Wage Effects of Field and Level Based Education-Occupation Mismatch: Turkish Case as a Developing Country Example

Yiğit Aydede[1], Benan Orbay[2] and Narod Erkol[3],

Abstract:

The aim of this study is to analyze field and level based education-occupation mismatch in Turkish labor market as an example of a developing country. Using three recent Labour Force Surveys from 2014 to 2016, we report the incidence of both types of mismatches using a clustering index called vertical (horizontal) relatedness index for education level (field)-occupation mismatch. Substantial portion of the labor force work in either level or field based mismatched jobs. Our findings interestingly show that although education level-occupation mismatch has a substantial effect on wages, education field-occupation mismatch effect is not significant. This result indicates that the most of the matched jobs for university graduates in a developing country like Turkey may not require specialization in any field of study. In addition, our data show that significant portion of the university graduates are over-educated (mismatched) for their jobs, thus, their education field does not make any significant effect on wages. This result is not in line with the studies for developed countries where education field-occupation mismatch creates a wage loss.

***JEL Classification*:** I20, I26, J24

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[1] corresponding author: Yigit Aydede, Saint Mary's University, Department of Economics, Halifax, Canada. E-mail: yigit.Aydede@smu.ca.

[2] Istanbul Bilgi University, Department of Business Administration, Istanbul, Turkey. Phone: 90 (212) 3117134, E-mail: benan.orbay@bilgi.edu.tr.

[3] Istanbul Bilgi University, School of Applied Sciences, Istanbul, Turkey. Phone: 90 (212)3115036, E-mail: narod.erkol@bilgi.edu.tr.

1. Introduction

Unemployment is one of the major economic problems all over the world. It is even more drastic problem for developing countries like Turkey. In addition to unemployment, education level-occupation (vertical) and education field-occupation (horizontal) mismatch appears to be an important problem in many countries. There are studies in the literature focusing the wage effects of these two types of mismatches.

Relatively earlier studies consider the match between years of schooling and schooling required for the occupation. This literature shows that there is substantial schooling mismatch. For instance, one out of three employees in Europe is either under- or overqualified. This ratio is even higher in Mediterranean part of the Europe. Regardless of the type and the reason of it, this mismatch has drastic consequences on economic efficiency, growth and competitiveness. There is a fair amount of literature analyzing the effects of education level mismatch on returns to education. These concepts were first pointed out and attracted the attention of researchers by Duncan and Hoffman (1981). They analyzed effects of educational mismatch on wages by defining a new wage education, which includes separate variables for over education, required education and under education. Since then, there has been a growing research on these issues for different data sets from different countries. One important discussion in this literature is on how to determine the required level of education for each occupation. There are three methods proposed: A Realized Matches (RM) method, Worker Self-Assessment (WSA) method and a Job Analysis (JA) method. Each of these methods has advantages and disadvantages. RM method uses the mean or mode of the completed schooling years of the workers to define required education level for a certain occupation. Verdugo and Verdugo (1989) use the mean and consider workers as over or under educated if their completed schooling years deviate at least one standard deviation from the mean. Kiker et al. (1997) use mode of the completed schooling years instead of mean and this method does not require an arbitrary choice of one standard deviation. The main problem with RM method is that it also reflects the demand and supply conditions in the labor market. On the other hand, determining required level of education using WSA is by definition subjective. As stated by Hartog (2000), respondents may prefer to overstate the required level of schooling for their job. Duncan and Hoffman (1981), Galasi (2008), Hartoog and Oosterbeek (1988), Alba-Ramirez (1993), Chevalier (2003) and Verhaest and Omey (2006) are among the studies using this method. Differing from the others Chevalier (2003) and Verhaest and Omey (2006) directly asked the workers whether they are over-schooled, under-schooled or rightly educated for their job. JA method uses information contained in occupational classifications. This type of measure is attractive because it depends on the technology of the job. But, clearly due to the cost issues these classifications may not be updated frequently and therefore, they may not be accurate. Hartog (2000) compared the results of wide range of studies using one of these three methods and concluded that effects of over/under educational mismatch on earnings do not depend on the type of measurement of required education. Empirical results in this literature are in general consensus on the effects of education level mismatch on wages. Returns to under-education are negative, whereas returns to over-education are positive but lower than the returns for required education (see for example, Hartog and Osterbeek (1988) for Netherlands, Ren and Miller (2011) for China, Budria and Moro-Egido (2008) for the Spanish case, Kiker et al. (1997) for Portugal, Di Pietro and Urwin (2006) for Italy, Groot (1996) for UK, Tsai (2010) for US,).

