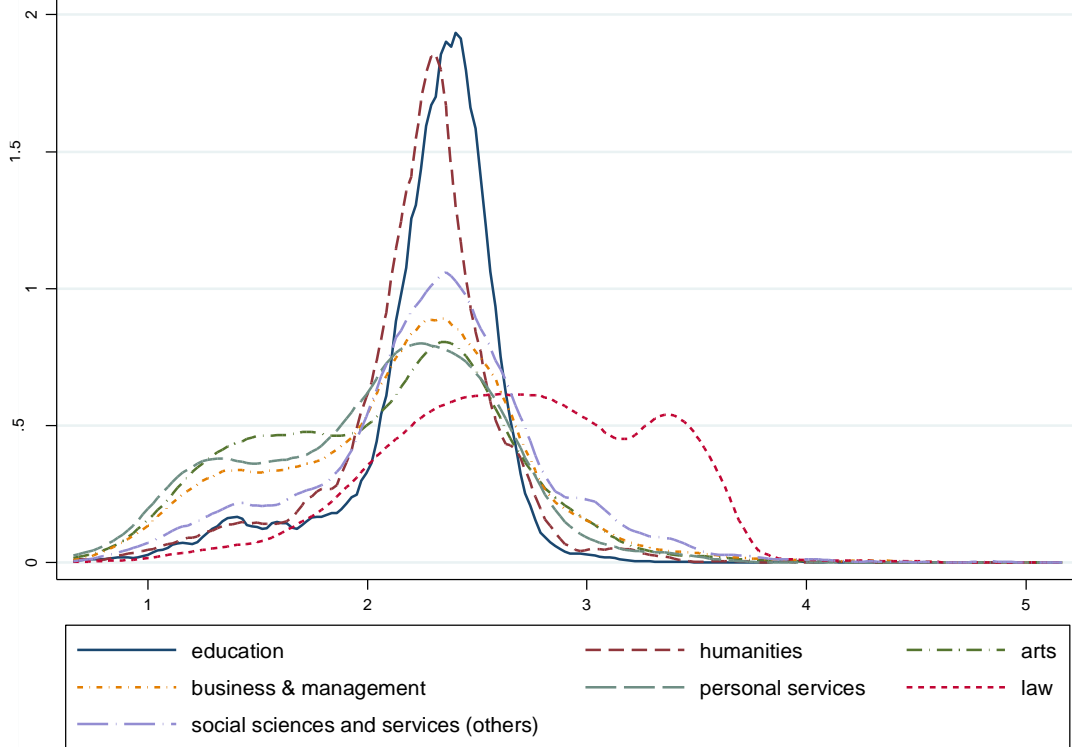
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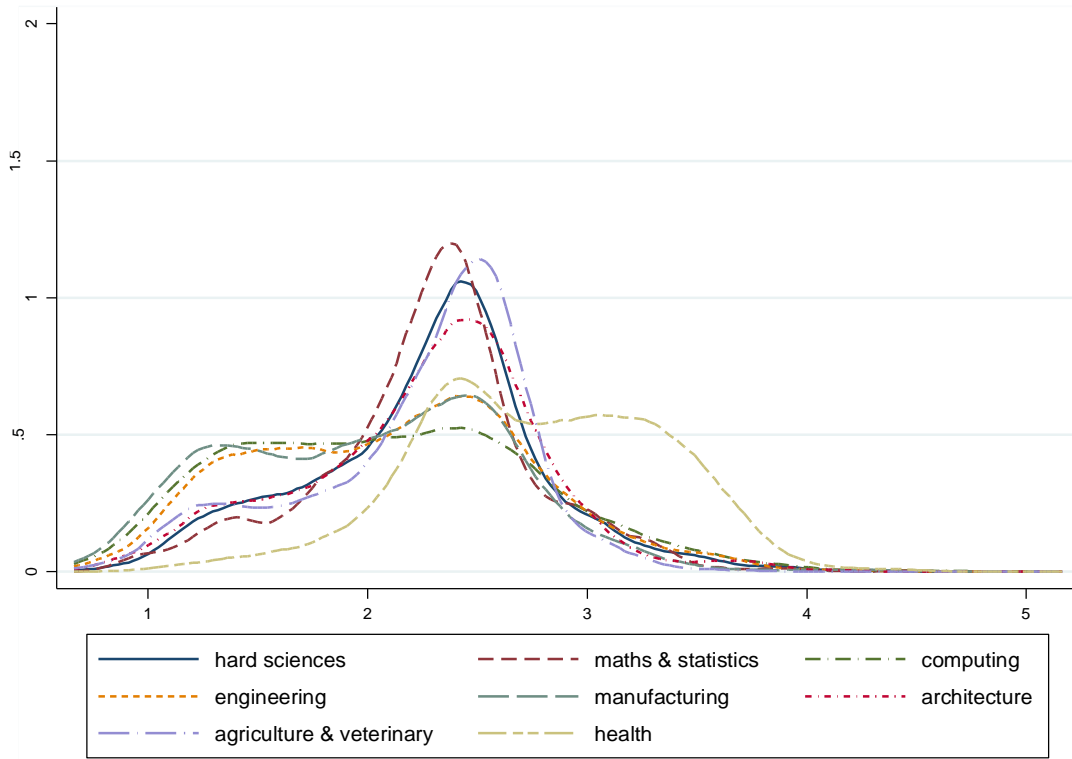
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## Tables and Figures

**Figure 1a: Kernel Density Estimate of (Log) Hourly Wage by Field of Study**



**Figure 1b : Kernel Density Estimate of (Log) Hourly Wage by Field of Study**



**Table 1: Selected OLS Estimates**

	(1)	(2)	(3)	(4)	(5)	(6)
education	0.129*** (0.005)	0.103*** (0.004)	0.093*** (0.004)	0.086*** (0.005)	0.013** (0.005)	0.020*** (0.005)
arts	-0.079*** (0.017)	-0.034** (0.015)	-0.036** (0.014)	-0.016 (0.014)	-0.038*** (0.013)	-0.047*** (0.013)
humanities	0.085*** (0.007)	-0.011* (0.006)	-0.008 (0.006)	0.038*** (0.007)	-0.038*** (0.007)	-0.036*** (0.007)
business & management	<i>reference category</i>					
law	0.550*** (0.018)	0.503*** (0.017)	0.498*** (0.017)	0.445*** (0.015)	0.310*** (0.013)	0.309*** (0.013)
personal services	-0.088*** (0.014)	-0.105*** (0.012)	-0.099*** (0.012)	-0.065*** (0.011)	-0.008 (0.010)	0.002 (0.010)
social sciences and services (others)	0.129*** (0.007)	0.064*** (0.006)	0.067*** (0.006)	0.059*** (0.006)	0.032*** (0.005)	0.029*** (0.005)
hard sciences	0.137*** (0.010)	0.132*** (0.009)	0.131*** (0.009)	0.130*** (0.009)	0.041*** (0.008)	0.045*** (0.008)
maths & statistics	0.120*** (0.014)	0.132*** (0.013)	0.119*** (0.013)	0.068*** (0.012)	-0.006 (0.012)	-0.009 (0.012)
computing	-0.121*** (0.020)	0.058*** (0.019)	0.058*** (0.019)	0.053*** (0.017)	0.017 (0.015)	0.008 (0.014)
engineering	-0.052*** (0.007)	0.007 (0.006)	0.007 (0.006)	0.051*** (0.006)	0.062*** (0.006)	0.067*** (0.006)
manufacturing	-0.141*** (0.017)	-0.075*** (0.015)	-0.077*** (0.015)	-0.005 (0.014)	-0.028** (0.012)	-0.011 (0.012)
architecture	0.073*** (0.010)	0.082*** (0.010)	0.087*** (0.009)	0.094*** (0.009)	0.034*** (0.008)	0.044*** (0.008)
agriculture & veterinary	0.110*** (0.010)	0.071*** (0.008)	0.070*** (0.008)	0.075*** (0.008)	-0.001 (0.007)	0.023*** (0.007)
health	0.646*** (0.010)	0.580*** (0.009)	0.574*** (0.009)	0.531*** (0.012)	0.405*** (0.011)	0.410*** (0.011)
basic controls	<i>no</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
family characteristics	<i>no</i>	<i>no</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
sector dummies and firm size (sq.)	<i>no</i>	<i>no</i>	<i>no</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
occupation dummies	<i>no</i>	<i>no</i>	<i>no</i>	<i>no</i>	<i>yes</i>	<i>yes</i>
nuts2 regions dummies	<i>no</i>	<i>no</i>	<i>no</i>	<i>no</i>	<i>no</i>	<i>yes</i>
adjusted R-squared	0.091	0.263	0.283	0.361	0.472	0.489
number of observations	77154	77154	77154	77154	77154	77154

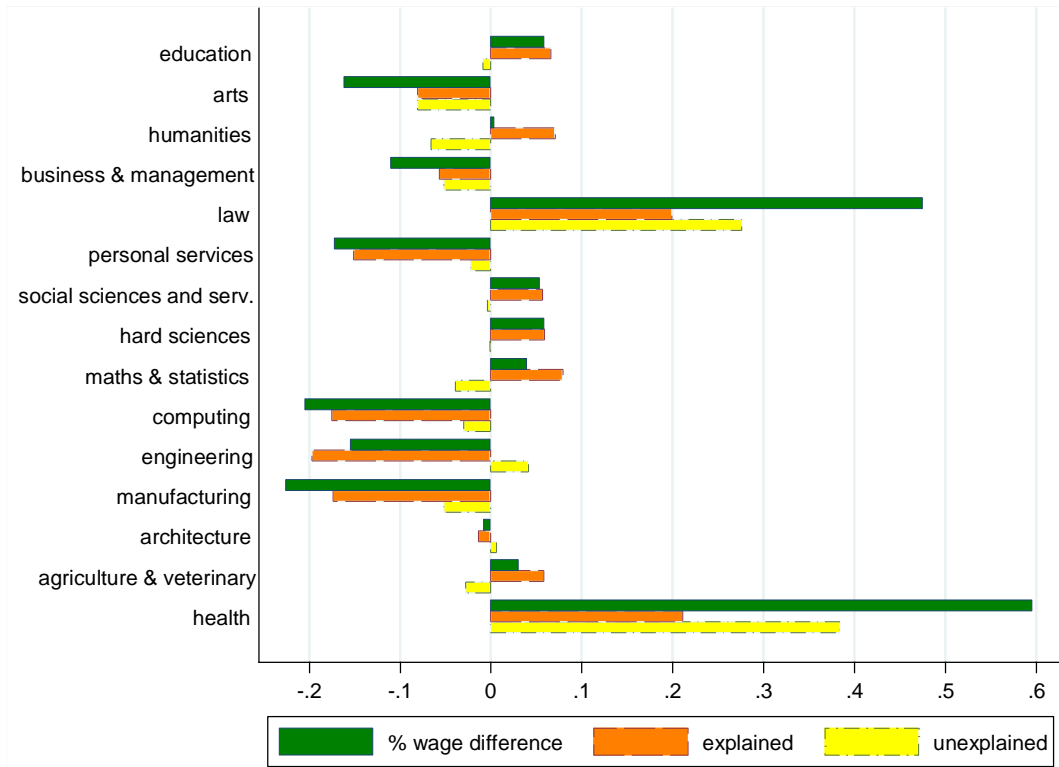
Note: robust standard errors in parenthesis, \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. Regression in column (2) contains controls for wave dummies, previous potential experience (quadratic) and current job tenure (quadratic). Regression in column (3) includes dummies for 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. Complete estimates are reported in Table A2 in the Appendix.

