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Wage Returns to Field of Study-Occupation Mismatch in Turkish Graduate Labor Market: Quantile Regression Approach

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ABSTRACT

In this paper, we estimate the income effects of horizontal mismatch and its interaction with fields of study for Turkish higher education graduates using the Turkish Labor Force Survey dataset. After controlling the vertical mismatch to reduce potential bias, our baseline findings show that one point (decrease) increase in the (mis)matching index leads to 21.9% wage (penalty) growth. However, the return to the matching varies significantly between fields of study. We also explore the extent to which the impact of horizontal mismatch is sensitive to the ability levels represented by the conditional quantile of the income distribution of graduates. Our quantile regression estimations point us to heterogeneous matching returns for different quantiles of fields of study. While the positive wage effect of matching is significantly valid at the above and below the median income in six and three majors respectively, the three majors' negative matching is above the median income.

Keywords: Horizontal mismatch, Inequality, Turkish graduate labor market, Wage returns, Quantile regression.

JEL Classification Codes: J30, J40

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INTRODUCTION

Any economic system should target to allocate the human resource effectively as the definition of economics, which encourages the efficient usage of all resources, puts forward. However, in a dynamic and evolutionary economic structure, the composition of sectors continuously changes, allocation of this resource may not always be adaptable to the environment to the same extent and this situation also led to hampering employment growth (Sahin et al. 2011). Moreover, dramatic increases in the proportion of graduates make it difficult to match them with suitable occupations (Freeman, 1976). Among eleven developed countries 26% of total employment suffers from overeducation, which is an incidence that workers have an education level greater than a job requires (Galasi, 2008). This number is similar in developing countries, calculated as 27% for 38 countries (Sam, 2018).

In Turkey, the number of graduates with two- or three-year vocational higher education or four-year faculty diploma soared 117% (from 3.2 to 10.3 million) between 2004-2019. The number of universities for the same period also rose from 53 to 206. This rapid expansion has amplified the size of employment problems of university graduates to the agenda. Particularly, it makes us question how this massive supply shock of additional graduates has been affected when they could not find a suitable job in their education field.

For the reasons above, the economy can utilize the skills of their labor force but sometimes they cannot, unlike the human capital theory based on neoclassical economics (Rumberger, 1987). When they fail to manage to fully utilize the labor force, the mismatch between job and qualification occurs and it affects efficiency and the labor market outcomes such as wage, job satisfaction, and job search (Allen and Van der Velden, 2001; DeLoach and Kurt, 2018). Vertical and horizontal mismatches are a sort of distinction that refers to two types of mismatches in literature. The educational mismatch is the situation in that workers have more (or less) educational levels than their job requires. For example, a person with a tertiary (secondary) education diploma is over-educated (under-educated) mismatch whose job requires secondary (tertiary) education. In this regard, over-education mismatch has been a well-documented topic due to the expansion of

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higher education. Studies found that over-education led to income penalties between 13% and 27%. Also, horizontal mismatch, which examined in recent years is defined as a mismatch between the field of study and occupation. After the first study by Robst (2007), the income penalty of limited studies is 10% to 32% (Kim, Ahn, and Kim, 2016)[1].

In this paper, we aim the effect of the horizontal mismatch of university graduates on income levels in Turkey. This subject is highly relevant because of the rapid expansion in the number of graduates and changing industry composition in a developing country. According to our knowledge, a study (Orbay, Aydede, and Erkol, 2021) examined this issue in Turkey and found no effect of the field of study on wages. They concluded that disequilibrium between supply-demand for skilled workers creates excessive relative supply and thus constant relative wages.

Our paper, however, deviates from two dimensions. Firstly, we analyze the effect of each field of study matching on wage following Robst (2007) This approach interacts with the field of study with matching indices and enables us to estimate wage return to each field as they are matched. On the other hand, contrary to the self-reported mismatch information in this paper, we utilized our objective matching measurements. Our findings show that after controlling vertical mismatch, there is significant variation in terms of wage return to matching in different majors.

Secondly, we observe the effect of horizontal mismatch on wages depending on unobservable worker ability of fields of study. Following McGuinness and Bennett (2007) and Kim, Ahn, and Kim (2016), we utilize quantile regression analysis by assuming that any conditional quantile of income distribution reflects these abilities. To our best knowledge, this paper is also the first study to analyze the wage effect of a mismatch for different fields of study using a quantile regression approach.

The rest of the paper is organized as follows. Section 2 introduces discussions about theoretical foundations and empirical findings of vertical and horizontal mismatches. Section 3 presents the data and horizontal mismatch indices used. In section 4 we present the Mincerian wage model to be estimated and regression results. Finally, in section 5 concluding remarks are given.

[1] Even before the expansion of universities, Unal (1990) pointed out to the employability and matching problems of Turkish graduates.

BACKGROUND

Theoretical Foundations of Mismatch

In the literature, we come across four theoretical arguments that concentrate on educational mismatch. Although most of these arguments relied on vertical mismatch, they can easily extend to the horizontal mismatch. The first one is the human capital theory which sees human capital as combining parts of schooling, experience, and on-the-job training. Therefore, once graduates join the labor market, they are matched with jobs that require less schooling than they acquired. As they gain experience and skills via on-the-job training, this mismatch case would disappear by climbing the job ladder. However, this status may be permanent for under-educated workers when they compensate for their lack of schooling with experience (Chiswick and Miller, 2009). Similarly, according to this theory, as the labor market adjusts horizontal mismatches would disappear and the earnings of workers with the same educational backgrounds will converge.