More recent studies starting with Robst (2007) show that the mismatch between the field of study and the occupation is also an important problem that result in labor markets. Robst (2007) is a leading study in this area and concludes that this type of mismatch results in significant wage penalty in US labor market. The extent of this wage penalty depends on the field of study. This penalty is less for graduates of some majors that emphasize general skills compared to some other majors which emphasize more specific skills. Nordin et al. (2010) also analyzed a similar issue for Swedish labor market and they show that there is a substantial income penalty for education-occupation mismatch for both men and women. Interestingly, income penalty is about twice as large as what is found for US men. Lemieux (2014) examined return to education for Canadian labor market and show that match between job and the field of study is an important channel determining productivity and earnings. In line with Robst (2007), he also showed that mismatch effect differs substantially depending on the field of study. Aydede and Dar (2017) looked at the issue from a different perspective. They compare return to education for internationally educated workers and native Canadian worker after controlling both horizontal and vertical matching quality and showed that even for well matched foreign workers return to education is substantially lower.

Another important debate in this literature is on how the empirical findings on wage effects of education level-occupation mismatch is related with the theoretical approaches, namely, human capital theory (Becker (1964)), job competition theory (Thurow (1975)) and assignment theory (Sattinger (1993)). According to human capital theory, investment on human capital is the main determinant of the productivity and thus, the wages. Over-education can only be observed temporarily, and disappears in the long run. Job competition approach however argue that productivity and wages merely depend on job characteristics not on the human capital stock of the job holders. Thus, the most attractive workers get the best paying jobs. Clearly, we can observe mismatch if employers in particular occupation need more employees than available in related field. Although there is no clear evidence in empirical literature on which theoretical approach provides a better explanation for wage differences resulting from mismatches, assignment theory appears to have more support for empirical findings. Because matching of workers and jobs is the main determinant of the productivity and hence wages according to the assignment theory.

Our study will focus on the wage effects of both horizontal and vertical mismatches in Turkey as an example of a developing country. There are only few studies analyzing wage effects of vertical mismatch in developing countries. Filiztekin (2011) examined vertical mismatch in Turkey. He used 1994 and 2002 Household Income and Consumption Surveys. Filiztekin (2011) mainly focuses on the wage effect differences of mismatch between formal and state sector and showed that, in fact, there is a significant difference. In a more recent study, Mercan et al. (2015) have looked at the same issue taking into account the sectoral differences using Turkish Labor Force Surveys (LFS) data for 2009. Their findings also showed that education level-occupation (vertical) mismatch is an important problem in Turkey's labor market. Acar (2017) has also investigates the wage effect of vertical mismatch on wages in Turkey. Her results indicate that, after controlling omitted variable bias, over-education and under-education have no significant effect on wages and thus, over-education is a waste of resources.

To the best of our knowledge, there are no studies analyzing education field-occupation (horizontal) mismatch for any developing country. Our study analyzes the education field-occupation (horizontal) mismatch in addition to education level-occupation (vertical) mismatch and wage effects of these mismatches for Turkey as a developing country. Results show that there is substantial horizontal and vertical mismatch in Turkish labor market. More that 40% of the university graduates in Turkey work in vertically mismatched jobs. In other words, they are either over-educated or under-educated for their jobs. Vertical mismatch is slightly lower for female workers. Besides, since experience is a substitute for education, this type of mismatch increase with age. Similarly, more than 40% of the labor force work in jobs which are unrelated with their education field, namely they work in horizontally mismatched jobs. Although horizontal mismatch is higher for females like vertical mismatch, it is not significantly different for different age groups. Besides, degree fields that provides occupation specific skills like law and health are among the fields which have highest matched ratios. Our findings on wage effects interestingly indicate that horizontal mismatch does not have any significant effect on wages. Only severe mismatch for education fields which provide occupation specific skills, such as law and health, have some wage effects. However, we observe a substantial wage effect as a result of vertical mismatch. More specifically, under-educated university graduates have significantly higher wages compared to their peers working in matched jobs. These results are quite attractive, because they indicate a warning on the development lag between the demand and supply side of the labor market. In Turkish case, there is an enormous increase in the number of universities and university graduates in last two decades. It is clear that demand side of the labor market can not respond well to such a rapid increase. We observe from our data that substantial portion of the university graduates work in weakly matched and mismatched jobs and most of them are over-educated. This means that, many workers work in jobs which do not require education field specific skills and thus, horizontal mismatch does not have wage effect.

