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1 July 2015

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There is no guarantee that the right candidate will be matched with the right job in labour markets. If the mismatch is substantial, the surplus education and the deficit in schooling lead to underutilization and a loss in productivity in the economy as a whole. The aim of this study is to understand the importance of these issues for Turkish Economy by analyzing the economic returns of educational mismatch in Turkey. First we explore educational mismatch levels in Turkey for nine different occupation areas in different regions and for different industries using four recent household surveys from 2009 to 2012, which include more than one million observations. Based on this data, we analyze effects of educational mismatch on wages in Turkish labor market by using the ORU models. Results indicate that wage loss of over-educated workers is substantially higher for higher age. Regional ORU estimations show that Istanbul is the region with highest benefit for additional required education. Over-education rewards and under-education penalties are also among the highest for İstanbul. Manufacturing is the industry with the highest population and with the highest wage effects for both over-education and under-education. Among the major occupations, wage effects are in general highest for office clerks. Finally, the cost of underutilization and productivity loss due to educational mismatch is substantial in Turkey.

***JEL Classification*:** J6, J15, J61

***Keywords*:** Educational mismatch, economic returns, underutilization, Turkey

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Global economic crisis has increased unemployment in all over the world. The impact on developing countries like Turkey is even more drastic. Despite the high unemployment rates, skill mismatch appears to be an important problem in many countries. Recent studies show that one out of three employees in Europe is either under or over qualified. This ratio is even higher in Mediterranean part of the Europe. On one side, for skill mismatch with over qualification, we observe low demand for low skill workers and high number of employees with higher education taking up jobs with low skill requirements. On the other side, for skill mismatch with under qualification, we observe that education level for available employees is not sufficient for existing jobs. Regardless of the type and the reason of it, skill mismatch has drastic consequences on economic efficiency, growth and competitiveness. More specifically, under education creates a substantial welfare loss due to misuse of human resources. On the other hand, workers with over education earn less and save less. Clearly, job satisfaction, motivation and efficiency is low and turnover ratio is high for over qualified workers. For the employer side, over education may decrease efficiency and production quality. Besides, high turnover rates also increases production cost, and creates important competition disadvantageous for the employers. As a solution for the over education problem, countries tend to lower expenditures on education, which in fact reduce their ability to react changing labor market conditions.

There is a fair amount of literature analyzing the effects of over/under educational mismatch on returns to education. These concepts were first pointed out and attracted the attention of researchers by Duncan and Hoffman (1981) (here after DH). DH's study 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. Clearly, workers with higher education than required are classified as over-educated and workers with lower education are classified as under-educated. 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) (here after VV) 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 a random choice such as one standard deviation. RM method generally considered inferior to the other two methods because it mainly reflects the demand and supply conditions in the labor market and for this reason, it may not be a good measure of true required level of education. 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. DH, 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 overschooled, underscholled 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. Chiswick and Miller (2009) also compared RM and WSA methods using US data which contains male native-born and immigrant workers and showed that general findings are independent from types of measurement. Santos (1995), Rumberger (1987) are among the other studies directly comparing these methods. Santos (1995) compared the RM and JA methods using Portugal's data. Rumberger (1987) compared WSA and JA methods for US data.

Empirical results in this literature are in general consensus on the effects of 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). Although most of the studies analyze the issue using samples including all workers, some studies analyze the returns investigating the differences in terms of gender (see Rumberger (1987) for US, Dolton and Vigoles (2000) for UK, Daly et al. (2000) for Germany, Budria and Moro-Egido (2009), for the Spanish and German cases). Some other studies, focus on more specific groups of interest. For example, seminal paper Duncan and Hoffman (1981) looked at the issue from gender-race (white/black man, white/black women) perspective. Chiswick and Miller (2008) analyzed the returns to mismatch for foreign-born and native-born workers.

Measuring required education for an occupation is a major problem in this literature. Additionally, as stated in various studies, this literature omits unobserved ability variable, which can be very explanatory on wage differentials. Clearly, this unobserved heterogeneity in workers' ability is still the main econometric challenge in ORU models. There are several ways to address this problem that can be grouped under three categories in the literature: (1) using a unique dataset based on a micro survey that has a question which identifies whether the worker's ability matches the required level of skill in the job; (2) Developing proxies for "ability" that captures the worker's otherwise unobserved skill level and its fitness to the job by using large datasets (labour force surveys or censuses); (3) Implementing special econometric frameworks that help remove the unobserved individual heterogeneity, such as Propensity Score Matching (PSM) and Fixed-Effect models (FE) (see Bauer (2002), Korpi and Tahlin (2009), Larno and Messina (2010)). Unfortunately, first two ways mainly depend on the availability of the data and it may not be possible to reach such data or create relevant proxy to measure ability for many countries. The econometric techiques mentioned as the third way to solve the unobserved ability issue, has their own cavities and do not drastically alter results obtained in previous ORU literature.