Contrary, job competition theory asserts that every occupation has different characteristics that identify productivity and hence the wage. After workers compete for these jobs, they would be matched by employers whose order is based on the proximity of job characteristics. In that situation, a horizontal mismatch is possible because of ability or other characteristics related to education. Therefore, workers with similar educational backgrounds have different earnings because of the nature of the jobs they hold (Nordin, Persson, and Rooth, 2010).

The third is the technological change theory that asserts that new (old) graduates will be over-educated (under-educated) because of their school-provided skills. However, whether this situation is permanent or transitory depends on the flexibility of production technologies (Kiker, Santos, and Oliviera, 1997). This is also valid for horizontal mismatch because advancing technologies may require more technical skills in some occupations than before. For example, executive positions are highly associated with computer science applications such as data science, machine learning, and artificial intelligence. In this case, the horizontal mismatch for economics and business administration graduates may become permanent.

The fourth is the assignment theory which deals with assigning different jobs to workers with different characteristics to maximize the output. According to this argument, together with the search theory, over- and undereducation and under- and over-utilization of skills have the same meaning, and workers who are weakly matched are less productive compared to their peers (Sattinger, 1993; Di Pietro and Urwin, 2006). Horizontal mismatches also exist and lower the productivity and then the wage level of workers than those with matched.

Selected Empirical Studies of Mismatch and Wages

Vertical Mismatch

In the literature, the measurement of vertical mismatch relied on schooling duration and survey responses. As expected, education mismatch takes into consideration the formal education years of the respondents (Duncan and Hoffman, 1981; Rumberger, 1987; Hartog and Oosterbeek, 1988; Hersch, 1991) by adapting over-, required- and under-education (ORU) approach (McGuinness and Sloane, 2011). In this specification, the difference between the schooling years of a worker and the required education of an occupation identifies whether he or she is mismatched or not.

Along with the raising ratio of graduates to the youth population in developing as well as developed countries, controversies over a mismatch in the job market and its impact on wages have been intensified among labor economists. In earlier studies, based on the assignment models (Tinbergen, 1956), a mismatch has been set up between the job and formal education level of the individual and this level has been used as a proxy for skills (Tsang and Levin, 1985; Sattinger, 1993). Additionally, further empirical studies of this approach conducted in the United States (Duncan and Hoffman, 1981; Rumberger, 1987), Netherlands (Hartog and Oosterbeek, 1988), and Spain (Alba-Ramirez, 1992) claim that over-educated people who have higher education level than their own is required to earn less than those who are matched with the same level, but more than those who are their co-workers. Conversely, under-educated people who have a lower education level than their own are required to earn more than those who are matched with the same level, but less than those who are their co-workers. Similarly, institutional arguments also emphasize formal education which is an observable characteristic for bargaining agreements (Di Pietro and Urwin, 2006). Later, this approach has been criticized because of the assumption that each job requires a certain skill level which is gained only through schooling and independent of attributes. According to the heterogeneous skill theory developed after the 2000s, the skill level is determined by not only workers' schooling but also their endowments. At the same time, as a lot of studies pointed out, the relationship between skill and education mismatch is poor because over or under-educated workers differ among themselves in terms of human capital within education levels (Badillo-Amador and Vila, 2013; Di Pietro and Urwin, 2006; Allen and Van der Velden, 2001). Also, skill mismatch explains the changes in wage levels even after education mismatch is controlled in the Mincerian equations. A detailed literature survey for the wage effect of vertical mismatch can be found by McGuinness, Pouliakas, and Redmond (2018).

For the studies covering the Turkish labor market, the first one is Filiztekin (2011). It obtains the same findings that over-educated people earn more than their colleagues but less than those with the same level of education. However, Acar (2016) used panel data and an instrumental variable approach to address unobservable skill and endogeneity. It reveals that there is no significant effect of mismatch on wages. On the other hand, Duman (2018) found less wage return for over-educated workers than those with required people. On the other hand, this gap got smaller in the private sector.

Horizontal Mismatch

Compared with the vertical mismatch, the horizontal mismatch is a recent topic. A seminal study on the link between the mismatch of occupation and field of study and income is Robst (2007) for graduates of the UK. This study used survey data asking respondents the extent to which their work and education are related. It found that a complete mismatch led to 10% wage losses for women and 11% for men. These losses were 2.1% for women and 2.8% for men for the partial mismatch.

As we put forward in vertical mismatch, the horizontal mismatch is measured by using either self-reporting of respondents as Robst (2007) applied or some relatedness indices derived from the ratio of graduates to total employees within an occupation[2]. For the former group, Kelly, O'Connell, and Smyth (2010) also analyzed the wage return to mismatch measuring with self-reporting data for Ireland and found a 5% wage loss. Moore and Rosenbloom (2016) also found wage penalties for horizontal mismatch. Sellami et al. (2018) observed that an income penalty is not inevitable in Belgian graduates when measurement error and unobserved heterogeneity are addressed. Robst and VanGilder (2016) also analyzed the wage penalty of economics and business graduates in the UK when they are mismatched and found that

[2] In the next section, we discussed the latter group of indices.

economics graduates suffer less from mismatching than business graduates. Montt (2015) concluded in cross-country analysis that the income penalty of the field of study only exists if graduates are also overqualified. Kim, Ahn, and Kim (2016) measured the return to the matching of Korean graduates and obtain the income penalty for lower quantiles of income distribution[3].