This study is organized as follows: Section 2 introduces the data and the descriptive analysis. Empirical results and discussions are given in Section 3. Section 4 presents the conclusions.

2. LFS Data and Education Level and Education Field Mismatch with Occupation

The present study uses four Labor Force Surveys (LFS) from 2014 to 2016. After pooling those three surveys and selecting only full-time civilian wage earners between 15 and 65 years of age working in only one permanent, private sector position. After these restrictions, our sample has 145,244 observations. The survey codes the major field of study in 21 basic learning areas by following the International Standard Classification of Education (ISCED). The field of study levels are available for those who are graduated either from a vocational high school (VHS) or from a public or private university. The education field mismatch include only university graduate workers where this sample has 28,897 observations. The reason of excluding the VHS graduates is the differences among skills and capabilities of VHS and university graduates from the same field. The data has 40 different occupation groups which is categorized by 9 major different levels by ISCO-08 (ILO). Lastly, survey provides the data about educational level, divided by seven different levels through workers who are not completed any educational institution and they are literate to households who hold master or doctorate degree.

LFS provides information about measuring workers' field and level mismatch in 3 different variables: (1) the highest degree a person obtained, (2) the occupation of the worker, (3) the education field. Using this information from the dataset we will determine mismatch of education level-occupation and education field-occupation using the indexes defined in Aydede and Dar (2017).

2.1 Education Level-Occupation Mismatch

Previous studies use ORU method to analyze education level mismatch. In ORU literature, most of the studies determine the required education using realized match method which reflects the "usual" or "reference" education of each occupation. Using this benchmark, these studies determine the over-education and under-education ratios.

Benchmark level of education is calculated by modal (Kiker et al., 1997) and average values of schooling years (Verdugo and Verdugo, 1989) in the literature. Using the same data with this study, Aydede and Orbay (2016) also use modal values as required education level and show that educational mismatch ratio in Turkey is around 54%. More specifically, they show that 21% of university graduates are employed in jobs requiring lower education level. However, we know from Aydede and Dar (2017) that size domination is an important problem in determining mismatch with ORU measures. Instead they define a clustering index called vertical relatedness index (*VRI*) to calculate education level-occupation mismatch ratio. This index is calculated using the formula given below:

$$VRI_{od} = \frac{L_{od}/L_o}{L_d/L_T}$$

where L is the number of workers, o is the occupation, d is the highest degree of education and T denotes the whole workforce. It measures the density of degree d in occupation o after removing the difference in size between 7 degrees in the entire workforce. It provides the answer of which occupation is most observed in degree d or which degree is most observed in occupation o. To omit the size domination problem, they define a normalized vertical relatedness index (*NVRI*) for each selected occupation and educational level in different class intervals from 0 to 1. This normalisation procedure enables to classify each degree relative to the most relevant one (*NVRI*=1) in an occupation for the whole population.

	Degree										
OCCUPATION	No Education	Primary School	Lower Secondary	Upper Secondary	Vocational High School	University	Master/ Doctorate	Total	Usual Mean	Mode (degree by)	VRI
GROUP1: Legislators and senior officials and managers	2	203	261	814	604	3531	595	**6010**	4.46	5	6
	0.00	0.016	0.029	0.16	0.09	0.46	1				
GROUP 2: Professionals	4	28	62	197	465	7235	1353	**9344**	5.02	5	6
	0.0005	0.00	0.002	0.018	0.029	0.48	1				
GROUP 3: Technicians and associate professionals	17	917	978	1696	3136	4900	172	**11816**	3.90	5	5
	0.00	0.11	0.16	0.51	0.77	1	0.44				
GROUP 4: Clerks	32	1066	1547	3400	3423	6692	160	**16320**	3.83	5	5
	0.00	0.07	0.2	0.79	0.67	1	0.23				
GROUP 5: Service workers and shop and market sales workers	475	7309	7213	6904	5873	3679	63	**31516**	2.69	1	3
	0.48	0.49	0.71	1	0.67	0.3	0				
GROUP 6: Skilled agricultural and fishery workers	29	406	137	57	41	13	0	**683**	1.58	1	0
	1	0.99	0.45	0.24	0.11	0.00	0				
GROUP 7: Craft and realted trade workers	493	9786	7152	2172	4820	1441	13	**25877**	2.21	1	1
	0.81	1	0.97	0.44	0.77	0.16	0				
GROUP 8: Plant and machine operators and assemblers	394	9495	6077	2142	3123	772	1	**21954**	2.01	1	1
	0.71	1	0.85	0.41	0.51	0.09	0				
GROUP 9: Elementary occupations	1016	10008	5462	2086	2464	684	4	**21724**	1.86	1	0
	1	0.6	0.44	0.24	0.24	0.05	0				
TOTAL	**2462**	**39218**	**28889**	**19468**	**23949**	**28897**	**2361**	**145244**			