**Table 2: Oaxaca-Blinder Decomposition**

<b>field of study</b>	<b>% wage difference</b>	<b>explained</b>	<b>unexplained</b>
education	0.058	0.066	-0.009
<i>z-stat</i>	15.38	17.25	-2.10
arts	-0.162	-0.081	-0.081
<i>z-stat</i>	-9.69	-6.84	-6.54
humanities	0.004	0.071	-0.066
<i>z-stat</i>	0.79	15.08	-11.84
business & management	-0.110	-0.057	-0.052
<i>z-stat</i>	-24.66	-16.94	-14.49
law	0.475	0.199	0.276
<i>z-stat</i>	26.28	17.91	21.78
personal services	-0.172	-0.151	-0.022
<i>z-stat</i>	-12.36	-14.99	-2.16
social sciences and services (others)	0.053	0.057	-0.004
<i>z-stat</i>	8.55	12.57	-0.75
hard sciences	0.058	0.059	-0.001
<i>z-stat</i>	5.97	8.99	-0.07
maths & statistics	0.040	0.079	-0.039
<i>z-stat</i>	2.89	9.12	-3.41
computing	-0.205	-0.175	-0.030
<i>z-stat</i>	-10.21	-14.11	-2.10
engineering	-0.155	-0.197	0.041
<i>z-stat</i>	-24.43	-43.27	8.31
manufacturing	-0.226	-0.174	-0.052
<i>z-stat</i>	-13.21	-15.17	-4.55
architecture	-0.008	-0.014	0.006
<i>z-stat</i>	-0.86	-1.96	0.75
agriculture & veterinary	0.030	0.058	-0.028
<i>z-stat</i>	3.37	8.62	-4.13
health	0.595	0.211	0.384
<i>z-stat</i>	65.37	25.88	35.81

Note: 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 (quadratic current job tenure (quadratic), dummies for marital status, number of children, dummies for occupation and sector, quadratic firm size and dummies for nuts2 regions. Detailed results are reported in Table A4 in the Appendix.

**Figure 2: Oaxaca-Blinder Decomposition**

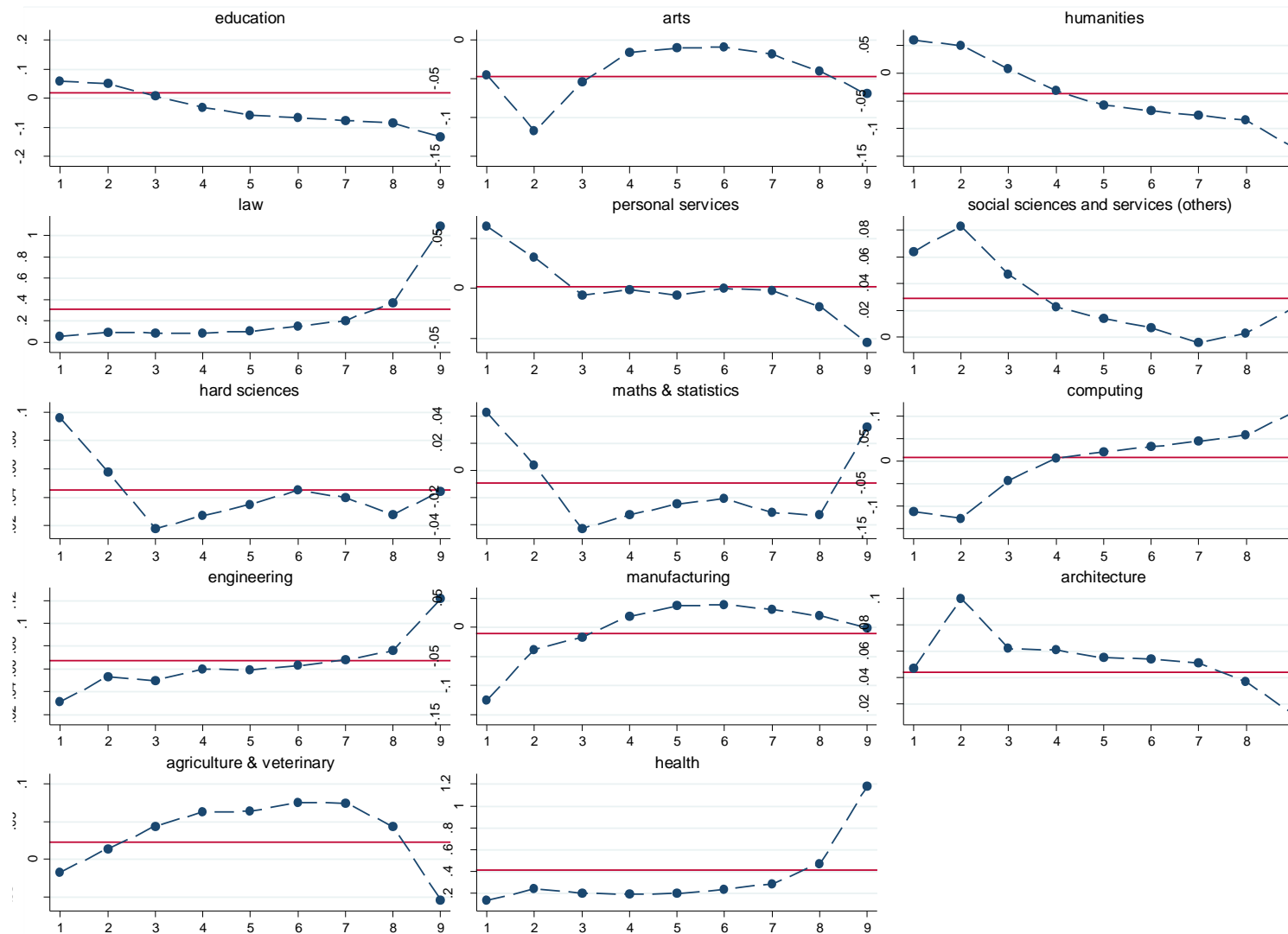


**Table 3: Selected RIF-Regression Estimates**

	<i>OLS</i>	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>
education	0.020*** (0.005)	0.151*** (0.014)	0.184*** (0.015)	0.097*** (0.009)	0.047*** (0.006)	0.010* (0.006)	-0.012** (0.006)	-0.049*** (0.006)	-0.108*** (0.007)	-0.148*** (0.011)
arts	-0.047*** (0.013)	-0.045 (0.039)	-0.117*** (0.039)	-0.054*** (0.020)	-0.016 (0.014)	-0.010 (0.012)	-0.009 (0.012)	-0.018 (0.012)	-0.040*** (0.015)	-0.069*** (0.027)
humanities	-0.036*** (0.007)	0.060*** (0.017)	0.051*** (0.018)	0.008 (0.011)	-0.031*** (0.009)	-0.057*** (0.007)	-0.067*** (0.007)	-0.076*** (0.007)	-0.084*** (0.008)	-0.133*** (0.014)
business & management	<i>reference category</i>									
law	0.309*** (0.013)	0.059** (0.023)	0.098*** (0.028)	0.089*** (0.017)	0.090*** (0.013)	0.106*** (0.011)	0.149*** (0.011)	0.205*** (0.012)	0.372*** (0.018)	1.087*** (0.049)
personal services	0.002 (0.010)	0.062* (0.033)	0.031 (0.031)	-0.007 (0.017)	-0.001 (0.012)	-0.007 (0.010)	0.000 (0.010)	-0.002 (0.010)	-0.018 (0.012)	-0.054*** (0.018)
social sciences and services (others)	0.029*** (0.005)	0.064*** (0.013)	0.083*** (0.014)	0.047*** (0.009)	0.023*** (0.006)	0.014*** (0.005)	0.007 (0.005)	-0.004 (0.005)	0.003 (0.007)	0.022* (0.013)
hard sciences	0.045*** (0.008)	0.096*** (0.020)	0.058*** (0.022)	0.018 (0.012)	0.027*** (0.009)	0.035*** (0.007)	0.045*** (0.007)	0.040*** (0.008)	0.028*** (0.010)	0.044** (0.020)
maths & statistics	-0.009 (0.012)	0.043 (0.028)	0.004 (0.034)	-0.043** (0.020)	-0.033** (0.014)	-0.025** (0.012)	-0.021* (0.012)	-0.031** (0.012)	-0.033** (0.015)	0.032 (0.028)
computing	0.008 (0.014)	-0.112*** (0.043)	-0.127*** (0.040)	-0.043** (0.020)	0.006 (0.013)	0.021* (0.011)	0.032*** (0.010)	0.044*** (0.011)	0.058*** (0.014)	0.109*** (0.030)
engineering	0.067*** (0.006)	0.031** (0.016)	0.053*** (0.016)	0.050*** (0.008)	0.060*** (0.006)	0.059*** (0.005)	0.063*** (0.005)	0.068*** (0.005)	0.076*** (0.006)	0.122*** (0.012)
manufacturing	-0.011 (0.012)	-0.125*** (0.037)	-0.038 (0.034)	-0.017 (0.018)	0.019 (0.012)	0.037*** (0.010)	0.039*** (0.010)	0.031*** (0.010)	0.020 (0.013)	-0.001 (0.024)
architecture	0.044*** (0.008)	0.047** (0.022)	0.100*** (0.023)	0.062*** (0.013)	0.061*** (0.009)	0.055*** (0.008)	0.054*** (0.007)	0.051*** (0.008)	0.037*** (0.010)	0.012 (0.018)
agriculture & veterinary	0.023*** (0.007)	-0.017 (0.019)	0.014 (0.020)	0.044*** (0.011)	0.063*** (0.008)	0.064*** (0.007)	0.076*** (0.007)	0.075*** (0.008)	0.044*** (0.010)	-0.055*** (0.017)
health	0.410*** (0.011)	0.132*** (0.020)	0.239*** (0.024)	0.201*** (0.014)	0.189*** (0.011)	0.197*** (0.009)	0.237*** (0.009)	0.285*** (0.010)	0.473*** (0.014)	1.184*** (0.030)
R-squared	0.489	0.267	0.401	0.404	0.364	0.324	0.300	0.284	0.272	0.250
number of observations	77154	77154	77154	77154	77154	77154	77154	77154	77154	77154

Note: robust standard errors in parenthesis, \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions contain controls for wave dummies, previous potential experience (quadratic), current job tenure (quadratic), dummies for marital status, number of children, dummies for occupation and sector, quadratic firm size and dummies for nuts2 regions.