Self-reported mismatch variables may create endogeneity with wages. According to Nordin, Persson, and Rooth (2010), the absence of satisfaction with wages results to report low relation between job and field of study. Therefore, some relatedness indices have been developed. In the latter group, Nordin, Persson, and Rooth (2010) found that in Sweden negative return was twice for men that found for US men. In fact, this income penalty size for Swedish women has been the same for US women. However, as men gain experience in the labor market, this penalty would begin to get compensated. Lemieux (2014), on the other hand, utilized from relatedness index primarily but also used information on respondents' reporting the extent to which their education is suitable for their job. It has been concluded that relatedness significantly and positively affects annual wages. Lindley and McIntosh (2015) questioned the sources of wage inequality among UK graduates and found that the primary reason stemmed from the inequality within the field of study. Their further analysis also showed that different job definitions within a subject, which is close to the horizontal mismatch concept, is not the largest source of that inequality. In another study analyzing the UK, Syed (2015) used early-level requirements of each occupation and relate them to majors to decide mismatch status. Findings have shown different (positive or negative) wage returns to mismatch for each major. Lastly, Aydede and Dar (2016) used a relatedness index of Canadian natives to estimate the cost of a mismatch of immigrants. They showed that their underutilization is negligible.

Lastly, studies examining the relationship between horizontal mismatch and wages in Turkish labor markets are so limited. While Suna et al. (2020) using self-reported information and Ege (2020) analyzed the reasons and incidence of horizontal mismatch among vocational high school and university graduates respectively, Orbay, Aydede, and Erkol (2021) is the most relevant study to our paper. They developed a relatedness index capturing vertical mismatch and found no significant wage effect of horizontal mismatch, arguing that except for regulated occupations, jobs do not need major-specific requirements in Turkey.

[3] Here we present some selected studies that link horizontal mismatch and wage. Detailed literature survey on this topic, see Sellami, Verhaest, and Van Trier (2018).

DATA, RELATEDNESS INDEX AND MISMATCH

In this paper, we use the 2019 Turkish Household Labor Force Survey (LFS) data conducted by TurkStat. The reason why we choose the 2019 wave of this survey is that consequent periods are subject to the COVID-19 pandemic shock. Undoubtedly this crisis has huge implications for labor markets. In addition, the inflationary environment in Turkey and exchange rate volatility has also effects on temporary effects on matching composition. To isolate these effects, we choose the most recent "relatively normal" period as a sample to be analyzed. This dataset represents the population and gives information about the demographic, economic, and employment structure of the Turkish labor market. Our main variables to calculate the (mis)match index are occupation and field of study information of workers. For both variables, the International Standard Classification of Education (ISCED-13) and the International Standard Classification of Occupation (ISCO-08) have been used to group those having vocational high school and two-year vocational higher education or four-year faculty degree at a university. We reduced our sample to workers with full-time employed, university degreed, and salaried status and ended up with 30,269 observations, representing 5.7 million people using sample weights.

After obtaining frequency distributions of 43 occupations and 22 fields of study, we calculated the relatedness index (RI) for 631 occupation-field of study pairs:

$$RI_{of} = \frac{\frac{L_{of}}{L_f}}{\frac{L_o}{L_t}} \tag{1}$$

In the formulation above, subscripts and represent occupation and field of study, respectively. Similar to Balassa's revealed comparative advantage index, this measurement takes one depending on the relative size between the nominator and denominator. However, the denominator contributes to the index in two respects. On the one hand, it takes simultaneously account the distribution of fields of study for each occupation and of occupations for each field of study. On the other hand, it rescales simple density using occupation share in the economy (Aydede and Dar, 2016; Orbay, Aydede, and Erkol, 2021).