Table 1. Occupation-Education Level: Distribution of Workers.

Table 1 above displays the distribution of workers depending on their education level and occupation. As it can easily be seen from Table 1, for most of the occupation groups, NVRI indicates a different education level than median and mode levels. For example, most crowded group (39218) in the labor force has level 1 education, when we eliminate this substantial size effect using NVRI, the most related education level for Group 5 occupation turns out to be education level 3 instead of 1. Similarly, for Group 1 occupation, due to the size effect, mode and median indicate that the most related education level is 5, however, according to NVRI level 6 is the most related education. These examples clarify the size domination problem of ORU measures. As it is well known, in ORU literature over-education and under-education is calculated by comparing worker's actual education with the required education level for related occupation which is calculated commonly by mode. Our examples, show that when the size effect is removed the most related education level can drastically change. For this reason, in our study we prefer to use *NVRI* for occupation-education level mismatch.

2.2 Education Field-Occupation and Education Level-Occupation Mismatches

Most of the studies analyzing education field-occupation mismatch use surveys containing explicit questions to measure mismatch between education field and occupation. Clearly, those surveys' data is limited in size and answers to questions can be subjective. Aydede and Dar (2017) used an index similar to *VRI* which they called horizontal relatedness index (*HRI*) to measure education field-occupation mismatch. The following formula defines *HRI*:

$$HRI_{of} = \frac{L_{of}/L_f}{L_o/L_T}$$

where L is the number of workers, o is the occupation, f is the education field and T denotes the whole workforce. It measures the relatedness of occupation o in major f by calculating the percentage of workers in major f working in occupation o adjusted by the size of occupation o in the entire workforce. Following Aydede and Dar (2017), we prefer to use this index to identify education field-occupation relatedness.

Table 2a shows the distribution of education level-occupation matched-mismatched labor force for each education level. Workers with *NVRI* value between 0.6-1.0 is accepted as matched, 0.4-0.6 weak matched and 0-0.4 mismatched. In line with previous research (see Acar (2017)) Table 2a shows that overall education level-occupation matched ratio in Turkish labor market is 61.7%, weak matched ratio is 14.6 and mismatch ratio is 23.7%. When we analyze separately for different education levels, we observe these ratios are similar for university graduates. But, for the upper secondary school graduates mismatched ratio reaches to 37.7%. Another important observation from Table 2a is that over-education ratios among weak matched and mismatched labor force for all education levels are quite high.

Table 2b and Table 2c display matched, weak matched and mismatched university graduates labor force distribution for gender groups and age groups respectively. Matched ratio for female labor force (64.3%) is slightly higher than male (56%). But more interesting observation is that among the mismatched labor force over-education ratio for females is substantially higher than males. On the other hand, matched labor force is higher for the younger population. When workers get older experience substitute education and older workers work in less matched jobs. More specifically, mismatched ratio for the workers below 30 is 24% and only 38% of those are under-educated, however, for the workers over 55 this ratio is around 47% and 85% of those are under-educated.