**Figure 3: Selected RIF-Regression Estimates**



Note: continuous lines represent the OLS estimates (as in the first column of Table 3) and dashed lines are the RIF-Regression estimates for different quantiles (as in the corresponding columns of Table 3).

**Table 4: RIF-Regression Decomposition**

	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>
<b>education</b>									
% wage difference	0.483	0.406	0.214	0.133	0.055	0.009	-0.037	-0.130	-0.286
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	10.69	22.66	4.69	-0.34	-7.77	-9.08	-7.41	-15.08	-16.50
<b>arts</b>									
% wage difference	-0.138	-0.293	-0.317	-0.229	-0.133	-0.088	-0.079	-0.082	-0.082
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	0.01	-2.07	-6.81	-4.70	-3.53	-2.59	-2.96	-3.63	-3.35
<b>humanities</b>									
% wage difference	0.398	0.260	0.094	0.030	-0.022	-0.062	-0.103	-0.135	-0.204
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	7.64	-8.10	-15.50	-13.61	-14.13	-11.97	-12.10	-8.08	-5.86
<b>business &amp; management</b>									
% wage difference	-0.128	-0.194	-0.155	-0.115	-0.084	-0.067	-0.036	-0.054	-0.133
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	-2.23	-6.49	-10.33	-13.07	-11.58	-11.51	-5.36	-10.25	-13.41
<b>law</b>									
% wage difference	0.554	0.407	0.322	0.345	0.425	0.499	0.563	0.688	0.665
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	9.05	-0.55	3.41	8.09	12.22	17.60	15.37	20.10	30.98
<b>personal services</b>									
% wage difference	-0.163	-0.258	-0.222	-0.159	-0.138	-0.124	-0.108	-0.115	-0.181
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	4.42	1.19	-1.72	-2.27	-3.13	-3.30	-2.49	-2.03	-2.28
<b>social sciences and services (others)</b>									
% wage difference	0.169	0.171	0.059	0.030	0.007	0.005	0.006	0.032	0.025
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	3.96	2.92	-0.38	-0.28	-3.37	-4.17	-5.80	-2.17	-1.95

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

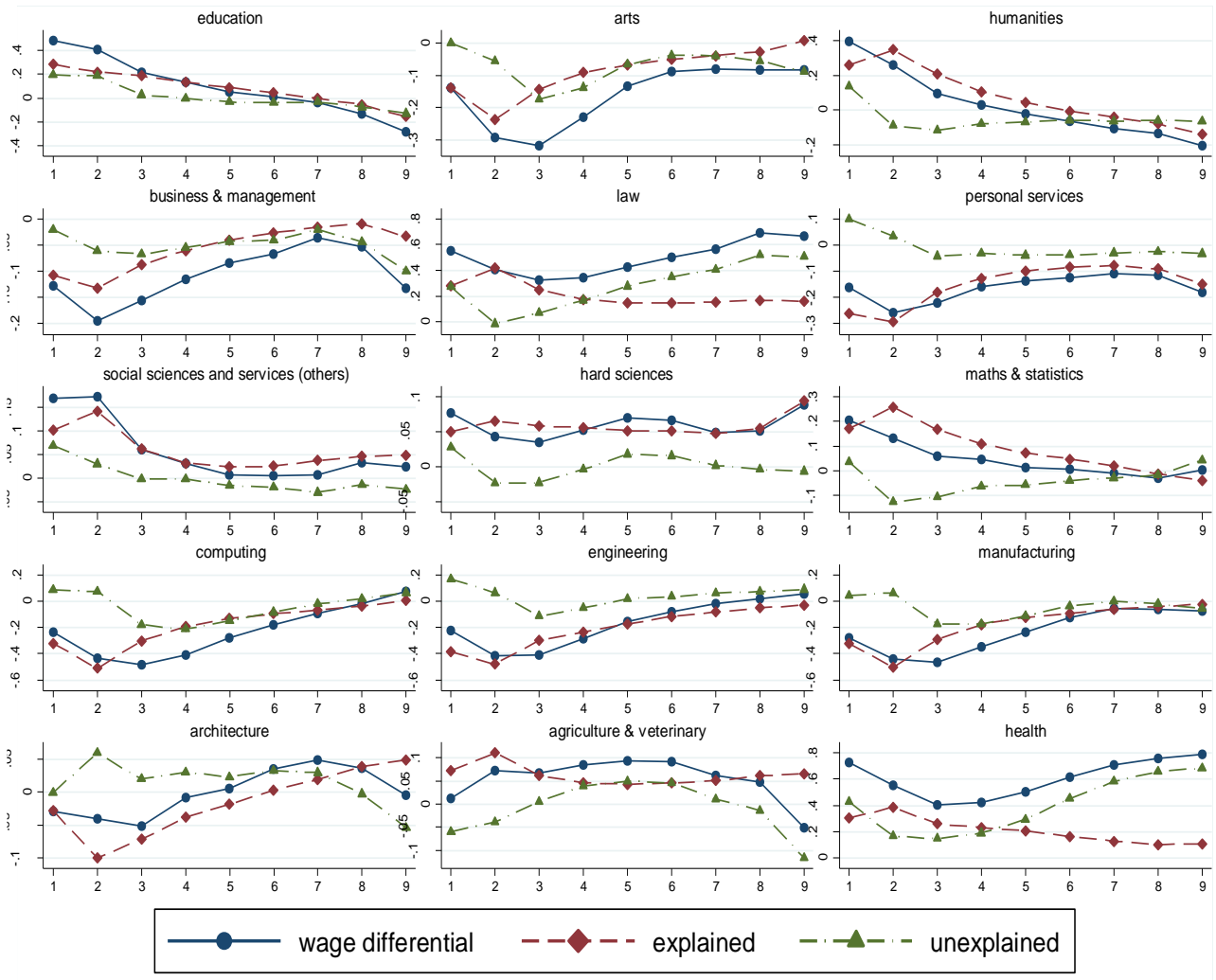


**Table 4 (continued): RIF-Regression Decomposition**

	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>
<b>hard sciences</b>									
% wage difference	0.077	0.043	0.036	0.052	0.070	0.067	0.049	0.051	0.088
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	1.44	-1.24	-1.77	-0.42	2.49	2.36	0.25	-0.40	-0.32
<b>maths &amp; statistics</b>									
% wage difference	0.204	0.131	0.058	0.044	0.013	0.006	-0.011	-0.032	0.002
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	0.75	-4.82	-6.71	-5.32	-5.66	-4.27	-2.88	-1.39	1.46
<b>computing</b>									
% wage difference	-0.235	-0.437	-0.484	-0.408	-0.278	-0.180	-0.091	-0.019	0.071
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	3.62	2.91	-8.12	-8.04	-5.23	-3.72	-0.91	0.92	1.75
<b>engineering</b>									
% wage difference	-0.221	-0.416	-0.409	-0.288	-0.156	-0.082	-0.018	0.020	0.059
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	13.49	6.22	-13.69	-5.79	2.28	5.36	10.59	10.78	8.12
<b>manufacturing</b>									
% wage difference	-0.280	-0.439	-0.467	-0.350	-0.235	-0.127	-0.059	-0.062	-0.078
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	1.96	2.73	-7.00	-6.68	-5.43	-1.76	0.04	-1.41	-2.59
<b>architecture</b>									
% wage difference	-0.029	-0.040	-0.051	-0.008	0.006	0.035	0.049	0.037	-0.005
<i>z-stat</i>	-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
<i>z-stat</i>	-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
<i>z-stat</i>	-0.05	2.87	1.38	2.97	2.60	4.11	3.88	-0.29	-3.95
<b>agriculture &amp; veterinary</b>									
% wage difference	0.013	0.072	0.067	0.086	0.093	0.092	0.061	0.047	-0.050
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	-2.83	-2.04	0.51	4.74	7.13	7.55	1.72	-1.92	-10.31
<b>health</b>									
% wage difference	0.730	0.554	0.406	0.420	0.501	0.617	0.710	0.758	0.791
<i>z-stat</i>	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
<i>z-stat</i>	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
<i>z-stat</i>	19.60	7.99	9.71	11.49	17.72	30.58	45.61	54.94	47.36

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

**Figure 4: RIF-Regression Decomposition**



## Appendix A: Additional Results

**Table A1: Percent of Observations by Field of Study and Wave**

	2009	2010	2011	2012	2013	2014	2015	pooled sample
education	18.74	16.64	16.68	15.25	14.60	13.89	14.04	15.42
arts	1.95	1.86	1.52	1.44	1.71	1.41	1.57	1.61
humanities	5.86	6.11	5.56	5.36	5.33	5.34	5.17	5.48
business & management	22.47	25.24	25.61	27.44	28.89	27.78	30.09	27.19
law	1.27	1.20	1.50	1.68	1.51	0.99	1.37	1.36
personal services	2.00	2.31	1.94	1.77	1.70	1.95	1.63	1.87
social sciences and services (others)	11.28	9.67	9.64	9.45	8.99	10.68	9.92	9.90
hard sciences	3.59	3.97	4.52	4.50	4.50	4.03	3.73	4.13
maths & statistics	1.68	1.67	1.72	1.69	1.72	1.71	1.61	1.68
computing	1.57	1.53	1.66	2.04	2.23	1.71	1.42	1.75
engineering	13.15	13.86	15.10	14.47	15.07	16.63	16.13	15.09
manufacturing	1.71	1.92	1.43	1.68	1.67	2.00	1.90	1.77
architecture	5.11	4.33	3.99	4.01	3.77	4.27	3.99	4.16
agriculture & veterinary	4.17	4.45	4.08	4.02	3.74	3.24	3.51	3.83
health	5.45	5.21	5.06	5.20	4.56	4.36	3.92	4.74
Number of observations	8159	9521	10806	11853	12196	11909	12710	77154