Leuven and Oosterbeek (2011) indicate that interpreting estimated coefficients in the relevant literature as the return to education can be misleading for individual and social investment decision on education due to the possible data problems mentioned above. Instead, these coefficients can be informative about the approximate cost of educational mismatch. Using these coefficient one can compute how much productivity increase can be obtained from reallocating workers to jobs that require their schooling.

In this study, we use simple ORU models, which are extensively used in previous literature mentioned above, to examine effects of educational mismatch in Turkey. As it is stated in a recent study Joona et al (2014), despite the data and estimation problems results of ORU models are remarkably consistent. First, our aim is to investigate degree of educational mismatch in Turkey for different regions, industries, genders, and occupations and to analyze returns to mismatch taking into account these gender, region and industry differences. Additionally, as suggested in Leuven and Oosterbeek (2011), we aim to determine the extent of the cost of underutilization in order to shed a light the economic consequences of educational mismatch. For this purpose, we use four recent household surveys from 2009 to 2012, which include more than one million observations. Based on this household survey data, we estimated ORU (**O**ver-education/**R**equired education/**U**nder-education) equations using both DH and VV models to analyze the returns to educational mismatch for Turkish labor market and to calculate approximate cost of underutilization. Filiztekin (2011) is the only study analyzing educational mismatch in Turkey. He used 1994 and 2002 Household Income and Consumption Surveys and showed that there is considerable mismatch in Turkish labor market. He mainly focus on the wage effect differences of mismatch between formal and state sector and showed that, in fact, there is a significant difference.

Results indicate that educational mismatch ratio in Turkey is around 54 percent and this ratio is substantially higher than most of the European countries. There is very serious over-education problem in jobs requiring elementary school level education. Sixty percent of the population works in such jobs and almost 48 percent of them are overeducated. On the other hand, 23 percent of population is employed in jobs requiring university education and 47 percent of those are under educated. When we analyze the wage effects of educational mismatch using ORU models, we observe from VV estimation that, being overeducated result in a 32.8 percent wage loss. On the other hand, on average, an undereducated worker's wage is 15.7 percent higher than the worker with equivalent actual education working in a matched job. In accordance with related literature, DH model estimations (with required education calculated with mean values) show that, rewards from over-education (2 percent) are substantially less than the benefits of required education (10.4 percent) and penalty of under-education is around 4.4 percent.

Subgroups analysis indicates that wage loss of over-educated workers is substantially higher for higher age. Regional ORU estimations show that Istanbul is the region with highest benefit for additional required education. Moreover, over-education rewards and under-education penalties are also among highest for İstanbul according to both DH and VV estimations. Manufacturing is the industry with the highest population and with the highest wage effects for both over-education and under-education. Finally, among the major occupations, wage effects of ORU variables are in general highest for office clerks.

In general, females suffer a bit more from underutilization. For example, wage loss for overeducated females is 34.2 percent whereas the same ratio for males is 31.7 percent. A more detailed analysis of over-education for different surplus degrees shows that, except middle school level, this difference exists at all levels of over-education in favor for males. Wage loss due to the overeducation is more substantial for higher age groups. For instance, wage loss of over-education at university level is 4.1 percent for 15-29 age group, however, the same ratio is 13.9 percent for age group of 45+. Finally, our results indicate that there is a substantial cost of underutilization in Turkey. The cost of underutilization for four years between 2009 and 2012 is about 6 billion TL or around 2 billion USD with 2012 prices only for workers with educational surplus working in jobs that require 5 years of schooling.

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.

1 LFS Data and educational mismatch

The present study uses four Labor Force Surveys (LFS) from 2009 to 2012. After pooling those four surveys and selecting only full-time civilian wage earners between 15 and 65 years of age working in private sector at a permanent job, we obtain more than 200 thousand observations.

In order to measure over-education (OE), required-education (RE) and, under-education (UE) for each worker we first used the RM method, which identifies the required level of education by the average values of years in schooling for each skill group. RM method justified based on the argument that the only objective criteria about the "required" level of education by skill levels can be revealed by the labor markets. RM method is criticized in this literature since it mainly reflects the demand and supply conditions in the labor market. WSA, on the other hand, is a subjective method by its nature and there is no available large data set in Turkey usable for this method. The only available data for WSA is European Working Conditions Surveys (EWCS) which is developed by Eurofound and available at UK Data Service by a special permission. But, the scope of these surveys is much narrower than the data that we use for RM method.