	Matched	Weak Matched			Mismatched			
Degree Level	Total	Over- educated	Under-educated	Total	Over- educated	Under-educated	Total	TOTAL
No education	2034	0	0	0	0	428	428	2462
%	**82,62**	**0,00**	**0,00**	**0,00**	**0,00**	**100,00**	**17,38**	**1,70**
Primary school	26403	6624	0	6624	0	6191	6191	39218
%	**67,32**	**100,00**	**0,00**	**16,89**	**0,00**	**100,00**	**15,79**	**27,00**
Lower secondary	18665	3392	1010	4402	2160	3662	5822	28889
%	**64,61**	**77,06**	**22,94**	**15,24**	**37,10**	**62,90**	**20,15**	**19,89**
Upper secondary	9961	1169	1000	2169	5206	2132	7338	19468
%	**51,17**	**53,90**	**46,10**	**11,14**	**70,95**	**29,05**	**37,69**	**13,40**
Vocational high school	13395	3187	1005	4192	5022	1340	6362	23949
%	**55,93**	**76,03**	**23,97**	**17,50**	**78,94**	**21,06**	**26,56**	**16,49**
University	17107	2622	1071	3693	3917	4180	8097	28897
%	**59,20**	**71,00**	**29,00**	**12,78**	**48,38**	**51,62**	**28,02**	**19,90**
Master/Doktorate	2064	73	0	73	224	0	224	2361
%	**87,42**	**100,00**	**0,00**	**3,09**	**100,00**	**0,00**	**9,49**	**1,63**
Total	89629	17067	4086	21153	16529	17933	34462	145244
%	**61,71**	**80,68**	**19,32**	**14,56**	**47,96**	**52,04**	**23,73**	

Table 2a. Education Level-Occupation Mismatch Distribution and Ratios for Education Levels.

	Matched	Weak Matched			Mismatched			
Gender	Total	Over- educated	Under-educated	Total	Over- educated	Under-educated	Total	TOTAL
Male	9932	1534	847	2381	3200	2218	5418	17731
%	**56,01**	**64,43**	**35,57**	**13,43**	**59,06**	**40,94**	**30,56**	**61,36**
Female	7175	1088	224	1312	717	1962	2679	11166
%	**64,26**	**82,93**	**17,07**	**11,75**	**26,76**	**73,24**	**23,99**	**38,64**
Total	17107	2622	1071	3693	3917	4180	8097	28897
%	**59,20**	**71,00**	**29,00**	**12,78**	**48,38**	**51,62**	**28,02**	

Table 2b. Education Level-Occupation Mismatch Distribution and Ratios for Gender Groups.

	Matched	Weak Matched			Mismatched			
Age	Total	Over- educated	Under-educated	Total	Over- educated	Under-educated	Total	TOTAL
Age<=30	8817	1779	146	1925	2118	1304	3422	14164
%	**62,25**	**92,42**	**7,58**	**13,59**	**61,89**	**38,11**	**24,16**	**49,02**
30<Age<=40	6261	651	464	1115	1343	1710	3053	10429
%	**60,03**	**58,39**	**41,61**	**10,69**	**43,99**	**56,01**	**29,27**	**36,09**
40<Age<=55	1878	174	394	568	426	990	1416	3862
%	**48,63**	**30,63**	**69,37**	**14,71**	**30,08**	**69,92**	**36,66**	**13,36**
55<Age	151	18	67	85	30	176	206	442
%	**34,16**	**21,18**	**78,82**	**19,23**	**14,56**	**85,44**	**46,61**	**1,53**
Toplam	17107	2622	1071	3693	3917	4180	8097	28897
%	**59,20**	**71,00**	**29,00**	**12,78**	**48,38**	**51,62**	**28,02**	

Table 2c. Education Level-Occupation Mismatch Distribution and Ratios for Age Groups.

Table 3a shows the education field-occupation mismatch distribution and ratios. As we can expect, degree fields that provides occupation specific skills like law and health are among the fields which has highest matched ratio. Engineering is also a degree which provides occupation specific skills however, only 49% of the employees with engineering degree works in matched jobs. This can be explained by considering the fact that engineering graduates have better analytical abilities and they can work in variety of jobs in addition to technical jobs. On the other hand, business administration, and social and behavioral science degrees which provide general skills have quite high matched ratios. Overall, 55% of the university graduate population in Turkish labor market work in matched jobs.