Table 1. NRI Matrix of Occupation and Field of Study

	Managers				Professionals						Tech. and assoc. prof.					Workers					
	11	12	13	14	21	22	23	24	25	26	31	32	33	34	35	41	42	43	44	51	52
Education	0.01	0.01	0.15	0.02	0.01	0	0.35	0.01	0.03	0.02	0.01	0	0.01	0.04	0	0.01	0.01	0.01	0.02	0	0.01
Arts	0.02	0.03	0.02	0.01	0.15	0.01	0.06	0.02	0.02	0.1	0.02	0	0.02	0.04	0.11	0.03	0.02	0.01	0.04	0	0.02
Humanities	0.01	0.01	0.04	0.02	0	0	0.05	0.01	0.01	0.29	0	0	0.01	0.05	0.01	0.01	0.01	0	0.01	0	0
Languages	0.02	0.04	0.12	0.08	0	0	0.25	0.03		0.07	0		0.02	0.02		0.03	0.02	0.04	0.07	0	0.01
Soc. and beh. sciences	0.09	0.11	0.08	0.06	0.01	0.01	0.03	0.16	0.03	0.11	0.01	0.01	0.08	0.03	0.03	0.06	0.11	0.05	0.08	0.01	0.01
Journalism and info.	0.05	0.09	0.11				0.04	0.09	0.08	0.36	0.02		0.05	0.05	0.24	0.01	0.05	0.05	0.07	0	0.03
Business admin.	0.06	0.09	0.04	0.05	0.01	0.02	0.01	0.1	0.04	0.01	0.02	0.03	0.08	0.05	0.03	0.06	0.08	0.06	0.06	0.01	0.02
Law	0.06	0.03	0.01	0.03		0	0.01	0.03	0.01	1	0		0.01	0.31		0.04	0.03	0.01	0.02	0.01	0
Bio, env, and rel. sci.	0.03	0.04	0.08		0.3	0.08	0.11	0.05	0.02	0.02	0.02	0.15	0.04	0.01		0.01	0.06	0.01	0.04		0.02
Physical science	0.07	0.15	0.09	0.03	0.22	0.02	0.13	0.02	0.14	0.01	0.04	0.05	0.03	0.02	0.02	0.03	0.04	0.02		0	0.01
Math and stat.	0.07	0.05	0.07	0.01	0.04		0.22	0.09	0.46	0.02	0	0.01	0.05		0.1	0.02	0.08	0.02	0.01		0.01
Info. and com. tech.	0.02	0.02	0.01	0.03	0.01		0	0.02	0.4	0.01	0.02	0.01	0.02	0.03	0.48	0.03	0.02	0.02	0.02	0.01	0.02
Engineering and trades	0.02	0.04	0.03	0.01	0.12	0	0.01	0.03	0.12	0	0.06	0.01	0.02	0	0.05	0.01	0.01	0.01	0.01	0	0.01
Manu. and processing	0.04	0.03	0.03	0.01	0.1	0.01	0.01	0.02	0.02	0	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0	0.01
Arch. and cons.	0.03	0.04	0.03	0.01	0.35	0	0.02	0.02	0.02	0.01	0.14		0.01	0.02	0	0.02	0.01	0.01	0.01	0.01	0.01
Agri., forest., fishery	0.11	0.07	0.06	0.05	0.36	0.01	0.03	0.03		0	0.06	0.02	0.03	0.04	0.01	0.03	0.06	0.03	0.01	0	0.03
Veterinary	0.03	0.06	0.01	0.04	0	0.61	0.02	0.01			0.02	0.38	0.02	0.01	0.01	0.02	0.01	0.01		0	0.01
Health	0.02	0.01	0.01	0.01	0	0.66	0.02	0		0	0	0.26	0.01			0.01	0.01	0	0.01	0	0.01
Welfare (soc. sciences)		0	0.01			0.03	0.02	0		0.1	0	0.08	0.02	0.04		0.01	0.02	0.01	0.02	0	0.02
Personal services	0.03	0.06	0.02	0.09	0	0	0.02	0.02	0.01	0	0.01	0.01	0.03	0.09	0	0.03	0.09	0.01	0.05	0.05	0.02
Occu. health and trans. ser.	0.01	0.03	0.01		0.09	0.16	0	0.06		0.01	0.11	0.07	0.03	0.05		0.02	0.01	0.04	0.08	0.02	0.03
Security services	0.04	0.05	0.16	0.02	0	0.05	0	0.15			0.03	0.06	0.01	0.01		0	0	0	0.01	0.01	0.01

Table 1. (continued). NRI Matrix of Occupation and Field of Study

		Education	Arts	Humanities	Languages	Soc. and beh. sci.	Journalism and info.	Business admin.	Law	Bio, env, and rel. sci.	Physical science	Math and stat.	Info. and com. tech.	Engineering and trades	Manu. and processing	Arch. and cons.	Agri., forest., fishery	Veterinary	Health	Welfare (soc. sciences)	Personal services	Occu. health and trans. ser.	Security services
Workers	53	0	0.01	0	0.01	0		0	0	0	0		0.01	0			0.01		0	0.02	0.01		
	54	0.02	0.01	0.01	0.03	0.05	0.02	0.04	0.02	0.01	0.02	0.01	0.01	0	0	0	0.03	0.02	0	0.02	0.03	0.03	0.29
	61	0		0		0	0.02	0					0.01	0		0.01	0.04	0.03			0.01		
	62					0.01		0						0									
	71	0	0	0		0		0					0	0	0	0	0		0	0	0		0
	72	0	0			0	0	0					0.01	0.01	0	0	0.01		0	0	0		
	73	0	0.01			0.01		0.01					0	0	0.01		0.01	0.02	0		0.01		
	74	0	0	0		0	0.06	0		0.01	0.01		0.03	0.03	0.01	0	0.01		0	0	0		0.01
	75	0	0.01	0		0	0.01	0	0.01		0.01	0	0.01	0	0.01	0	0.01	0	0	0	0	0.01	0
Plant oper.	81	0	0	0	0	0		0	0	0.01	0.01		0	0	0.01	0.01	0	0	0	0	0		0
	82		0.01				0.02	0			0		0.01	0.01	0		0		0				
	83	0	0	0	0	0	0	0	0	0			0	0	0	0	0	0	0	0	0	0.01	0
Elem. Occup.	91	0	0	0		0		0		0	0		0	0	0	0	0.01	0	0	0	0	0	0
	92	0		0	0.01			0			0		0	0	0	0.01	0		0		0		
	93	0	0.01	0	0	0	0	0	0.01	0	0		0	0	0	0.01	0	0	0	0	0	0	0
	94	0	0			0		0	0				0	0	0	0.01					0	0	
	95													0.01									
	96	0		0	0.01	0		0.01	0.01		0		0	0	0	0	0.01		0	0	0	0	

Authors' own calculations using 2019 Turkish LFS data. Rows represent occupation codes of ISCO-08 classification. Occupation names are available at https://ilostat.ilo.org/resources/concepts-and-definitions/classification-occupation/. Columns shows field of study names based on ISCEDF13.