Note: weighted descriptive statistics





**Table A3: Complete OLS Estimates**

	(1)	(2)	(3)	(4)	(5)	(6)
constant	2.153*** (0.004)	1.649*** (0.007)	1.684*** (0.008)	1.724*** (0.008)	1.977*** (0.008)	2.133*** (0.009)
education	0.129*** (0.005)	0.103*** (0.004)	0.093*** (0.004)	0.086*** (0.005)	0.013** (0.005)	0.020*** (0.005)
arts	-0.079*** (0.017)	-0.034** (0.015)	-0.036** (0.014)	-0.016 (0.014)	-0.038*** (0.013)	-0.047*** (0.013)
humanities	0.085*** (0.007)	-0.011* (0.006)	-0.008 (0.006)	0.038*** (0.007)	-0.038*** (0.007)	-0.036*** (0.007)
business & management			<i>reference category</i>			
law	0.550*** (0.018)	0.503*** (0.017)	0.498*** (0.017)	0.445*** (0.015)	0.310*** (0.013)	0.309*** (0.013)
personal services	-0.088*** (0.014)	-0.105*** (0.012)	-0.099*** (0.012)	-0.065*** (0.011)	-0.008 (0.010)	0.002 (0.010)
social sciences	0.129*** (0.007)	0.064*** (0.006)	0.067*** (0.006)	0.059*** (0.006)	0.032*** (0.005)	0.029*** (0.005)
hard sciences	0.137*** (0.010)	0.132*** (0.009)	0.131*** (0.009)	0.130*** (0.009)	0.041*** (0.008)	0.045*** (0.008)
maths & statistics	0.120*** (0.014)	0.132*** (0.013)	0.119*** (0.013)	0.068*** (0.012)	-0.006 (0.012)	-0.009 (0.012)
computing	-0.121*** (0.020)	0.058*** (0.019)	0.058*** (0.019)	0.053*** (0.017)	0.017 (0.015)	0.008 (0.014)
engineering	-0.052*** (0.007)	0.007 (0.006)	0.007 (0.006)	0.051*** (0.006)	0.062*** (0.006)	0.067*** (0.006)
manufacturing	-0.141*** (0.017)	-0.075*** (0.015)	-0.077*** (0.015)	-0.005 (0.014)	-0.028** (0.012)	-0.011 (0.012)
architecture	0.073*** (0.010)	0.082*** (0.010)	0.087*** (0.009)	0.094*** (0.009)	0.034*** (0.008)	0.044*** (0.008)
agriculture & veterinary	0.110*** (0.010)	0.071*** (0.008)	0.070*** (0.008)	0.075*** (0.008)	-0.001 (0.007)	0.023*** (0.007)
health	0.646*** (0.010)	0.580*** (0.009)	0.574*** (0.009)	0.531*** (0.012)	0.405*** (0.011)	0.410*** (0.011)
year 2009			<i>reference category</i>			
year 2010		-0.017** (0.007)	-0.016** (0.007)	-0.017*** (0.006)	-0.019*** (0.006)	-0.012** (0.006)
year 2011		0.023*** (0.007)	0.025*** (0.007)	0.027*** (0.006)	0.028*** (0.006)	0.036*** (0.006)
year 2012		0.043*** (0.007)	0.044*** (0.006)	0.044*** (0.006)	0.047*** (0.006)	0.054*** (0.006)
year 2013		0.052*** (0.007)	0.053*** (0.006)	0.056*** (0.006)	0.061*** (0.006)	0.069*** (0.006)
year 2014		0.063*** (0.007)	0.012* (0.007)	0.043*** (0.006)	0.059*** (0.006)	0.069*** (0.006)
year 2015		0.062*** (0.006)	0.011 (0.007)	0.045*** (0.006)	0.067*** (0.006)	0.077*** (0.006)
adjusted R-squared	0.091	0.263	0.283	0.361	0.472	0.489
number of observations	77154	77154	77154	77154	77154	77154

Note: robust standard errors in parenthesis, \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

**Table A3 (continued): Complete OLS Estimates**

	(2)	(3)	(4)	(5)	(6)
(pot.) previous experience	0.021*** (0.001)	0.019*** (0.001)	0.021*** (0.001)	0.018*** (0.001)	0.017*** (0.001)
(pot.) previous experience squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
job tenure	0.056*** (0.001)	0.052*** (0.001)	0.042*** (0.001)	0.036*** (0.001)	0.037*** (0.001)
job tenure squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
single		<i>reference category</i>			
married		0.118*** (0.005)	0.106*** (0.005)	0.097*** (0.005)	0.112*** (0.005)
other marital status		0.063*** (0.016)	0.054*** (0.015)	0.042*** (0.014)	0.049*** (0.014)
number of children		-0.061*** (0.002)	-0.053*** (0.002)	-0.037*** (0.001)	-0.037*** (0.001)
firm size			0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
firm size squared			-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
agriculture, manufacturing and other industries			-0.270*** (0.006)	-0.251*** (0.006)	-0.257*** (0.006)
construction			-0.191*** (0.012)	-0.214*** (0.011)	-0.252*** (0.011)
trade, transportation, accommodation and service activities			-0.320*** (0.007)	-0.312*** (0.007)	-0.338*** (0.007)
information and communication			0.039*** (0.015)	-0.050*** (0.013)	-0.106*** (0.013)
financial, insurance and real estate activities			0.148*** (0.010)	0.137*** (0.009)	0.101*** (0.009)
professional, scientific and technical activities			-0.278*** (0.010)	-0.297*** (0.009)	-0.336*** (0.008)
public administration and defense			<i>reference category</i>		
education			-0.030*** (0.005)	-0.165*** (0.005)	-0.161*** (0.005)
health and social services			-0.086*** (0.009)	-0.112*** (0.009)	-0.108*** (0.009)
other service activities			-0.141*** (0.008)	-0.217*** (0.008)	-0.219*** (0.008)
adjusted R-squared		0.283	0.361	0.472	0.489
number of observations		77154	77154	77154	77154

Note: robust standard errors in parenthesis, \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

**Table A3 (continued): Complete OLS Estimates**

	(5)	(6)
legislators, senior officials and managers	0.112***	0.105***
	(0.005)	(0.005)
professionals		<i>reference category</i>
technicians and associate professionals	-0.268***	-0.263***
	(0.005)	(0.005)
clerks	-0.362***	-0.349***
	(0.005)	(0.005)
service workers, shop and market sales	-0.365***	-0.356***
	(0.006)	(0.005)
craft and related workers	-0.536***	-0.511***
	(0.010)	(0.010)
other blue-collar occupations	-0.610***	-0.577***
	(0.009)	(0.009)
Istanbul		<i>reference category</i>
Thrace		-0.234***
		(0.010)
Southern Marmara - West		-0.243***
		(0.008)
Izmir		-0.166***
		(0.008)
Southern Aegean		-0.238***
		(0.010)
Northern Aegean		-0.247***
		(0.008)
Eastern Marmara - South		-0.209***
		(0.008)
Eastern Marmara - North		-0.178***
		(0.008)
Ankara		-0.128***
		(0.007)
Central Anatolia - West and South		-0.238***
		(0.007)
Mediterranean region - West		-0.185***
		(0.009)
Mediterranean region - Middle		-0.220***
		(0.008)
Mediterranean region - East		-0.210***
		(0.010)
Central Anatolia - Middle		-0.195***
		(0.008)
Central Anatolia - East		-0.213***
		(0.009)
Western Black Sea - West		-0.222***
		(0.011)
Western Black Sea - Middle and East		-0.215***
		(0.009)
Middle Black Sea		-0.187***
		(0.008)
Eastern Black Sea		-0.233***
		(0.008)
Northeastern Anatolia - West		-0.145***
		(0.009)
Northeastern Anatolia - East		-0.114***
		(0.011)
Eastern Anatolia - West		-0.191***
		(0.010)
Eastern Anatolia - East		-0.131***
		(0.011)
Southeastern Anatolia - West		-0.212***
		(0.010)
Southeastern Anatolia - Middle		-0.133***
		(0.010)
Southeastern Anatolia - East		-0.148***
		(0.012)
adjusted R-squared	0.472	0.489
number of observations	77154	77154

Note: robust standard errors in parenthesis, \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.



**Table A4: Selected OLS Estimates by Age Groups**

	pooled	age groups		
	sample	23-30	31-40	41-65
education	0.020*** (0.005)	0.132*** (0.011)	0.012 (0.008)	-0.062*** (0.008)
arts	-0.047*** (0.013)	-0.055** (0.024)	-0.035* (0.019)	-0.036 (0.022)
humanities	-0.036*** (0.007)	0.028* (0.017)	-0.067*** (0.011)	-0.044*** (0.009)
business & management		<i>reference category</i>		
law	0.309*** (0.013)	0.195*** (0.023)	0.293*** (0.021)	0.369*** (0.022)
personal services	0.002 (0.010)	0.030 (0.024)	0.006 (0.017)	0.002 (0.015)
social sciences	0.029*** (0.005)	0.076*** (0.012)	0.032*** (0.009)	0.001 (0.008)
hard sciences	0.045*** (0.008)	0.035** (0.016)	0.041*** (0.013)	0.052*** (0.013)
maths & statistics	-0.009 (0.012)	0.001 (0.025)	-0.004 (0.018)	-0.032 (0.020)
computing	0.008 (0.014)	0.006 (0.018)	0.065** (0.025)	0.133*** (0.050)
engineering	0.067*** (0.006)	0.067*** (0.010)	0.071*** (0.009)	0.090*** (0.010)
manufacturing	-0.011 (0.012)	-0.029 (0.019)	-0.018 (0.018)	0.071*** (0.022)
architecture	0.044*** (0.008)	0.104*** (0.016)	0.057*** (0.014)	-0.004 (0.013)
agriculture & veterinary	0.023*** (0.007)	0.043*** (0.016)	-0.014 (0.012)	0.048*** (0.010)
health	0.410*** (0.011)	0.345*** (0.025)	0.431*** (0.018)	0.405*** (0.017)
adjusted R-squared	0.489	0.508	0.425	0.366
number of observations	77154	19962	29830	27956

Note: robust standard errors in parenthesis, \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions contain controls for wave dummies, previous potential experience (quadratic), current job tenure (quadratic), dummies for marital status, number of children, dummies for occupation and sector, quadratic firm size and dummies for nuts2 regions.