	NHRIC			
FOS	Matched	Weak Mathced	Mismatched	Total
Teacher training and education science	904	0	903	1807
%	**50,0**	**0,0**	**50,0**	**6,3**
Arts	307	0	510	817
%	**37,6**	**0,0**	**62,4**	**2,8**
Humanities	230	49	398	677
%	**34,0**	**7,2**	**58,8**	**2,3**
Social and behavioural science	1906	196	536	2638
%	**72,3**	**7,4**	**20,3**	**9,1**
Journalism and information	33	0	68	101
%	**32,7**	**0,0**	**67,3**	**0,3**
Business and administration	7804	1141	955	9900
%	**78,8**	**11,5**	**9,6**	**34,3**
Law	233	0	121	354
%	**65,8**	**0,0**	**34,2**	**1,2**
Life science	1	0	284	285
%	**0,4**	**0,0**	**99,6**	**1,0**
Physical science	293	184	328	805
%	**36,4**	**22,9**	**40,7**	**2,8**
Mathematics and statistics	130	0	220	350
%	**37,1**	**0,0**	**62,9**	**1,2**
Computing	1	149	662	812
%	**0,1**	**18,3**	**81,5**	**2,8**
Engineering and engineering trades	2589	518	2147	5254
%	**49,3**	**9,9**	**40,9**	**18,2**
Manufacturing and processing	74	0	1039	1113
%	**6,6**	**0,0**	**93,4**	**3,9**
Architecture and building	825	12	461	1298
%	**63,6**	**0,9**	**35,5**	**4,5**
Agriculture, forestry and fishery	6	0	668	674
%	**0,9**	**0,0**	**99,1**	**2,3**
Veterinary	21	0	65	86
%	**24,4**	**0,0**	**75,6**	**0,3**
Health	539	0	112	651
%	**82,8**	**0,0**	**17,2**	**2,3**
Social services	28	0	185	213
%	**13,1**	**0,0**	**86,9**	**0,7**
Personal services	143	56	659	858
%	**16,7**	**6,5**	**76,8**	**3,0**
Transport services and environtal protection	21	1	61	83
%	**25,3**	**1,2**	**73,5**	**0,3**
Security services	35	0	86	121
%	**28,9**	**0,0**	**71,1**	**0,4**
TOTAL	16123	2306	10468	28897
%	**55,8**	**8,0**	**36,2**	

Table 3a. Education Field-Occupation Mismatch Distribution and Ratios for education fields.

Gender	Matched	Weak Matched	Mismatched	TOTAL
Male	9150	1772	6809	17731
%	**51,60**	**9,99**	**38,40**	**61,36**
Female	6973	534	3659	11166
%	**62,45**	**4,78**	**32,77**	**38,64**
Total	16123	2306	10468	28897
%	**55,79**	**7,98**	**36,23**	

Table 3b. Education Field-Occupation Mismatch Distribution and Ratios for gender groups.

Similar to the results for education level-occupation mismatch, matched education field-occupation ratio is slightly higher for female labor force than male. However, as it can easily be observed from Table 3c, education field-occupation mismatch ratios do not change significantly for different age groups.

Age	Matched	Weak Matched	Mismatched	TOTAL
Age<=30	8102	975	5087	14164
%	**57,20**	**6,88**	**35,91**	**49,02**
30<Age<=40	5788	918	3723	10429
%	**55,50**	**8,80**	**35,70**	**36,09**
40<Age<=55	1996	384	1482	3862
%	**51,68**	**9,94**	**38,37**	**13,36**
55<Age	237	29	176	442
%	**53,62**	**6,56**	**39,82**	**1,53**
Toplam	16123	2306	10468	28897
%	**55,79**	**7,98**	**36,23**	

Table 3c. Education Field-Occupation Mismatch Distribution and Ratios for age groups.

3. Statistical framework and estimation results

In the literature it is well documented that estimated returns to education is significant. But there are different reasons identified for why education may have positive effects on earnings. Since the education provides specific skills, it helps individuals to find better paying occupations. Also, regardless of the occupation, this acquired skills increases workers' overall productivity level. Lemieux (2015) calls these channels "occupation upgrading" and "pure education" effects. The third reason is the interaction between two channels which measures the matching quality of the education and occupation: workers become more productive if they work in jobs that are a good match for their education. To analyze the impact of education on earnings we model each of three channels explained above. The occupation upgrading and specialization are controlled in Mincer-type functions by binary variables that identify occupation and education field fixed effects. The Mincer wage function used by Lemieux (2015) enhance the model and include the effect of matching quality. So, the three channels that has an effect on earnings measured by either a continuous variable of years of schooling or a binary variable that controls for the degree of education. In 3.1 and 3.2 the model of wage functions will be specified with respect to two aspects of "good matching": the effect of education field - occupation mismatch the effect of education level - occupation mismatch on wage earnings.