There are various mismatch measurements that use indirect information and relate occupations and fields of study[4]. While some studies use only the nominator part of the relatedness index using share itself (Nordin, Persson, and Rooth, 2010) or the mode value of the field of study within an occupation (Nieto, Matano and Ramos, 2015), others use network type indices such as degree centrality (Narin and Hayes, 2017) and concentration for each occupation (Lindley and Mcintosh, 2015). However, since the network approach treats only the most common field of study within an occupation as a tie and there is no obvious majority within occupations, we proceed to use the index for our analysis. We also normalize the index () to range between zero to one.

Table 1 shows the NRI values of occupation and field of study pairs. Among them, pair with the highest is and legal, social, and cultural professionals (26) and law majors. We can state that law graduates are most likely to match in their occupation. Nature and the labor market projections of this job definition may tend to stay these graduates in a specific occupation. Moreover, the fact that this pair is followed by Health and Veterinary graduates with Health Professionals (22) supports this finding[5]. Since these jobs at the same time require some accreditation processes to professional associations (bar association, medical chambers) based on their diploma, graduates with other fields of study could find any position in these occupations. However, there are exceptions to this finding like education major, which is eleventh in terms of linking to teaching professionals (23) and second in salaried workers. The potential reason for this result is that in recent years these graduates' probability of being employed in the public sector has decreased due to a reduction in civil servant appointments. Meanwhile, these graduates might opt for another occupation group. Production and specialized services managers (13) have the second highest value among education graduates. The other two majors having the highest matching are information and communication technologies (with Information and Communications Technicians (35)), Mathematics, and Statistics (with Information and Communications Technology Professionals (25)). The lowest values are accommodated in low-skilled occupation categories (workers, plant machine operators, and elementary occupations) as expected.

On the other hand, business and administration graduates who are the largest major (1,743,791) in the salaried worker groups have no NRI value greater than .10. This implies that these graduates did not engage in an occupation as law and health graduates. There are many reasons why such a major concentrated their graduates with their jobs like "managers" occupation. One may be that because most of them -especially men due to the avoidance of compulsory military service for a short time- have graduated from Open Education Faculty, during their education they already had a job mismatched with that major and did not change it after graduation. On the contrary, engineering graduates have been significantly positioned in "professional" occupations.

MODEL AND ESTIMATION RESULTS

Wage Model and Relatedness

In this section, we present the models to be estimated using the Mincer type earning function. Let subscripts , , , , and be individual, education field, occupation, industry, and region respectively, our baseline model including as the continuous form is following:

$$\ln W_{ifosr} = \alpha + p_{sr} + X_i'\beta + \delta over_i + \pi under_i + \theta NRI_{fo} + D_r + D_o + D_f + \varepsilon_{ifosr} \quad (2)$$

In the equation above is the hourly wage by worker with the field of study and occupation . is the industry concentration index to control the relative importance of the industry in the region . is worker-level characteristic vector capturing age and experience (and their squares) as well as binary variables of gender marital status and working in the private/public sector, and formal and informal sector. and were measured using the ORU approach and added to the equation to control vertical mismatch. , , and region, occupation, and field of study fixed effects, respectively.

We also estimate equation (2) by splitting normalized values into four categories as Aydede and Dar (2016) applied. Our aim here is to understand how the matching elasticity of wages differs among different intervals. This may provide us with important insights especially when low matching intensities suffer from low wage gains or losses.

Another dimension like Robst (2007), we examined is the field of study-specific wage returns to the matching. By using adding an interaction term to equation (2) we can estimate the following equation:

$$\ln W_{ifosr} = \alpha + p_{sr} + X_i'\beta + \delta over_i + \pi under_i + \theta NRI_{fo} + \left(NRI_{fo} * D_f\right)'\delta + D_r + D_o + D_f + \varepsilon_{ifosr} \quad (3)$$

[4] For more information on these groups of indices and their advantages and limitations, please see Narin and Hayes (2017).

[5] It is also consistent with the UNI-VERI database provided by the Human Resources Office of the Presidency of the Republic of Turkey.