**Table A5: Detailed Oaxaca-Blinder Decomposition**

<b>field of study</b>	education	arts	humanities	business & management	law	personal services	social science and services	hard sciences	maths & statistics	computing	engineering	manufacturing	architecture	agriculture & veterinary	health
<b>% wage difference</b>	0.058	-0.162	0.004	-0.110	0.475	-0.172	0.053	0.058	0.040	-0.205	-0.155	-0.226	-0.008	0.030	0.595
<b>explained</b>	0.066	-0.081	0.071	-0.057	0.199	-0.151	0.057	0.059	0.079	-0.175	-0.197	-0.174	-0.014	0.058	0.211
<i>wave</i>	-0.003	-0.003	-0.001	0.003	0.001	-0.003	-0.001	0.001	0.000	0.003	0.002	0.000	-0.002	-0.002	-0.002
<i>work experience</i>	0.011	-0.031	0.058	-0.009	0.024	0.008	0.039	-0.002	-0.014	-0.121	-0.051	-0.046	-0.011	0.024	0.037
<i>family characteristics</i>	0.007	-0.007	0.006	-0.002	0.003	-0.005	0.002	-0.002	0.005	-0.020	-0.007	-0.004	-0.004	0.003	0.007
<i>sector and firm size</i>	-0.070	-0.050	-0.088	0.038	0.081	-0.020	0.036	-0.013	-0.013	-0.030	-0.048	-0.059	-0.006	0.030	0.080
<i>occupation</i>	0.140	-0.013	0.109	-0.097	0.079	-0.127	-0.027	0.070	0.094	-0.040	-0.099	-0.056	0.003	0.025	0.096
<i>nuts2 regions</i>	-0.018	0.022	-0.013	0.009	0.010	-0.003	0.008	0.004	0.007	0.033	0.007	-0.008	0.007	-0.021	-0.007
<b>unexplained</b>	-0.009	-0.081	-0.066	-0.052	0.276	-0.022	-0.004	-0.001	-0.039	-0.030	0.041	-0.052	0.006	-0.028	0.384
<i>wave</i>	0.000	0.002	0.001	-0.001	-0.001	0.002	0.000	0.002	0.000	-0.003	0.001	0.001	0.000	0.001	0.002
<i>work experience</i>	-0.148	0.041	-0.112	0.009	-0.041	-0.040	-0.062	0.041	0.012	0.095	0.130	0.056	-0.032	-0.052	0.043
<i>family characteristics</i>	-0.005	-0.107	0.027	-0.007	0.086	-0.017	-0.002	-0.016	-0.064	-0.003	0.011	0.055	-0.006	0.074	0.023
<i>sector and firm size</i>	0.053	-0.004	0.105	0.044	0.145	0.019	0.024	0.033	-0.095	0.034	0.076	0.043	0.011	0.028	0.008
<i>occupation</i>	-0.109	-0.047	-0.084	-0.035	0.202	-0.006	-0.024	-0.035	0.064	-0.020	0.030	0.013	0.006	-0.019	0.115
<i>nuts2 regions</i>	-0.009	0.003	-0.001	0.002	-0.001	0.012	-0.002	-0.015	-0.027	0.077	0.034	0.005	0.004	0.000	-0.022
<i>constant</i>	0.208	0.031	-0.003	-0.064	-0.114	0.009	0.063	-0.011	0.071	-0.209	-0.241	-0.225	0.024	-0.061	0.216

Note: 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 (quadratic), current job tenure (quadratic), dummies for marital status, number of children, dummies for occupation and sector, quadratic firm size and dummies for nuts2 regions.

**Table A6: Detailed RIF-Regression Decomposition**

quantile	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>	
<b>education</b>	<b>% wage difference</b>	<b>0.483</b>	<b>0.406</b>	<b>0.214</b>	<b>0.133</b>	<b>0.055</b>	<b>0.009</b>	<b>-0.037</b>	<b>-0.130</b>	<b>-0.286</b>
	<b>explained</b>	<b>0.287</b>	<b>0.219</b>	<b>0.186</b>	<b>0.134</b>	<b>0.088</b>	<b>0.048</b>	<b>-0.004</b>	<b>-0.055</b>	<b>-0.156</b>
	<i>wave</i>	0.001	-0.001	-0.003	-0.005	-0.005	-0.004	-0.004	-0.006	-0.005
	<i>work experience</i>	0.027	0.024	0.023	0.018	0.015	0.010	0.006	0.003	-0.010
	<i>family characteristics</i>	0.015	0.015	0.009	0.006	0.004	0.003	0.003	0.003	0.005
	<i>sector and firm size</i>	0.130	0.008	0.023	0.001	-0.029	-0.071	-0.126	-0.182	-0.307
	<i>occupation</i>	0.139	0.198	0.147	0.122	0.112	0.119	0.130	0.145	0.198
	<i>nuts2 region</i>	-0.024	-0.025	-0.013	-0.008	-0.008	-0.010	-0.013	-0.018	-0.038
	<b>unexplained</b>	<b>0.196</b>	<b>0.187</b>	<b>0.028</b>	<b>-0.002</b>	<b>-0.033</b>	<b>-0.039</b>	<b>-0.033</b>	<b>-0.075</b>	<b>-0.130</b>
	<i>wave</i>	0.000	0.003	0.002	0.001	-0.001	0.000	0.000	-0.001	-0.001
	<i>work experience</i>	0.356	-0.429	-0.317	-0.197	-0.134	-0.104	-0.088	-0.135	-0.311
	<i>family characteristics</i>	-0.051	-0.014	-0.005	0.002	0.007	0.013	0.012	0.004	0.021
	<i>sector and firm size</i>	0.563	-0.099	-0.138	-0.083	-0.051	-0.019	0.026	0.083	0.207
	<i>occupation</i>	0.335	-0.326	-0.233	-0.177	-0.155	-0.172	-0.185	-0.205	-0.257
	<i>nuts2 region</i>	-0.019	-0.015	-0.009	-0.005	-0.004	-0.004	-0.005	-0.008	-0.019
	<i>constant</i>	-0.989	1.066	0.728	0.458	0.305	0.247	0.206	0.188	0.230
<b>arts</b>	<b>% wage difference</b>	<b>-0.138</b>	<b>-0.293</b>	<b>-0.317</b>	<b>-0.229</b>	<b>-0.133</b>	<b>-0.088</b>	<b>-0.079</b>	<b>-0.082</b>	<b>-0.082</b>
	<b>explained</b>	<b>-0.138</b>	<b>-0.237</b>	<b>-0.143</b>	<b>-0.092</b>	<b>-0.067</b>	<b>-0.051</b>	<b>-0.040</b>	<b>-0.027</b>	<b>0.007</b>
	<i>wave</i>	0.000	0.001	-0.004	-0.004	-0.004	-0.003	-0.005	-0.004	-0.005
	<i>work experience</i>	-0.047	-0.078	-0.049	-0.035	-0.027	-0.021	-0.015	-0.013	-0.009
	<i>family characteristics</i>	-0.019	-0.018	-0.009	-0.005	-0.004	-0.003	-0.003	-0.002	-0.002
	<i>sector and firm size</i>	-0.084	-0.146	-0.082	-0.048	-0.033	-0.027	-0.021	-0.017	-0.007
	<i>occupation</i>	-0.026	-0.032	-0.015	-0.008	-0.005	-0.005	-0.006	-0.007	-0.010
	<i>nuts2 region</i>	0.037	0.035	0.016	0.009	0.007	0.008	0.011	0.016	0.040
	<b>unexplained</b>	<b>0.000</b>	<b>-0.056</b>	<b>-0.174</b>	<b>-0.137</b>	<b>-0.066</b>	<b>-0.037</b>	<b>-0.040</b>	<b>-0.055</b>	<b>-0.089</b>
	<i>wave</i>	0.007	0.000	0.000	0.000	0.003	0.001	0.003	0.002	0.004
	<i>work experience</i>	-0.031	-0.104	0.324	0.307	0.108	0.020	0.008	-0.005	-0.081
	<i>family characteristics</i>	-0.138	-0.181	-0.181	-0.052	-0.093	-0.045	-0.063	-0.116	-0.207
	<i>sector and firm size</i>	-0.059	-0.079	-0.016	0.020	0.007	-0.021	-0.011	0.010	0.091
	<i>occupation</i>	-0.171	-0.168	-0.015	0.041	0.007	-0.005	-0.025	-0.027	-0.053
	<i>nuts2 region</i>	-0.022	0.023	0.082	0.073	0.027	-0.013	-0.041	-0.024	-0.055
	<i>constant</i>	0.415	0.453	-0.369	-0.527	-0.125	0.027	0.089	0.105	0.212
<b>humanities</b>	<b>% wage difference</b>	<b>0.398</b>	<b>0.260</b>	<b>0.094</b>	<b>0.030</b>	<b>-0.022</b>	<b>-0.062</b>	<b>-0.103</b>	<b>-0.135</b>	<b>-0.204</b>
	<b>explained</b>	<b>0.259</b>	<b>0.347</b>	<b>0.208</b>	<b>0.107</b>	<b>0.047</b>	<b>-0.006</b>	<b>-0.041</b>	<b>-0.077</b>	<b>-0.139</b>
	<i>wave</i>	0.000	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001
	<i>work experience</i>	0.076	0.121	0.084	0.061	0.047	0.037	0.032	0.034	0.045
	<i>family characteristics</i>	0.015	0.017	0.008	0.006	0.004	0.004	0.003	0.001	0.000
	<i>sector and firm size</i>	0.074	0.055	0.004	-0.051	-0.081	-0.121	-0.149	-0.200	-0.308
	<i>occupation</i>	0.115	0.172	0.119	0.094	0.082	0.080	0.083	0.102	0.156
	<i>nuts2 region</i>	-0.023	-0.018	-0.006	-0.002	-0.002	-0.004	-0.007	-0.012	-0.032
	<b>unexplained</b>	<b>0.139</b>	<b>-0.088</b>	<b>-0.114</b>	<b>-0.076</b>	<b>-0.069</b>	<b>-0.057</b>	<b>-0.063</b>	<b>-0.058</b>	<b>-0.065</b>
	<i>wave</i>	-0.001	0.005	0.002	0.000	0.001	0.000	0.000	0.001	0.003
	<i>work experience</i>	0.284	-0.457	-0.263	-0.166	-0.105	-0.068	-0.058	-0.068	-0.227
	<i>family characteristics</i>	0.041	0.039	0.027	0.008	0.001	0.008	0.015	0.023	0.046
	<i>sector and firm size</i>	0.457	-0.153	-0.101	-0.013	0.031	0.067	0.122	0.155	0.272
	<i>occupation</i>	0.017	-0.371	-0.197	-0.144	-0.118	-0.119	-0.122	-0.137	-0.186
	<i>nuts2 region</i>	0.013	0.008	0.007	0.004	0.000	-0.002	-0.004	-0.011	-0.017
	<i>constant</i>	-0.671	0.842	0.413	0.233	0.121	0.057	-0.016	-0.020	0.044