3.1 Wage Earnings and Education Field-Occupation Mismatch

In order to understand education field-occupation mismatch effects on wage earnings, we first estimated the following equation:

$$\ln(w_{ifo}) = \beta x_i + b_f + c_o + \alpha\, m_{(f,o)} + \varepsilon_{ifo} \qquad (1)$$

where individual i working on occupation o with the education field f earns hourly wage w. Vector x includes all other conventional variables such as, gender, age, age square, marital status. Binary variables b_f and c_0 control for differences in education field f and occupation o, respectively. The term $m_{(f,o)}$ is the matching level of education field f and occupation o and the α is the wage premium which measures the extent to which education field f is valuable in occupation o.

The match quality of education field and occupation could also be correlated with a person's ability. However, in the literature, the unmeasured ability is a problem and there are many studies that try to control the unobserved ability by using different methodologies. In this paper, we follow Lemieux (2015) who shows why the ordinary least square (OLS) results of equation (1) is valid when that equation is used to estimate average effects. The results for this regression analysis are given in Table 4 (1).

lnwage	(1) Coef.	(2) Coef.
Age	0.0726***	0.0768***
	(0.0056)	(0.0098)
Age square	-0.001***	-0.0008***
	(0.000)	(0.000)
NHRI range (Base: NHRI $\geq$ 0.8)		
0.6 $\leq$ NHRI<0.8	0.019	-0.077
	(0.021)	(0.036)
0.4 $\leq$ NHRI<0.6	0.006	-0.234
	(0.021)	(0.114)
0.2 $\leq$ NHRI<0.4	-0.023	0.015
	(0.021)	(0.128)
NHRI<0.2	-0.040**	-0.18***
	(0.018)	(0.046)
Gender	-0.052***	-0.057**
	(0.010)	(0.027)
Observations	28,897	6,259
R-squared	0.481	0.528
FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. (1) OLS estimates of weekly wage earnings with NHRI.
(2) OLS estimates of weekly wage earnings with NHRI for law, health and engineering majors.

Interestingly, estimation results indicate that overall education field-occupation mismatch has no significant effect on wages in Turkish labor market. However, as we can observe from Table 4 (2), when we only consider majors providing occupation specific skills although weak match of education field-occupation still does not have any effect on wages, severe mismatch has a significant wage penalty. More specifically, severely mismatched workers with law, health and engineering degrees earn 18% less compared to the workers with the matched workers with the same degree.

As we stated before, we used Turkish labor market data as an example of a developing country. Similar to many developing countries, number of universities and university graduates rapidly increased in last two decades. As it is shown in Figure 1, the number of universities in Turkey is 193 today, however in 1980, there was only 19 universities. When there is such a rapid increase in supply side, demand side may not be able to create that many jobs for those university graduates. As we observe from Table 2a almost 40% of the university graduates work in weakly matched and mismatched jobs and a significant portion of them are over-educated. Clearly, when an important portion of university graduates work in jobs where they are over-educated, it is not surprising that education field-occupation mismatch do not have any significant effect on wages. On the other hand, after such rapid increase, universities may not be able to hire high quality academicians. Besides, with increasing number of universities it has become quite easy to enter universities and thus, university students' central exam scores and ability levels drastically dropped in last decades. As a result, it is quite likely that skill levels of most of the university graduates are below the required levels. That may clearly be another reason that education field-occupation mismatch has no significant effect on wages.