In the literature skill groups are identified by occupation categories. In LFS, these categories are given by 9 different levels by ISCO-88 (ILO). In order to introduce a more detailed classification that identifies the required education for each worker, we created a new set of skill categories by extending 9 ISCO-88 occupation categories for each industry level, which is also given in 21 (NACE-Rev.2) different levels. Since our data include only civilian wage earners, we drop industries of Public Administration and Defense and Activities of Extra Territorial Organizations. Thus, the new industry-occupation classification has 171 different skill categories (19x9). The distribution of workers by these categories is reported in Appendix.

LFS provides information about workers' education in 3 different variables: (1) the highest degree a person obtained, (2) if the person has no education, whether he is illiterate or not, (3) if the person's highest degree is a vocational high school or a college, the field of study. To develop years in schooling from these three variables that also reflect educational ranks such as illiterate, literate without schooling, and general-vocational high school degrees, we develop a new variable as follows: 1 illiterate, 3 literate without schooling, 5 elementary school, 8 middle school, 11 high school – general, 13 high school – vocational, and 15 college, university, and above. Except for 1, 3, and 13, the numbers reflect actual years of schooling required for obtaining a degree in their categories. We also checked the data so that wage differentials between those educational attainments justify the marginal increments from 1 to 3 and 11 to 13.

The required education in the RM method reflects the “usual” or “reference” education of each skill group. This 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. Table 1 reports educational mismatch calculated by modal values of years of education (REM).

Table 1: Incidence of yearly educational mismatch by modal values between 2009-2012 - weighted

	Required education by mode (REM) – (x1000)					
Attained	Elementary School	Middle School	High school General	High school Vocational	University and above	Total
Illiterate	62	1	3	0	2	68
Literate without schooling	212	4	14	1	7	236
Elementary school	**2.398**	41	199	10	157	2.804
Middle school	1.244	**81**	215	9	143	1.692
High school - general	460	16	**312**	16	289	1.092
High school - vocational	611	16	237	**36**	330	1.229
University and above	120	4	133	25	**1.048**	1.329
Total	**5.107**	**160**	**1.112**	**96**	**1.975**	**8.450**
			% Distribution			
Illiterate	1,21	0,63	0,27	0,00	0,10	0.81
Literate without schooling	4,15	2,50	1,26	1,04	0,35	2.79
Elementary school	**46,96**	25,63	17,90	10,42	7,95	33.19
Middle school	24,36	**50,63**	19,33	9,38	7,24	20.02
High school - general	9,01	10,00	**28,06**	16,67	14,63	12.92
High school - vocational	11,96	10,00	21,31	**37,50**	16,71	14.54
University and above	2,35	2,50	11,96	26,04	**53,06**	15.73
Total	**60.43**	**1.90**	**13.16**	**1.14**	**23.38**	**100.00**

Notes: (1) Bold and underlined numbers reflect educational match. (2) Numbers reflect the population values calculated by survey weights.

The first striking result that we observe from Table 1 is that overall educational mismatch ratio in Turkey is around 54%. This ratio is quite above the educational mismatch ratio in Europe which is reported as 33% in Galasi (2008). Moreover, 60% of the population are employed in jobs requiring elementary school level education and 48% of that population are over educated. On the other hand, only 23% of population are employed in jobs requiring university education and 47% of those are under educated. All these percentages show that the educational mismatch problem is drastic in Turkey. In details,

- 48% of population working in jobs requiring elementary school education
- 22% of population working in jobs requiring middle school education
- 33% population working in jobs general high school education
- 25% population working in jobs requiring vocational high school education

are over educated. Besides,

- 21% of university graduates,
- 70% of vocational high school graduates,
- 43% of general high school graduates and
- 74% of middle school graduates

are employed in jobs requiring lower education level.

When the reference level of education is calculated by average values, the distribution of educational mismatch across industries and occupations cannot include matched-education. One solution to this problem, as in Verdugo and Verdugo (1989), workers may be considered to have a matched-education if their actual education is within the one standard deviation around the mean level of schooling required by their respective industry and occupation. Since there is no rational behind the choice of one standard deviation, Kiker et al. (1997) suggest to use the modal value instead of the mean level of schooling years. The following table, which uses modal values for RE is intended to provide a general idea about regional and occupation-wise educational mismatch.