**Table A6 (continued): Detailed RIF-Regression Decomposition**

	quantile	q1	q2	q3	q4	q5	q6	q7	q8	q9
<b>business &amp; management</b>	<b>% wage difference</b>	<b>-0.128</b>	<b>-0.194</b>	<b>-0.155</b>	<b>-0.115</b>	<b>-0.084</b>	<b>-0.067</b>	<b>-0.036</b>	<b>-0.054</b>	<b>-0.133</b>
	<b>explained</b>	<b>-0.108</b>	<b>-0.132</b>	<b>-0.088</b>	<b>-0.060</b>	<b>-0.041</b>	<b>-0.027</b>	<b>-0.016</b>	<b>-0.009</b>	<b>-0.034</b>
	<i>wave</i>	-0.001	0.001	0.003	0.005	0.005	0.005	0.004	0.005	0.005
	<i>work experience</i>	-0.004	-0.010	-0.009	-0.008	-0.008	-0.007	-0.007	-0.010	-0.016
	<i>family characteristics</i>	-0.005	-0.005	-0.003	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	<i>sector and firm size</i>	-0.007	-0.002	0.008	0.016	0.032	0.048	0.066	0.089	0.111
	<i>occupation</i>	-0.106	-0.131	-0.094	-0.075	-0.072	-0.075	-0.083	-0.100	-0.150
	<i>nuts2 region</i>	0.015	0.014	0.006	0.004	0.004	0.004	0.005	0.008	0.018
	<b>unexplained</b>	<b>-0.020</b>	<b>-0.062</b>	<b>-0.067</b>	<b>-0.055</b>	<b>-0.043</b>	<b>-0.041</b>	<b>-0.020</b>	<b>-0.044</b>	<b>-0.099</b>
	<i>wave</i>	-0.002	-0.004	0.000	-0.001	0.001	-0.001	0.000	0.000	-0.006
	<i>work experience</i>	-0.079	0.015	0.185	0.064	0.058	0.009	-0.023	-0.075	-0.228
	<i>family characteristics</i>	0.020	0.030	-0.015	-0.003	-0.001	-0.004	-0.010	-0.016	-0.032
	<i>sector and firm size</i>	0.023	0.072	0.131	0.047	0.029	0.006	0.013	-0.009	0.033
	<i>occupation</i>	-0.144	-0.114	-0.007	-0.009	0.005	0.007	0.005	-0.015	-0.062
	<i>nuts2 region</i>	-0.002	0.008	0.001	0.002	0.003	0.001	0.003	-0.004	-0.032
<i>constant</i>	0.163	-0.069	-0.362	-0.155	-0.138	-0.057	-0.009	0.074	0.227	
<b>law</b>	<b>% wage difference</b>	<b>0.554</b>	<b>0.407</b>	<b>0.322</b>	<b>0.345</b>	<b>0.425</b>	<b>0.499</b>	<b>0.563</b>	<b>0.688</b>	<b>0.665</b>
	<b>explained</b>	<b>0.281</b>	<b>0.420</b>	<b>0.250</b>	<b>0.176</b>	<b>0.148</b>	<b>0.147</b>	<b>0.155</b>	<b>0.168</b>	<b>0.160</b>
	<i>wave</i>	-0.001	0.001	0.003	0.004	0.004	0.003	0.001	0.002	0.001
	<i>work experience</i>	0.033	0.050	0.029	0.021	0.016	0.014	0.014	0.015	0.024
	<i>family characteristics</i>	0.007	0.008	0.004	0.003	0.002	0.001	0.001	0.001	0.002
	<i>sector and firm size</i>	0.139	0.211	0.117	0.073	0.061	0.067	0.074	0.073	0.009
	<i>occupation</i>	0.093	0.137	0.088	0.069	0.059	0.056	0.059	0.067	0.101
	<i>nuts2 region</i>	0.010	0.014	0.009	0.006	0.005	0.006	0.007	0.010	0.023
	<b>unexplained</b>	<b>0.273</b>	<b>-0.013</b>	<b>0.072</b>	<b>0.170</b>	<b>0.277</b>	<b>0.352</b>	<b>0.408</b>	<b>0.521</b>	<b>0.505</b>
	<i>wave</i>	0.006	0.005	-0.010	-0.005	-0.006	-0.007	0.010	0.010	0.000
	<i>work experience</i>	-0.215	-0.523	-0.219	-0.070	0.170	0.252	0.541	0.306	-0.244
	<i>family characteristics</i>	-0.048	0.156	0.168	0.091	0.094	0.075	0.173	0.131	0.055
	<i>sector and firm size</i>	0.100	-0.260	0.103	0.144	0.078	0.160	0.311	0.318	0.077
	<i>occupation</i>	0.263	0.027	0.375	0.406	0.385	0.212	0.175	0.054	-0.182
	<i>nuts2 region</i>	-0.018	-0.056	-0.030	0.014	0.004	0.044	0.041	0.049	-0.023
<i>constant</i>	0.184	0.637	-0.316	-0.411	-0.448	-0.384	-0.842	-0.348	0.822	
<b>personal services</b>	<b>% wage difference</b>	<b>-0.163</b>	<b>-0.258</b>	<b>-0.222</b>	<b>-0.159</b>	<b>-0.138</b>	<b>-0.124</b>	<b>-0.108</b>	<b>-0.115</b>	<b>-0.181</b>
	<b>explained</b>	<b>-0.261</b>	<b>-0.293</b>	<b>-0.180</b>	<b>-0.126</b>	<b>-0.099</b>	<b>-0.085</b>	<b>-0.079</b>	<b>-0.091</b>	<b>-0.148</b>
	<i>wave</i>	0.000	0.000	-0.004	-0.004	-0.004	-0.004	-0.004	-0.005	-0.004
	<i>work experience</i>	0.006	0.008	0.005	0.004	0.004	0.004	0.005	0.008	0.017
	<i>family characteristics</i>	-0.010	-0.011	-0.006	-0.004	-0.003	-0.002	-0.002	-0.002	-0.004
	<i>sector and firm size</i>	-0.081	-0.081	-0.042	-0.019	-0.005	0.006	0.019	0.032	0.014
	<i>occupation</i>	-0.173	-0.199	-0.126	-0.099	-0.088	-0.089	-0.096	-0.123	-0.169
	<i>nuts2 region</i>	-0.004	-0.009	-0.007	-0.004	-0.002	-0.001	-0.001	-0.001	-0.001
	<b>unexplained</b>	<b>0.098</b>	<b>0.035</b>	<b>-0.042</b>	<b>-0.032</b>	<b>-0.039</b>	<b>-0.038</b>	<b>-0.030</b>	<b>-0.025</b>	<b>-0.033</b>
	<i>wave</i>	0.003	0.003	0.000	0.002	0.002	0.001	0.003	0.002	0.002
	<i>work experience</i>	-0.170	-0.053	0.205	0.040	0.049	0.078	0.015	-0.027	-0.220
	<i>family characteristics</i>	-0.062	-0.061	-0.084	-0.001	0.057	0.026	0.030	0.022	0.032
	<i>sector and firm size</i>	-0.049	-0.038	0.044	0.003	0.026	-0.003	0.004	-0.018	0.063
	<i>occupation</i>	-0.023	-0.090	-0.024	-0.002	0.018	0.015	0.007	0.000	0.000
	<i>nuts2 region</i>	0.019	0.016	0.026	0.004	0.005	-0.003	0.001	0.019	-0.008
<i>constant</i>	0.380	0.258	-0.209	-0.078	-0.195	-0.152	-0.090	-0.022	0.099	
<b>social sciences</b>	<b>% wage difference</b>	<b>0.169</b>	<b>0.171</b>	<b>0.059</b>	<b>0.030</b>	<b>0.007</b>	<b>0.005</b>	<b>0.006</b>	<b>0.032</b>	<b>0.025</b>
	<b>explained</b>	<b>0.101</b>	<b>0.141</b>	<b>0.062</b>	<b>0.032</b>	<b>0.023</b>	<b>0.025</b>	<b>0.037</b>	<b>0.046</b>	<b>0.048</b>
	<i>wave</i>	0.001	0.000	-0.001	-0.002	-0.001	-0.002	0.000	-0.001	-0.001
	<i>work experience</i>	0.047	0.077	0.050	0.038	0.029	0.025	0.023	0.025	0.038
	<i>family characteristics</i>	0.004	0.004	0.002	0.001	0.001	0.001	0.001	0.000	0.000
	<i>sector and firm size</i>	0.062	0.078	0.031	0.016	0.015	0.020	0.032	0.044	0.042
	<i>occupation</i>	-0.024	-0.029	-0.027	-0.026	-0.024	-0.024	-0.024	-0.030	-0.047
	<i>nuts2 region</i>	0.011	0.011	0.006	0.004	0.003	0.004	0.005	0.007	0.016
	<b>unexplained</b>	<b>0.068</b>	<b>0.030</b>	<b>-0.002</b>	<b>-0.001</b>	<b>-0.016</b>	<b>-0.020</b>	<b>-0.030</b>	<b>-0.014</b>	<b>-0.024</b>
	<i>wave</i>	0.003	0.006	0.001	0.000	0.000	0.000	-0.002	-0.001	0.000
	<i>work experience</i>	0.144	-0.214	-0.147	-0.070	-0.021	-0.041	-0.029	-0.043	-0.100
	<i>family characteristics</i>	-0.018	-0.023	-0.007	-0.026	-0.015	-0.018	-0.013	0.000	0.029
	<i>sector and firm size</i>	0.221	-0.074	-0.069	-0.017	0.000	0.017	0.024	0.022	0.081
	<i>occupation</i>	0.070	-0.154	-0.078	-0.028	-0.020	-0.008	0.000	-0.006	-0.005
	<i>nuts2 region</i>	0.004	-0.023	-0.012	-0.003	-0.001	0.004	0.004	0.007	-0.002
<i>constant</i>	-0.356	0.510	0.310	0.143	0.040	0.025	-0.014	0.008	-0.027	