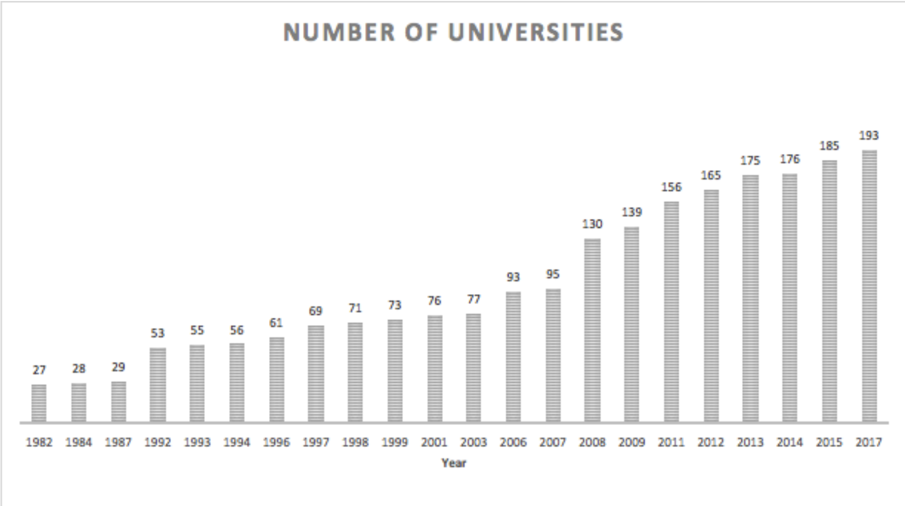

Figure 1: Number of Universities in Turkey

3.2 Wage Earnings and Education Level-Occupation Mismatch

A similar analysis has been done in this section to examine education level-occupation mismatch effects on wages. The estimated is the following:

$$\ln(w_{ilo}) = \beta x_i + a_l + c_o + \lambda\, m_{(l,o)} + \varepsilon_{ilo} \qquad (2)$$

where individual i working on occupation o with the education level l earns hourly wage w. Vector x includes all other conventional variables such as, gender, age, age square, marital status. Binary variables a_l and c_0 control for differences in education level l and occupation o, respectively. The term $m_{(l,o)}$ is the matching level of education level f and occupation o and the λ is the wage premium which measures the extent to which education level l is valuable in occupation o. The results for the regression analysis are given in Table 5.

lnwage	(1) Coef.
Age	0.078***
	(0.008)
Age square	-0.001***
	(0.000)
OU*lnNVRI	
Matched	Base
	(0.000)
Over-educated	0.045***
	(0.010)
Under-educated	-0.450***
	(0.108)
Gender	-0.076***
	(0.018)
Observations	28,897
R-squared	0.409
FE	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. OLS estimates of weekly wage earnings with NVRI.

Table 5 reports that, in contrast with the results for education field-occupation mismatch, there is significant wage penalty for education level and occupation mismatch in Turkish labor market. The coefficients of multiplicative variables show the percentage change in weakly wages as a result of a percentage change in NVRI for over educated and under educated workers separately. 1% increase in NVRI (i.e a reduction in over-education) increases the wage of over-educated workers by 0.045 %. For example, suppose that worker's weakly wage is $500 and her NVRI is 0.35 (mismatched category). If this person moves to a job where her NVRI is 0.70 i.e. she moves to matched category job, her weekly wage will increase from $500 to $522.5 (4.5%). Similarly, 1% increase in NVRI reduces the wage for an under-educated worker 0.45%. Our data includes only university graduates, therefore, if a person works in a job that requires master's or PhD degree with 0.35 NVRI value. If we put her back to a job that only requires bachelor's degree with 0.7 NVRI value, her wage will decrease 45%. This result indicates that jobs that require master's or PhD degree are quite high paying jobs.

4. Conclusions

Education-occupation mismatch, regardless whether it is level or field base, is considered as one of the important productivity loss reasons. Empirical analysis in the related literature show that there is a substantial wage effect in various developed countries. This study contributes to this literature looking at this issue from a developing country perspective. Turkish labor market data show that both horizontal and vertical mismatch is at quite serious level. Important portion of the university graduates in Turkey work vertically or horizontally or both ways mismatched jobs. In contrast with the studies using developed countries' data, our findings on wage effects interestingly indicate that, in Turkish labor market, horizontal mismatch does not have any significant effect on wages except for the severe mismatch cases for education fields which provide occupation specific skills, such as law and health. However, wage effects of vertical mismatch are substantial as in developed countries.

There is an enormous increase in the number of universities and university graduates in last two decades in Turkey. Above findings show us that demand side of the labor market can not respond well to such a rapid change in the supply side. As a results, substantial portion of the university graduates work in weakly matched and mismatched jobs and most of them are over-educated. Clearly, many workers work in jobs which do not require education field specific skills and thus, horizontal mismatch does not have any wage effect.

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