Table 2: Distribution of educational mismatch by occupation and region– calculated by modal RE– (2009-2012) - %

		Regions												
Occupation		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Total**
1	**OE**	-	-	-	-	-	-	-	-	-	-	-	-	-
	UE	37.0	53.9	40.4	41.5	35.5	51.8	53.4	51.5	69.2	68.8	56.7	80.5	42.5
	M	63.0	46.1	59.6	58.5	64.5	48.2	46.6	48.5	30.8	31.2	43.3	19.5	57.5
2	**OE**	-	-	-	-	-	-	-	-	-	-	-	-	-
	UE	1.5	4.3	3.0	3.1	0.7	5.7	13.2	5.8	7.7	10.0	0.5	7.6	2.8
	M	98.5	95.7	97.0	96.9	99.3	94.3	86.8	94.2	92.3	90.0	99.5	92.4	97.2
3	**OE**	1.4	0.9	0.9	1.1	2.6	1.6	5.0	3.0	1.7	1.6	5.0	3.8	1.6
	UE	59.2	69.5	57.8	65.1	54.8	61.8	62.6	63.9	66.6	66.7	63.2	65.2	60.7
	M	39.4	29.6	41.3	33.8	42.6	36.6	32.4	33.1	31.8	31.7	31.8	31.0	37.6
4	**OE**	14.7	16.0	18.3	16.6	18.4	19.9	22.4	19.2	19.5	17.3	18.6	9.8	16.8
	UE	49.3	47.7	46.0	52.0	45.3	43.5	45.2	47.2	48.3	47.4	54.9	50.9	48.0
	M	36.0	36.3	35.6	31.4	36.3	36.6	32.4	33.6	32.2	35.3	26.5	39.3	35.2
5	**OE**	34.8	42.2	37.5	44.4	40.5	35.7	41.3	39.7	45.7	38.0	35.9	26.6	37.5
	UE	31.3	23.6	27.2	24.6	25.2	29.3	25.0	24.9	18.4	23.0	29.5	37.8	28.2
	M	33.9	34.2	35.2	31.0	34.3	35.0	33.7	35.3	35.9	39.0	34.6	35.6	34.3
6	**OE**	23.3	30.6	32.2	20.4	30.0	38.2	43.2	45.3	69.4	40.0	39.1	21.0	30.7
	UE	1.0	8.2	2.7	5.2	2.6	5.3	5.8	-	-	-	19.6	20.4	4.3
	M	75.7	61.2	65.1	74.4	67.4	56.5	51.0	54.7	30.6	60.0	41.3	58.6	65.0
7	**OE**	44.6	53.3	46.9	55.2	51.0	46.3	57.4	54.0	56.9	59.7	50.8	46.6	49.2
	UE	8.1	3.2	4.3	2.5	2.8	6.6	3.6	2.7	3.0	8.5	11.6	16.1	6.0
	M	47.4	43.5	48.8	42.3	46.3	47.1	39.0	43.2	40.0	31.8	37.6	37.2	44.8
8	**OE**	39.8	54.2	47.0	59.4	54.3	49.5	55.2	56.0	51.2	52.3	59.1	37.7	48.3
	UE	7.5	1.5	2.8	2.1	1.7	3.3	1.8	0.9	2.4	2.9	5.8	7.4	4.3

	M	52.7	44.3	50.2	38.5	44.0	47.2	43.0	43.0	46.3	44.8	35.1	54.9	47.4
9	**OE**	33.4	42.2	41.7	44.9	45.6	40.6	48.7	46.8	50.5	51.5	44.9	37.0	40.7
	UE	9.6	3.5	5.1	4.3	3.1	10.6	5.1	3.2	2.6	10.4	14.6	18.1	7.5
	M	57.0	54.3	53.2	50.9	51.3	48.8	46.3	50.0	46.9	38.1	40.5	44.9	51.8
Total	**OE**	27.3	38.8	33.4	41.2	34.0	34.1	42.9	40.4	41.6	40.4	38.8	32.2	33.7
	UE	23.4	17.5	18.7	17.1	18.0	21.2	16.5	16.6	17.5	21.1	23.3	25.6	20.4
	M	49.3	43.6	47.8	41.7	48.0	44.8	40.6	43.0	40.9	38.4	37.9	42.1	45.9

Notes: Regions are given in Table 4. Occupation codes: 1 Legislators, Senior Officials and Managers, 2 Professionals, 3 Technicians and Associate Professionals, 4 Office Clerks, 5 Service Workers and Shop & Market Sales Workers, 6 Skilled Agricultural and Fishery Workers, 7 Craft and Related Trades Workers, 8 Plant and Machine Operators and Assemblers, 9 Elementary Occupations

Highest matched education level is observed among professionals. On the other hand, highest under-education and over-education is observed among technicians and associate professional and crafts and related trade workers respectively. For skilled agricultural and fishery workers and office clerks over-education levels vary substantially among regions. For instance, for office clerks, over-education level is 9.8 percent in Southeast Anatolia, whereas, it is 22.4 percent in Central Anatolia. These variations are related with regional education level differences. For skilled agricultural and fishery workers under-education levels also substantially differ among regions. Crafts and related trade workers and elementary occupations are the other occupations for which we observe notable differences in under-education among regions. .