Table 2. Frequency Distribution of Income Percentiles in Degree Field (%)

Degree Field/Income Quantile	10th	25th	50th	75th	90th	100th	Total
Education	3.60	10.01	15.41	29.91	31.22	9.84	100
Arts	12.15	25.50	26.15	16.39	8.41	11.39	100
Humanities	6.63	10.85	27.81	32.33	16.06	6.32	100
Languages	5.74	12.26	26.29	23.21	17.75	14.76	100
Social and Behavioral Science	6.08	15.24	26.59	27.81	11.30	12.98	100
Journalism and Information	15.82	21.20	16.79	24.90	12.16	9.12	100
Business and administration	9.79	20.90	27.13	22.03	9.85	10.30	100
Law	8.90	11.73	22.10	12.29	12.02	32.97	100
Biology	4.59	16.88	23.20	26.56	16.87	11.90	100
Physical Science	6.20	11.96	23.01	23.85	19.84	15.14	100
Math and Statistics	1.27	14.06	23.39	25.50	22.16	13.63	100
Information and communication	15.01	35.56	28.12	11.47	2.84	7.00	100
Engineering	7.59	15.97	28.63	19.55	12.59	15.67	100
Manufacturing and process.	12.32	24.28	27.40	13.37	10.24	12.38	100
Architecture and const.	9.90	15.34	26.26	19.28	16.60	12.62	100
Agriculture, forestry and fishery	9.94	17.29	20.19	19.94	24.67	7.96	100
Veterinary	9.77	13.05	13.38	38.57	18.52	6.71	100
Health	5.81	11.21	17.96	32.48	9.17	23.36	100
Social services	14.62	26.17	28.29	24.90	1.99	4.03	100
Personal services	11.64	25.98	27.27	17.83	8.22	9.07	100
Occupational health and transport	13.97	16.97	25.29	20.43	15.75	7.60	100
Security services	4.71	5.61	22.00	33.81	23.59	10.27	100

Source: Authors' own calculations using 2019 Turkish LFS data.

In this specification, the vector would be informative regarding the separate effect of for each graduate section. Therefore, the higher values mean that the degree of matching in this field of study would provide higher wage-earning.

Estimating equation (3) with OLS assumes that the wage return of (mis)matching is constant for all income levels. However, different income quantiles might have been affected by different values because wage distributions represent the unobservable abilities of workers (Kim, Ahn, and Kim, 2016). This assumption is reasonable to control abilities when the last cohorts have similar education and experience levels (McGuinness and Bennett, 2007). To examine such a relationship, we used a quantile regression estimator as previous studies applied. However, instead of traditional regression quantiles, we adapted the modified version based on moment conditions that define conditional means developed by Machado and Santos Silva (2019). This approach also simplifies the process of managing incidental parameter problems.

Table 2 shows the distribution of employees across income percentiles for each degree field. It seems unequal and different distribution patterns in between fields. More than half of the graduates of ten majors (arts, journalism and information, business and administration, information and communication,

Table 3. Baseline Specification of Hourly Wage Regression

Variables	(1) Continuous NRI	(2) NRI classified
Industry concentration	-0.280**	-0.279**
	(0.001)	(0.001)
Experience	0.034**	0.034**
	(0.000)	(0.000)
Experience^2	-0.074**	-0.074**
	(0.000)	(0.000)
Female	-0.080**	-0.081**
	(0.000)	(0.000)
Public	0.310**	0.312**
	(0.000)	(0.000)
Illegal	-0.365**	-0.364**
	(0.002)	(0.002)
Married	0.112**	0.112**
	(0.000)	(0.000)
Over-educated	0.157**	0.156**
	(0.000)	(0.000)
Under-educated	-0.192**	-0.193**
	(0.005)	(0.005)
NRI	0.217**	
	(0.002)	
0.25-0.50		0.054**
		(0.001)
0.50-0.75		-0.080**
		(0.002)
0.75-1		0.271**
		(0.002)
Constant	2.859**	2.869**
	(0.002)	(0.002)
Observations	30,269	30,269
R-squared	0.573	0.574
Region fixed effects	yes	yes
Field fixed effects	yes	yes
Occupation fixed effects	yes	yes

Robust standard errors in parentheses ** p<0.01, * p<0.05, + p<0.1
Sample weights have been used.
In column (2), base category for NRI is 0-025.
Base category of vertical mismatch is required education.

engineering, manufacturing and processing, architecture and construction, social services, personal services, occupational health, and transportation) have been positioned at the lower-income distribution. On the other hand, law, health, and engineering fields have the highest share at the top percentile.

Another concern in estimating equations (2) and (3) is the possible endogeneity between and error terms. In education economics literature it is claimed that this problem in return of education context leads to unobserved ability bias and the instrumental variables approach can be used as a remedy. However, Card (1999) found that the bias was smaller than expected. When we contain this bias in the effect of the field of study or mismatch or relatedness on the wage, we could not find a suitable instrument that is not correlated with an error term and correlated with . Meanwhile, Altonji et. al. (2012) and Nordin, Persson and Rooth (2010) used some proxies, but they saw no significant changes in their results. In addition, Lemieux (2014) and Aydede and Dar (2016) also suggested that OLS is still valid to estimate the average effect of the field of study on wages.

Estimation Results

Table 3 presents baseline specifications to see matching returns. All controls are significant and consistent with expectations. Effects of over- and under-education mismatches are also consistent with the literature, meaning that over-educated (under-educated) workers earn less (more) than their well-matched peers. In column (1), our variable of interest, has a significant and positive coefficient, meaning that as the matching of the field of study with occupation increased wage rose by %21.7. This finding is consistent with Robst (2007) and most of the following studies using its approach. If we interpret conversely, those who are one point mismatched with their subject face a 21.7% of income penalty.