**Table A6 (continued): Detailed RIF-Regression Decomposition**

	quantile	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>
<b>hard sciences</b>	<b>% wage difference</b>	<b>0.077</b>	<b>0.043</b>	<b>0.036</b>	<b>0.052</b>	<b>0.070</b>	<b>0.067</b>	<b>0.049</b>	<b>0.051</b>	<b>0.088</b>
	<b>explained</b>	<b>0.050</b>	<b>0.066</b>	<b>0.058</b>	<b>0.056</b>	<b>0.052</b>	<b>0.051</b>	<b>0.048</b>	<b>0.055</b>	<b>0.094</b>
	<i>wave</i>	-0.001	0.000	0.002	0.003	0.003	0.002	0.001	0.002	0.001
	<i>work experience</i>	-0.009	-0.017	-0.011	-0.007	-0.005	-0.002	0.000	0.005	0.016
	<i>family characteristics</i>	-0.005	-0.005	-0.003	-0.002	-0.001	-0.001	-0.001	0.000	0.000
	<i>sector and firm size</i>	-0.018	-0.028	-0.003	0.003	0.002	-0.002	-0.011	-0.022	-0.032
	<i>occupation</i>	0.080	0.113	0.071	0.057	0.051	0.051	0.055	0.065	0.097
	<i>nuts2 region</i>	0.003	0.003	0.002	0.002	0.002	0.002	0.003	0.005	0.012
	<b>unexplained</b>	<b>0.028</b>	<b>-0.023</b>	<b>-0.023</b>	<b>-0.004</b>	<b>0.018</b>	<b>0.016</b>	<b>0.002</b>	<b>-0.004</b>	<b>-0.006</b>
	<i>wave</i>	0.003	0.004	0.004	0.004	0.000	0.004	-0.001	0.002	0.000
	<i>work experience</i>	0.019	-0.027	0.179	0.101	0.060	0.029	0.057	0.070	0.098
	<i>family characteristics</i>	0.016	0.046	0.015	0.015	0.003	0.000	-0.032	-0.054	-0.090
	<i>sector and firm size</i>	-0.009	-0.016	0.022	0.003	0.008	0.004	0.012	0.062	0.169
	<i>occupation</i>	0.101	-0.066	0.015	-0.022	-0.021	-0.037	-0.053	-0.077	-0.140
	<i>nuts2 region</i>	-0.015	-0.003	-0.002	-0.018	-0.014	-0.018	-0.019	-0.024	-0.016
	<i>constant</i>	-0.087	0.038	-0.256	-0.086	-0.018	0.035	0.037	0.017	-0.027
<b>maths &amp; statistics</b>	<b>% wage difference</b>	<b>0.204</b>	<b>0.131</b>	<b>0.058</b>	<b>0.044</b>	<b>0.013</b>	<b>0.006</b>	<b>-0.011</b>	<b>-0.032</b>	<b>0.002</b>
	<b>explained</b>	<b>0.170</b>	<b>0.258</b>	<b>0.167</b>	<b>0.108</b>	<b>0.072</b>	<b>0.047</b>	<b>0.018</b>	<b>-0.013</b>	<b>-0.042</b>
	<i>wave</i>	0.000	0.000	-0.001	0.000	0.000	0.000	-0.001	0.000	0.000
	<i>work experience</i>	-0.022	-0.035	-0.021	-0.014	-0.010	-0.008	-0.007	-0.006	-0.005
	<i>family characteristics</i>	0.010	0.012	0.007	0.004	0.003	0.002	0.002	0.003	0.006
	<i>sector and firm size</i>	0.059	0.108	0.075	0.039	0.011	-0.014	-0.048	-0.098	-0.175
	<i>occupation</i>	0.115	0.160	0.099	0.075	0.065	0.064	0.068	0.083	0.124
	<i>nuts2 region</i>	0.009	0.012	0.007	0.004	0.003	0.004	0.003	0.004	0.009
	<b>unexplained</b>	<b>0.034</b>	<b>-0.127</b>	<b>-0.108</b>	<b>-0.064</b>	<b>-0.059</b>	<b>-0.041</b>	<b>-0.029</b>	<b>-0.018</b>	<b>0.043</b>
	<i>wave</i>	-0.006	-0.001	-0.004	-0.003	0.000	0.001	0.001	0.000	0.001
	<i>work experience</i>	0.381	-0.038	0.012	0.012	0.020	0.032	0.035	0.025	-0.021
	<i>family characteristics</i>	-0.346	-0.226	-0.088	-0.046	-0.031	0.043	0.029	0.025	0.001
	<i>sector and firm size</i>	-0.054	-0.278	-0.184	-0.114	-0.092	-0.095	-0.073	-0.045	-0.155
	<i>occupation</i>	0.517	0.029	0.036	0.024	-0.003	-0.006	-0.010	-0.014	0.038
	<i>nuts2 region</i>	-0.085	-0.048	-0.007	-0.002	-0.005	-0.006	-0.009	-0.026	-0.058
	<i>constant</i>	-0.373	0.436	0.127	0.064	0.052	-0.010	-0.002	0.017	0.236
<b>computing</b>	<b>% wage difference</b>	<b>-0.235</b>	<b>-0.437</b>	<b>-0.484</b>	<b>-0.408</b>	<b>-0.278</b>	<b>-0.180</b>	<b>-0.091</b>	<b>-0.019</b>	<b>0.071</b>
	<b>explained</b>	<b>-0.321</b>	<b>-0.512</b>	<b>-0.305</b>	<b>-0.194</b>	<b>-0.131</b>	<b>-0.096</b>	<b>-0.070</b>	<b>-0.037</b>	<b>0.006</b>
	<i>wave</i>	-0.001	0.001	0.003	0.005	0.006	0.004	0.004	0.005	0.003
	<i>work experience</i>	-0.153	-0.243	-0.152	-0.113	-0.090	-0.077	-0.071	-0.077	-0.113
	<i>family characteristics</i>	-0.047	-0.047	-0.026	-0.016	-0.011	-0.009	-0.009	-0.006	-0.009
	<i>sector and firm size</i>	-0.129	-0.210	-0.115	-0.054	-0.021	0.002	0.022	0.055	0.126
	<i>occupation</i>	-0.048	-0.067	-0.040	-0.032	-0.029	-0.031	-0.032	-0.036	-0.050
	<i>nuts2 region</i>	0.057	0.055	0.026	0.016	0.014	0.014	0.016	0.021	0.050
	<b>unexplained</b>	<b>0.087</b>	<b>0.075</b>	<b>-0.180</b>	<b>-0.214</b>	<b>-0.147</b>	<b>-0.084</b>	<b>-0.021</b>	<b>0.018</b>	<b>0.065</b>
	<i>wave</i>	0.001	-0.002	-0.007	-0.010	-0.014	-0.007	-0.006	0.001	0.010
	<i>work experience</i>	-0.129	-0.107	0.088	0.193	0.215	0.149	0.109	0.065	0.258
	<i>family characteristics</i>	-0.015	-0.037	-0.053	-0.074	-0.037	-0.023	-0.092	-0.028	0.161
	<i>sector and firm size</i>	-0.022	-0.044	0.017	0.065	0.114	0.061	0.094	0.013	-0.041
	<i>occupation</i>	-0.123	-0.144	0.019	0.085	0.107	0.074	0.042	-0.027	-0.120
	<i>nuts2 region</i>	-0.015	0.045	0.078	0.152	0.139	0.116	0.101	0.064	0.100
	<i>constant</i>	0.391	0.362	-0.321	-0.625	-0.671	-0.454	-0.269	-0.070	-0.301

**Table A6 (continued): Detailed RIF-Regression Decomposition**

quantile	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>	
<b>engineering</b>	<b>% wage difference</b>	<b>-0.221</b>	<b>-0.416</b>	<b>-0.409</b>	<b>-0.288</b>	<b>-0.156</b>	<b>-0.082</b>	<b>-0.018</b>	<b>0.020</b>	<b>0.059</b>
	<b>explained</b>	<b>-0.388</b>	<b>-0.481</b>	<b>-0.296</b>	<b>-0.235</b>	<b>-0.174</b>	<b>-0.116</b>	<b>-0.082</b>	<b>-0.053</b>	<b>-0.032</b>
	<i>wave</i>	-0.002	0.000	0.002	0.003	0.003	0.002	0.003	0.003	0.003
	<i>work experience</i>	-0.076	-0.100	-0.065	-0.055	-0.045	-0.035	-0.029	-0.029	-0.035
	<i>family characteristics</i>	-0.019	-0.016	-0.009	-0.005	-0.003	-0.003	-0.003	-0.002	-0.003
	<i>sector and firm size</i>	-0.192	-0.237	-0.112	-0.063	-0.032	-0.003	0.021	0.050	0.098
	<i>occupation</i>	-0.117	-0.137	-0.113	-0.115	-0.097	-0.078	-0.076	-0.081	-0.108
	<i>nuts2 region</i>	0.017	0.009	0.001	0.001	0.001	0.001	0.003	0.006	0.014
	<b>unexplained</b>	<b>0.167</b>	<b>0.065</b>	<b>-0.112</b>	<b>-0.052</b>	<b>0.018</b>	<b>0.034</b>	<b>0.064</b>	<b>0.072</b>	<b>0.090</b>
	<i>wave</i>	0.008	0.000	-0.007	-0.006	-0.002	0.000	0.003	0.000	0.006
	<i>work experience</i>	-0.189	-0.094	0.242	0.426	0.348	0.203	0.138	0.107	0.086
	<i>family characteristics</i>	0.014	0.043	0.028	0.008	0.015	0.012	0.013	0.010	0.009
	<i>sector and firm size</i>	0.061	0.056	0.106	0.150	0.102	0.038	0.033	0.024	0.050
	<i>occupation</i>	-0.164	-0.032	0.114	0.154	0.122	0.082	0.059	0.039	-0.012
	<i>nuts2 region</i>	0.004	0.037	0.055	0.057	0.042	0.028	0.033	0.038	0.045
	<i>constant</i>	0.433	0.055	-0.650	-0.841	-0.610	-0.328	-0.215	-0.147	-0.094
<b>manufacturing</b>	<b>% wage difference</b>	<b>-0.280</b>	<b>-0.439</b>	<b>-0.467</b>	<b>-0.350</b>	<b>-0.235</b>	<b>-0.127</b>	<b>-0.059</b>	<b>-0.062</b>	<b>-0.078</b>
	<b>explained</b>	<b>-0.322</b>	<b>-0.503</b>	<b>-0.293</b>	<b>-0.178</b>	<b>-0.122</b>	<b>-0.091</b>	<b>-0.059</b>	<b>-0.042</b>	<b>-0.022</b>
	<i>wave</i>	0.001	0.000	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001	0.001
	<i>work experience</i>	-0.062	-0.104	-0.067	-0.050	-0.038	-0.031	-0.025	-0.024	-0.025
	<i>family characteristics</i>	-0.010	-0.010	-0.006	-0.003	-0.002	-0.002	-0.002	-0.001	-0.002
	<i>sector and firm size</i>	-0.154	-0.262	-0.145	-0.073	-0.037	-0.015	0.008	0.031	0.069
	<i>occupation</i>	-0.089	-0.113	-0.064	-0.044	-0.036	-0.034	-0.034	-0.040	-0.057
	<i>nuts2 region</i>	-0.007	-0.014	-0.009	-0.007	-0.007	-0.007	-0.005	-0.006	-0.008
	<b>unexplained</b>	<b>0.042</b>	<b>0.064</b>	<b>-0.174</b>	<b>-0.172</b>	<b>-0.113</b>	<b>-0.036</b>	<b>0.001</b>	<b>-0.020</b>	<b>-0.056</b>
	<i>wave</i>	0.007	0.010	-0.001	0.000	0.004	0.002	-0.003	-0.002	-0.001
	<i>work experience</i>	-0.166	-0.265	0.147	0.310	0.222	0.228	0.096	0.013	-0.053
	<i>family characteristics</i>	0.037	-0.031	-0.018	0.055	0.114	0.010	0.007	0.089	0.160
	<i>sector and firm size</i>	0.089	0.083	0.058	0.092	0.024	0.017	0.022	0.032	0.043
	<i>occupation</i>	-0.102	-0.073	0.084	0.117	0.082	0.078	0.013	-0.011	-0.046
	<i>nuts2 region</i>	-0.031	-0.013	0.011	0.007	0.019	0.042	0.015	0.011	-0.012
	<i>constant</i>	0.208	0.352	-0.455	-0.754	-0.578	-0.413	-0.149	-0.152	-0.147
<b>architecture</b>	<b>% wage difference</b>	<b>-0.029</b>	<b>-0.040</b>	<b>-0.051</b>	<b>-0.008</b>	<b>0.006</b>	<b>0.035</b>	<b>0.049</b>	<b>0.037</b>	<b>-0.005</b>
	<b>explained</b>	<b>-0.028</b>	<b>-0.100</b>	<b>-0.072</b>	<b>-0.038</b>	<b>-0.018</b>	<b>0.003</b>	<b>0.019</b>	<b>0.039</b>	<b>0.049</b>
	<i>wave</i>	0.001	0.000	-0.002	-0.003	-0.003	-0.003	-0.002	-0.003	-0.002
	<i>work experience</i>	-0.031	-0.051	-0.030	-0.018	-0.012	-0.007	-0.003	0.004	0.022
	<i>family characteristics</i>	-0.009	-0.010	-0.006	-0.004	-0.003	-0.002	-0.002	-0.002	-0.003
	<i>sector and firm size</i>	-0.030	-0.067	-0.045	-0.021	-0.005	0.011	0.026	0.041	0.036
	<i>occupation</i>	0.036	0.019	0.004	0.002	0.000	-0.002	-0.005	-0.007	-0.015
	<i>nuts2 region</i>	0.006	0.009	0.007	0.005	0.005	0.005	0.006	0.006	0.011
	<b>unexplained</b>	<b>-0.001</b>	<b>0.060</b>	<b>0.020</b>	<b>0.030</b>	<b>0.023</b>	<b>0.033</b>	<b>0.030</b>	<b>-0.003</b>	<b>-0.054</b>
	<i>wave</i>	-0.002	0.001	0.000	0.000	0.000	0.001	-0.001	0.000	0.000
	<i>work experience</i>	-0.001	-0.063	0.094	0.007	0.015	0.016	-0.014	-0.020	-0.126
	<i>family characteristics</i>	0.011	0.027	0.046	0.020	-0.017	0.012	-0.014	-0.022	-0.034
	<i>sector and firm size</i>	0.015	0.041	0.067	0.072	0.039	-0.007	-0.021	-0.056	-0.029
	<i>occupation</i>	0.073	0.063	0.051	0.029	0.025	0.012	0.003	-0.026	-0.089
	<i>nuts2 region</i>	-0.006	0.013	0.016	0.019	0.009	0.003	-0.001	-0.004	-0.018
	<i>constant</i>	-0.091	-0.021	-0.253	-0.116	-0.047	-0.005	0.078	0.126	0.243