2 Statistical framework and estimation results

The wage effect of educational mismatched has generally been investigated by two models. The first model which is due to Duncan and Hoffman (1981), decomposes the actual years of education (AE) into required years of schooling (RE), years of over-education (OE), and years of under-education (UE) as follows:

$$AE = RE + OE - UE, \tag{1}$$

where

$$OE = \begin{cases} AE - RE, \text{ if } & AE > RE \\ 0, \text{ otherwise} \end{cases},$$

$$UE = \begin{cases} RE - AE, \text{ if } & AE < RE \\ 0, \text{ otherwise} \end{cases}.$$

Hence, OE and UE cannot both be positive, either one or both must be zero. With this disaggregation, a usual human capital earning function (usually a Mincer equation) is used to identify market returns to RE, UE, and OE for different regions and population groups. Hence, our earning equation is specified as follows:

$$\ln(w_i) = \beta_0 + \beta_1 OE_i + \beta_2 RE_i + \beta_3 UE_i + \mathbf{bx_i} + u_i, \tag{2}$$

where w denotes hourly wage for worker i and vector $\mathbf{x}$ includes all other conventional variables such as, gender, age, age square, marital status, regional and year fixed effects and so on. After matching RE values with workers by their skill levels (9 occupations under each of 19 industry levels), a simple calculation generates OE and UE values. To avoid unreliable mean values in years of education (RE), we exclude cells (industry/occupation category) that include less than 20 workers. In line with the literature, the coefficient of RE reveals the percentage change in hourly wage in response to the change in years of schooling required by the industry/occupation. A person working in an industry/occupation that requires 8 years of schooling earns more than a person who works in an industry/occupation that requires 7 years of schooling. Since RE is unique to each industry/occupation cell, it also controls industry and occupation fixed effects. The coefficient of OE indicates the returns to surplus education and is expected to be positive but less than the returns to RE. This implies the underutilization of excess education in the labour force and the gap between returns to RE and OE indicates the magnitude of this underutilization. The wage penalty for the deficit in education is reported by the coefficient of UE. It is generally found to be negative and less than returns to RE and OE in the literature. This also implies the loss in productivity in the labor force.

The second model which is suggested by Verdugo and Verdugo (1989) identifies the worker's surplus and deficit education in the same earning function by two binary variables, OED and UED, which take value of 1 if the worker is overeducated or undereducated, respectively, and 0 if the individual is correctly matched. The resulting earning equation can be written as follows:

$$\ln(w_i) = \beta_0 + \beta_1 AE_i + \beta_2 OED_i + \beta_3 UED_i + \mathbf{b}\mathbf{x_i} + u_i. \quad (3)$$

This specification also reveals the wage effects of educational mismatch, but unlike the DH model, it is conditional on the actual education (AE). The coefficient of OED again reveals the level of underutilization when it is negative. Suppose two workers have 10 years of schooling, but if person a works in an industry/occupation that requires 7 years of schooling, he would earn less than person B who just works in a job that requires 10 years of schooling. The reverse is true if person A works in a job that requires 14 years of schooling. That is, she earns more than person B whose education matches the requirement of 10 years. Therefore, the coefficients of OED and UED are expected to be negative and positive, respectively, as generally found in the literature. And also these findings are consistent with findings of the DH model. A positive return to OE in the DH model means that person who works in a job that requires schooling less than the schooling that she attained, and although it is lower, she earns a positive return on her surplus schooling. Since this positive effect is captured in the VV model by the absolute value of the OED's coefficient, it also reflects the degree of underutilization of the over-education.

Some descriptive features of selective variables are given in Appendix. We first report the estimation results of (2) and (3) in Table 3 with full details then we move to less detailed subpopulation results that report only the estimation results for ORU variables.

Table 3: Estimates of standard and ORU models of earnings

	Standard		DH-RE		DH-REM		VV	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Age	0.068	91.75	0.071	91.76	0.070	87.53	0.079	100.48
Age square	-0.001	-78.12	-0.001	-76.56	-0.001	-72.73	-0.001	-83.50
City	0.048	17.49	0.040	14.35	0.046	16.17	0.046	16.18
Female	-0.083	-34.04	-0.122	-50.45	-0.115	-46.51	-0.096	-39.43
Married	0.068	27.29	0.076	29.17	0.074	27.99	0.071	27.03
Firm's size (Base = up to 10)								
10-24	0.114	38.66	0.139	46.23	0.152	49.85	0.146	47.97
25-49	0.162	60.13	0.186	70.74	0.199	74.12	0.193	71.98
50-249	0.230	84.07	0.256	100.30	0.268	103.08	0.258	99.11
250-499	0.308	69.82	0.340	77.33	0.356	79.22	0.336	74.68
500+	0.408	88.98	0.446	98.92	0.464	100.70	0.438	95.55
ORU Variables								
AE	0.030	98.65					0.079	210.65
RE			0.104	211.16				
OE			0.020	34.90				
UE			-0.044	-64.23				
REM					0.072	213.58		
OEM					0.024	65.18		
UEM					-0.065	-110.82		
OED							-0.328	-106.41
UED							0.157	47.36
Fixed Effects								
Year	Yes		Yes		Yes		Yes	
Industry	Yes		No		No		No	
Occupation	Yes		No		No		No	
Region	Yes		Yes		Yes		Yes	
Constant	0.324	15.48	-0.948	-69.25	-0.597	-43.34	-0.864	-62.85
Number of observations	203163		203062		202837		203062	
R2	0.51		0.47		0.45		0.45	