We dig this analysis a little further to see if there is variation among coefficients of different ranges. To do so, we adopted the methodology of Aydede & Dar (2016) converting into categories based on their values. In this regard column (2) which we separate each quarter showed that each category has a different wage return. Moreover, compared to the lowest quarter, this effect has been increasing as matching climb to higher. Put differently, higher matching means higher wage returns for the Turkish graduate labor market. The third quarter is the exception to this finding, meaning that matching in this range led to an 8% income penalty. However, it disappears as moves to the higher quarter.

We proceed with our analysis to obtain a field of study-specific effects of matching on wage using Table 4. The coefficient of alone turned out to be negative. This implies that when the matching variable does not interact with major groups, the effect of in Table 2 would be positive since most of the fields of study have a positive effect on higher segments of wage.

In column (1) using OLS estimation, after capturing the other covariates, we first saw that the effect of each major varied substantially. Among them graduates of social services, if they match with their right occupation, have the highest return, 1.73 times greater than that of those with humanities diplomas. It follows the law 1.69 times. Contrary, language graduates suffered from income loss (%32) when they were assigned to the occupations that previous graduates mostly preferred. On the other hand, we realized that higher average or maximum values of majors approximately correspond to higher wage return to matching. We tested whether there is any pattern between the two variables and found a correlation coefficient of .03 for average and .20 for maximum . In other words, if workers having majors with tighter among occupations are assigned to an occupation whose within this major is high, their wage return would be more likely to rise.

Columns (2) to (6) of Table 4 report quantile regression estimation results[6]. We built five different quantiles of the conditional distribution of wages. If we consider OLS results average effects, other columns would be the return of the mismatching for a given income quantile. Then we observed different coefficients of and its interactions with the field of study across quantiles even though their average is close to OLS. For example, wage return to business and administration matching is 8% (compared to humanities graduates) in the 90th quantile while its average return is 25.5%. In the education major, 17.7% matching return at the beginning and 34.8% one at the end of distribution was observed. However, a significant average effect of .259 in column (1) implies that matching of the graduates slightly provides wage growth, especially in higher wage levels. Language graduates, on the other hand, significantly face an income penalty (97.1%) toward the highest wage distribution. Contrarily, law, information and communication, engineering, architecture and construction, health, and social services provide statistically significant wage premiums

[6] Here we present the coefficients of and its field of study interactions only. We share the coefficients of other control variables upon request.

$$p_{sr} = \frac{\frac{total\ workers\ in\ industry\ i\ of\ region\ r}{total\ workers\ in\ region\ r}}{\frac{total\ workers\ in\ industry\ i}{total\ workers}}$$

Table 4. OLS and Quantile Hourly Wage Regression Results with Interacted Model

Variables	(1) OLS	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Over-educated	0.156**	0.112**	0.132**	0.155**	0.180**	0.204**
	(0.000)	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)
Under-educated	-0.189**	-0.096	-0.138*	-0.186**	-0.238**	-0.288**
	(0.005)	(0.082)	(0.067)	(0.063)	(0.076)	(0.098)
NRI	-0.094**	0.015	-0.034	-0.091+	-0.153*	-0.212**
	(0.004)	(0.064)	(0.053)	(0.050)	(0.059)	(0.077)
NRI # field:						
Education	0.259**	0.177+	0.214**	0.257**	0.303**	0.348**
	(0.005)	(0.095)	(0.078)	(0.073)	(0.088)	(0.114)
Arts	0.378**	-0.388	-0.043	0.356	0.789*	1.202**
	(0.019)	(0.336)	(0.277)	(0.260)	(0.311)	(0.404)
Languages	-0.324**	0.277	0.006	-0.307	-0.647**	-0.971**
	(0.014)	(0.242)	(0.200)	(0.187)	(0.224)	(0.291)
Social and behavioral science	0.286**	0.238	0.260	0.285	0.312	0.339
	(0.015)	(0.256)	(0.211)	(0.198)	(0.237)	(0.308)
Journalism and information	0.401**	0.486+	0.448+	0.404+	0.356	0.311
	(0.014)	(0.284)	(0.234)	(0.219)	(0.263)	(0.341)
Business and administration	0.255**	0.566**	0.426*	0.264	0.088	-0.080
	(0.012)	(0.209)	(0.173)	(0.162)	(0.194)	(0.251)
Law	0.688**	0.394**	0.527**	0.679**	0.845**	1.003**
	(0.004)	(0.070)	(0.058)	(0.054)	(0.065)	(0.084)
Biology	-0.552**	-0.223	-0.372	-0.543*	-0.729**	-0.906**
	(0.015)	(0.281)	(0.232)	(0.217)	(0.260)	(0.337)
Physical science	0.217**	0.616*	0.436+	0.228	0.003	-0.212
	(0.016)	(0.307)	(0.253)	(0.237)	(0.284)	(0.369)
Math and statistics	-0.225**	0.111	-0.040	-0.215	-0.405+	-0.586*
	(0.013)	(0.240)	(0.198)	(0.186)	(0.222)	(0.288)
Information and communication	0.143**	-0.003	0.063	0.139+	0.222*	0.300*
	(0.006)	(0.102)	(0.084)	(0.079)	(0.095)	(0.123)
Engineering	0.555**	0.538**	0.546**	0.555**	0.565**	0.574**
	(0.008)	(0.150)	(0.124)	(0.116)	(0.139)	(0.180)
Manufacturing and process.	0.103**	0.270	0.195	0.108	0.013	-0.077
	(0.016)	(0.274)	(0.226)	(0.212)	(0.254)	(0.329)
Architecture and const.	0.328**	0.208+	0.262**	0.325**	0.392**	0.457**
	(0.007)	(0.119)	(0.098)	(0.092)	(0.110)	(0.143)
Agriculture, forestry and fishery	0.126**	0.190	0.161	0.128	0.092	0.057
	(0.009)	(0.154)	(0.127)	(0.119)	(0.143)	(0.185)
Veterinary	0.177**	0.354*	0.274*	0.182	0.082	-0.013
	(0.008)	(0.145)	(0.119)	(0.112)	(0.134)	(0.174)
Health	0.284**	0.125	0.197**	0.279**	0.369**	0.454**
	(0.005)	(0.080)	(0.066)	(0.062)	(0.074)	(0.096)
Social services	0.730**	0.513+	0.611*	0.724**	0.847**	0.964**
	(0.016)	(0.305)	(0.251)	(0.236)	(0.282)	(0.366)
Personal services	-0.365**	-0.027	-0.179	-0.356	-0.547	-0.730
	(0.026)	(0.465)	(0.383)	(0.359)	(0.430)	(0.558)
Occupational health and transport	0.508**	0.273	0.379	0.502	0.635	0.762
	(0.037)	(0.683)	(0.563)	(0.528)	(0.633)	(0.821)
Security services	0.258**	0.351+	0.309+	0.260	0.208	0.158
	(0.014)	(0.210)	(0.173)	(0.163)	(0.195)	(0.252)
Observations	30,269	30,269	30,269	30,269	30,269	30,269