**Table A6 (continued): Detailed RIF-Regression Decomposition**

quantile	<i>q1</i>	<i>q2</i>	<i>q3</i>	<i>q4</i>	<i>q5</i>	<i>q6</i>	<i>q7</i>	<i>q8</i>	<i>q9</i>	
<b>agriculture &amp; veterinary</b>	<b>% wage difference</b>	<b>0.013</b>	<b>0.072</b>	<b>0.067</b>	<b>0.086</b>	<b>0.093</b>	<b>0.092</b>	<b>0.061</b>	<b>0.047</b>	<b>-0.050</b>
	<b>explained</b>	<b>0.073</b>	<b>0.111</b>	<b>0.061</b>	<b>0.046</b>	<b>0.043</b>	<b>0.046</b>	<b>0.051</b>	<b>0.061</b>	<b>0.066</b>
	<i>wave</i>	0.000	0.000	-0.002	-0.003	-0.003	-0.002	-0.003	-0.003	-0.003
	<i>work experience</i>	0.030	0.042	0.023	0.017	0.013	0.012	0.014	0.018	0.037
	<i>family characteristics</i>	0.007	0.007	0.003	0.002	0.001	0.001	0.001	0.000	0.000
	<i>sector and firm size</i>	0.032	0.052	0.028	0.019	0.021	0.027	0.034	0.042	0.037
	<i>occupation</i>	0.040	0.047	0.027	0.021	0.017	0.016	0.015	0.018	0.029
	<i>nuts2 region</i>	-0.037	-0.037	-0.017	-0.010	-0.008	-0.008	-0.010	-0.014	-0.034
	<b>unexplained</b>	<b>-0.060</b>	<b>-0.039</b>	<b>0.006</b>	<b>0.040</b>	<b>0.050</b>	<b>0.046</b>	<b>0.011</b>	<b>-0.014</b>	<b>-0.116</b>
	<i>wave</i>	0.000	0.005	-0.001	0.001	0.000	0.000	0.002	0.002	0.000
	<i>work experience</i>	0.070	-0.066	-0.020	-0.061	-0.052	-0.072	-0.036	-0.029	-0.195
	<i>family characteristics</i>	0.078	0.214	0.119	0.065	0.064	0.054	0.056	0.038	0.058
	<i>sector and firm size</i>	0.044	0.026	0.083	0.063	0.052	0.016	-0.007	-0.013	0.019
	<i>occupation</i>	0.091	0.028	0.009	0.001	-0.005	-0.021	-0.038	-0.071	-0.161
	<i>nuts2 region</i>	0.023	0.028	0.010	-0.003	-0.005	-0.003	-0.007	-0.010	-0.022
	<i>constant</i>	-0.366	-0.273	-0.195	-0.026	-0.005	0.072	0.040	0.068	0.185
	<b>health</b>	<b>% wage difference</b>	<b>0.730</b>	<b>0.554</b>	<b>0.406</b>	<b>0.420</b>	<b>0.501</b>	<b>0.617</b>	<b>0.710</b>	<b>0.758</b>
<b>explained</b>		<b>0.303</b>	<b>0.387</b>	<b>0.259</b>	<b>0.230</b>	<b>0.207</b>	<b>0.165</b>	<b>0.127</b>	<b>0.102</b>	<b>0.107</b>
<i>wave</i>		0.000	0.000	-0.002	-0.002	-0.003	-0.002	-0.003	-0.003	-0.003
<i>work experience</i>		0.041	0.069	0.048	0.037	0.030	0.026	0.023	0.022	0.028
<i>family characteristics</i>		0.014	0.017	0.009	0.006	0.004	0.003	0.003	0.002	0.003
<i>sector and firm size</i>		0.121	0.135	0.092	0.100	0.103	0.072	0.043	0.017	0.003
<i>occupation</i>		0.139	0.179	0.116	0.093	0.076	0.068	0.064	0.065	0.082
<i>nuts2 region</i>		-0.013	-0.013	-0.005	-0.003	-0.003	-0.002	-0.002	-0.003	-0.006
<b>unexplained</b>		<b>0.427</b>	<b>0.167</b>	<b>0.147</b>	<b>0.190</b>	<b>0.294</b>	<b>0.452</b>	<b>0.583</b>	<b>0.657</b>	<b>0.685</b>
<i>wave</i>		0.006	0.005	0.002	0.003	0.003	0.003	0.001	-0.005	-0.003
<i>work experience</i>		0.045	-0.370	-0.118	0.187	0.298	0.285	0.221	0.071	-0.127
<i>family characteristics</i>		-0.015	0.018	0.015	0.048	0.042	0.035	0.026	0.023	0.063
<i>sector and firm size</i>		0.199	-0.284	-0.210	-0.257	-0.150	-0.065	-0.037	0.043	0.091
<i>occupation</i>		0.229	-0.149	0.063	0.201	0.186	0.073	-0.014	-0.099	-0.148
<i>nuts2 region</i>		-0.033	-0.019	-0.006	-0.009	-0.005	-0.013	-0.021	-0.028	-0.047
<i>constant</i>		-0.004	0.965	0.401	0.017	-0.080	0.134	0.406	0.653	0.856

## **Appendix B: Definition of Fields of Study**

- 1) **education:** education science, training for pre-school teachers, teacher training without subject specialization, teacher training with subject specialization.
- 2) **arts:** audio-visual techniques and media production, fashion, interior and industrial design fine arts, handicrafts, music and performing arts.
- 3) **humanities:** humanities, religion and theology, history and archaeology, philosophy and ethics, languages, language acquisition, literature and linguistics.
- 4) **business and management:** business and administration (including accounting and taxation, finance, banking and insurance, management and administration, marketing and advertising, secretarial and office work, wholesale and retail sales, work skills), transport services, environment (including environmental sciences, natural environments and wildlife).
- 5) **law:** law.
- 6) **personal services:** domestic services, hair and beauty services, hotel, restaurants and catering, sports, travel, tourism and leisure.
- 7) **social sciences and services (other):** economics, political sciences, psychology, sociology and cultural studies), journalism and information (including journalism and reporting, library, information and archival studies), welfare (including care of the elderly and of disabled adults, child care and youth services, social work and counselling).
- 8) **hard sciences:** biology, biochemistry, environment (including environmental sciences, natural environments and wildlife), chemistry, earth sciences and physics.
- 9) **mathematics and statistics:** mathematics, statistics.
- 10) **computing:** information and communication technologies (ICTs, including computer use, database and network design and administration, software and applications development and analysis), computer sciences, computing, computer programming, informatics technologies (including, web design, web programming, web management, graphics, data base programming, computer technical services).
- 11) **engineering:** engineering and engineering trades (including chemical engineering and processes environmental protection technology, electricity and energy, electronics and automation, mechanics and metal trades, motor vehicles, ships and aircraft).
- 12) **manufacturing:** manufacturing and processing (including food processing, materials, textiles, mining and extraction).
- 13) **architecture:** architecture and construction (including architecture and town planning, building and civil engineering).
- 14) **agriculture and veterinary:** agriculture (crop and livestock production, horticulture), forestry, fisheries, veterinary.



15) **Health:** dental studies, medicine, nursing and midwifery, medical diagnostic and treatment technology, therapy and rehabilitation, pharmacy, traditional and complementary medicine and therapy.

**Source:** This list is adapted from the list provided by TURKSTAT (2016) and ISCED Fields of Education and Training, 2013 (UNESCO, 2014).