Notes: (1) Standard errors are robust corrected for heteroskedasticity and serial correlation. (2) DH-RE, DH-REM, and VV denote the Duncan-Hoffman (1981) model with RE calculated with mean values, the Duncan-Hoffman model with RE calculated with modal values, and the Verdugo - Verdugo (1989) model calculated with a 1-standard deviation band, respectively.

In the first column of Table 3, the estimation results of a standard earning equation are given. All coefficients are significant with robust standard errors corrected for heteroskedasticity and serial correlation. The coefficient of the actual education years indicates that every additional year of education increases hourly wage by 3 percent. The estimation results for the ORU variables which are obtained by decomposing the AE, are given in the second, third and fourth coefficient columns of Table 3. Second column gives DH model estimation results where RE calculated with mean values. First, the coefficient of RE of this model implies that every additional year in education that is required for a specific industry/occupation is associated with 10 percent increase in hourly wage. Second, a surplus year in education increases hourly wage only 2 percent beyond the usual level, which is much lower payoff for each education year relative to 10 percent. Finally, here is a substantial penalty associated with deficit years of education. That is, every year of education less than the usual level reduces workers' wage by 4.4 percent. These coefficients differ slightly when RE is calculated with modal values (see third coefficient column in Table 3). For example, additional years of RE increase hourly wages by 7 percent instead of 10 percent, surplus year of education benefit is 2.4 percent and penalty for under education years is 6.5 percent with modal values. The last coefficient column reveals the estimation results according to the VV model. As stated before, VV model is conditional on AE. The coefficient of AE indicates that every additional year in actual education increase hourly wages by 7.9 percent. But, being overeducated result in a 32.8 percent wage loss. On the other hand, on average, an undereducated worker's wage is 15.7 percent higher than the worker with equivalent AE working in a matched job. Below we now report ORU results by subpopulation groups.

Table 4: Estimates of ORU models of earnings by location and demographics

	Standard	DH			VV			
	AE	RE	OE	UE	AE	OED	UED	Obs.
City								
Rural	0.025	0.082	0.014	-0.038	0.059	-0.235	0.091	26,209
Urban	0.031	0.106	0.021	-0.044	0.081	-0.335	0.166	176,853
Regions (NUTS 1)								
Istanbul	0.075	0.124	0.024	-0.053	0.097	-0.396	0.215	41,714
West Marmara	0.041	0.080	0.015	-0.038	0.059	-0.254	0.094	13,481
Aegean	0.055	0.101	0.017	-0.041	0.076	-0.335	0.144	28,682
East Marmara	0.047	0.091	0.020	-0.038	0.067	-0.275	0.121	25,991
West Anatolia	0.070	0.114	0.019	-0.059	0.090	-0.382	0.124	26,701
Mediterranean	0.054	0.097	0.021	-0.038	0.073	-0.288	0.126	20,488
Centre Anatolia	0.042	0.084	0.021	-0.024	0.061	-0.242	0.136	8,682
West Black Sea	0.048	0.092	0.011	-0.043	0.069	-0.301	0.091	10,614
East Black Sea	0.046	0.087	0.008	-0.042	0.068	-0.311	0.105	7,112
Northeast Anatolia	0.043	0.081	0.018	-0.032	0.060	-0.204	0.125	4,542
Mideast Anatolia	0.038	0.086	0.003	-0.027	0.062	-0.268	0.187	4,102
Southeast Anatolia	0.047	0.088	0.029	-0.028	0.066	-0.192	0.186	10,953
Gender								
Male	0.029	0.102	0.020	-0.042	0.076	-0.317	0.147	160,973
Female	0.036	0.107	0.019	-0.051	0.089	-0.342	0.199	42,089
Age groups								
15-29	0.036	0.071	0.016	-0.023	0.055	-0.211	0.151	77,048
30-45	0.063	0.113	0.013	-0.055	0.084	-0.389	0.110	96,741
45+	0.075	0.126	0.009	-0.065	0.098	-0.508	0.147	29,273

Note: (1) All coefficients are significant at 1% level and standard errors are robust corrected for heteroskedasticity and serial correlation. (2) DH and VV denote the Duncan-Hoffman (1981) model with RE calculated with mean values and the Verdugo - Verdugo (1989) model, respectively.