Robust standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1
Base category for field of study is humanities.
Sample weights and fixed effects as in table 3 have been included in each column.
Base category of vertical mismatch is required education.

matching-especially at higher income distribution. In a nutshell, we can state that in most fields wage return to graduates when they approach occupations most related to their majors depends on unobserved ability, which is assumingly identified by the quantile of income. In this sense, our results are complementary to Robst (2007), and Orbay, Aydede, and Erkol (2021), which estimate the only average effect of horizontal mismatch irrespective of the income distribution of workers. Indeed, the results in Table 3 are found similar to Orbay, Aydede, and Erkol in terms of magnitude. On the other hand, it is observed in this study that this varies with a different set of abilities of workers. They also help to broaden the findings of Kim, Ahn, and Kim (2016) investigate the effect of a horizontal mismatch for all fields. They found that Korean workers face income penalties in all income distributions. However, we find that the income effect of horizontal mismatch in a group of similar abilities is not homogenous between different fields of study.

CONCLUSION

In this paper, we examined how the horizontal mismatch affects income in Turkish graduate labor markets by controlling vertical mismatch. We also observed these return differences across fields of study and income quantiles to see different effects of mismatch across unobservable ability levels. Firstly, we found that our matching index positively affects wage level on average, meaning that as workers are employed in non-related occupations, they would face a 21.7% income penalty. Even though this effect turned out to be negative at the upper-middle value of the index, it is then positive at the highest quarter. Secondly, each field of study that Turkish graduates have completed has a different wage return to matching. Even though four majors provide negative wage returns, the positive impact of the rest varies significantly. In addition, these returns are positively correlated with matching.

Quantile regression results also showed heterogeneity in wage return across fields and quantiles. Some of the majors such as business and administration, journalism, information, and veterinary significantly provide wage growth only below the median income. In six of them, wage growth is above the median income level. Finally, only graduates of three majors have a negative income penalty as they find jobs related to their major and this effect proliferates above the median income level. Our results indicate that unobservable ability is an important aspect to evaluate the different field of study effects of mismatch on labor market outcomes. Hence, our policy implications of results are twofold. Firstly, policymakers should pay attention to the heterogeneous effect of mismatch between the field of study for different segments of the economy while reducing income inequality. Since our results also show the effect on different income distributions, it helps to construct a policy set regarding who should be targeted. For example, because business administration and economics graduates are positively affected by matching when they are at the lower income quantile, subsidies would rapidly change the labor market outcomes of this segment.

Subsidies to firms to hire a qualified workforce for qualified jobs should be discussed. On the other hand, certification requirements for a while to perform some jobs would show firms productivity gains if they employed workers suitable for their education. In addition, as seen in the literature, these efforts to overcome horizontal mismatch help to enhance the efficiency of the economy.

Secondly, officials of statistical branches in Turkey should pay attention to questions related to the mismatch. In this study, we use only objective measurements to estimate the wage effect of mismatch. We would take the opportunity to compare the results if TurkStat asked respondents in the labor force survey their mismatch status in a subjective way. Moreover, the panel structure of this dataset also would enable us to control the unobserved heterogeneity of workers.

Our findings seem to contradict human capital theory because they assert that horizontal mismatch is a temporary situation. However, a long-term perspective using longitudinal data may approve this argument. Similarly, job competition theory focusing on job characteristics seems to lack a field of study dimension to see the wage differentials among workers. Using more disaggregated occupation classifications while developing a matching index may change our results. Therefore, future research should focus on this issue. Nonetheless, our findings are consistent with other studies confirming the assignment theory which claims that field of study and occupation jointly matter to estimate wage return.

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