In Table 4 ORU estimations are presented by location and age groups for DH and VV models. Since we observed from Table 3 that there is a slight difference between the coefficients of two DH models where RE is calculated with mean and modal values respectively. In Table 4 we presented only the DH model estimations with RE calculated with mean values. First, DH model estimates show that while RE wage effect show a substantial increase in magnitude for higher age groups, OE rewards declines and UE penalties rise for higher ages. According to VV model results, AE's wage effect also increase for higher age groups. Estimates also indicate that wage loss of overeducated workers are substantially higher for higher age groups which also points out to a more significant loss from underutilization. When we analyze DH model ORU estimations by location, we observe that Istanbul is the region with highest benefit for additional RE. Interestingly, OE rewards are highest in Southeast Anatolia and UE penalties are highest in West Anatolia in addition to Istanbul. This can be explained by the observation that average education level of the labor force is the lowest in Southeast Anatolia and it is the highest in West Anatolia (see Table A3 in the Appendix). VV estimation results are also in accordance with DH results. Istanbul is the region where the wage effects of AE, OED and UED are highest. It is possible to note here that these are regions facing highest loss due to underutilization.

Table 5: Estimates of ORU models of earnings by industries and occupations

	Standard	**DH**			**VV**			
	AE	RE	OE	UE	AE	OED	UED	Obs.
Major industries								
(3) *Manufacturing*	0.049	0.111	0.023	-0.035	0.073	-0.318	0.209	75,197
(6) *Construction*	0.050	0.106	0.012	-0.031	0.075	-0.373	0.160	12,604
(7) *Wholesale and Retail Trade*	0.046	0.091	0.026	-0.039	0.068	-0.228	0.116	40,154
(8) *Transportation and Storage*	0.052	0.098	0.027	-0.051	0.076	-0.314	0.086	10,409
(9) *Accommodation and Food Services*	0.030	0.078	0.015	-0.025	0.045	-0.134	0.074	15,932
(14) *Administrative and Support Services*	0.029	0.048	0.014	-0.024	0.038	-0.127	0.058	14,784
Major occupations								
(3) *Technicians and Associate Professionals*	0.054	0.130	0.091	-0.035	0.068	0.016	<u>0.110</u>	16,727
(4) *Office Clerks*	0.038	0.197	0.039	-0.039	0.083	-0.163	0.232	20,120
(5) *Service, Shop & Market Sales Workers*	0.023	0.056	0.033	-0.014	0.035	-0.051	0.052	37,672
(7) *Craft and Related Trades Workers*	0.021	0.086	0.029	-0.007	0.032	-0.055	0.124	41,190
(8) *Plant and Machine Operators*	0.018	<u>0.011</u>	0.022	-0.011	0.020	-0.006	<u>0.081</u>	36,548
(9) *Elementary Occupations*	0.017	0.045	0.019	-0.014	0.020	-0.007	<u>0.036</u>	33,152

Note: (1) All coefficients are significant at 1% level, except for the underlined ones. (2) Standard errors are robust corrected for heteroskedasticity and serial correlation. (2) DH and VV denote the Duncan-Hoffman (1981) model with RE calculated with mean values and the Verdugo - Verdugo (1989) model, respectively.

Table 5 displays ORU estimations for some major industries and occupations. Manufacturing is the industry where wage effects of almost all ORU variables are among the highest. It must also be noted that manufacturing has the highest number of observations. These effects are also relatively high in transportation and storage industry. Among the major occupations, wage effects of ORU variables are in general highest for office clerks. Only over-education for technicians and associate professionals is associated with higher wage benefits compared to office clerks (9.1 percent versus 3.9 percent).

4 Cost of underutilization

As the literature on over-education generally suggests, our results indicate that the returns to surplus schooling are positive but less than those for required education. This fact is taken as an underutilization problem of the work force with surplus education and named as "the great training robbery" by Berg (1970) and Vahey (2000). In a conventional ORU model, the gap between the coefficients of RE and OE captures the degree of this underutilization: for any given RE, the lower the return to surplus schooling, the higher the underutilization. However, the details on the extent of over-education in terms of different levels of schooling are not revealed by this gap. Suppose that a worker has a surplus education of 5 years. These surplus years could be the difference between a 3-year RE (literate without schooling) and an 8-year of actual schooling (middle school) or could be between an 8-year RE (middle school) and an 11-year of actual schooling (high school – general). How much of this overall a 5-year gap is attributable to different educational degrees is an important question and the answer would reveal information about the extent of underutilization for different degrees.

In order to incorporate the disaggregated OE with an earning function, we apply a version of the VV model as described in (2) with following changes:

$$\ln(w_i) = \beta_0 + \beta_1 AE_i + \beta_2 UEMD_i + \sum_{E=8}^{15} \beta_E OEMD_{Ei} + \mathbf{bx_i} + u_i, \tag{4}$$

where UEMD is a binary variable which take the value of 1 if worker *i* has schooling less than the modal value of schooling years of her industry/occupation and 0 otherwise. Unlike a conventional VV model, Equation 4 disaggregates OEMD into 4 dichotomous variables for each of the following degrees: middle school (8), high school – general (11), high school – vocational (13), and university and beyond (15).[1] These binary variables take values of 1 and 0 depending on the specific level of surplus education of related observation. For example, if the person with a vocational high school degree (13 years) is working in a job that requires an elementary degree (5 years), OEMD(8), OEMD(11), and OEMD(13) take the value of 1 and OEMD(15) takes 0. Table 7 reports the estimation results of (4) in six different specifications.

The first column reports the estimation results on the entire sample. Similar to our earlier findings, all coefficients of OEMDs are negative and significant indicating a strong underutilization in the case of over-education. The degree of this underutilization varies by different educational levels. For a person with a specific surplus education, the sum of these coefficients shows the total wage effect of over-education. For example if a person with a middle school degree is working in a job that requires only 5 years of education, her wage would be 11 percent less than the person who has the same

[1] Since the minimum modal value of RE is 5, the surplus education starts at middle school level, which is 8 years of schooling.

degree but working in an appropriate job. Accordingly, when the person's educational attainment goes up, the sum of OEMDs will reflect the total wage effect of his surplus education. Therefore each individual coefficient reflects the incremental or marginal wage effect of surplus education for a given degree of education. For example the wage effect of over-education at the general high school degree is 9.9 percent while at the vocational high school (VHS) degree it is 23.3 percent.

Table 7: Underutilization of the over-education by surplus degrees – LFS with the VV model using modal values – (2009-2012)

	All	**Male**	**Female**	**15-29**	**30-45**	**45+**
	Coef./t	Coef./t	Coef./t	Coef./t	Coef./t	Coef./t
AE	0.074	0.072	0.08	0.049	0.082	0.094
	209.4	165.38	126.39	93.7	165.25	84.26
UEMD	0.007	0.004	0.023	0.036	-0.042	0.01
	2.53	1.2	4.35	8.41	-11.25	1.3
OEMDs						
Middle school	-0.11	-0.115	-0.065	-0.013	-0.178	-0.217
	-38.91	-36.89	-9.33	-2.92	-43.67	-23.88
High school - general	-0.099	-0.091	-0.146	-0.085	-0.095	-0.156
	-25.78	-21.4	-15.42	-15.98	-16.09	-10.75
High school - vocational	-0.233	-0.224	-0.257	-0.155	-0.278	-0.282
	-63.51	-52.9	-34.16	-32.81	-48.2	-16.31
University and above	-0.059	-0.048	-0.074	-0.041	-0.059	-0.139
	-9.84	-6.56	-6.94	-5.72	-5.81	-4.54
Number of observations	203163	161058	42105	77048	96741	29273
R2	0.457	0.444	0.509	0.47	0.429	0.443

Note: (1) Only the ORU variables are reported. (2) Standard errors are robust corrected for heteroskedasticity and serial correlation.

This relatively high marginal effect of over-schooling at the VHS level is interesting, and perhaps expected, because it is in line with a common sense that a worker with a technical expertise from a vocational school suffers the most when she works at a job that doesn't require her expertise relative to her colleague who works in a matching job. Another interesting observation is that the marginal wage effect of over-education at the university level is the lowest among all degrees. This reflects the fact that if a university graduate works at a job that requires a VHS degree, her wage would only be 6 percent lower on average relative to someone else who works at a job that requires a university degree.

Table 7 also reports the estimation results of (4) for different subgroups. In general, females suffer more from underutilization. For example, wage loss for females is 14.6 percent at high school level whereas the same ratio for males is 9.1 percent. This difference exists at all levels of over-education in favor for males. This can be explained as the general well known disadvantages of being female in labor market. Similarly, wage loss due to the over-education is more substantial for higher age groups. For instance, wage loss of over-education at university level is 4.1 percent for 15-29 age group, however, the same ratio is 13.9 percent for age group of 45+. Clearly, reward for experience is substantial, thus, if someone over 45 works in a job that requires VHS degree, her earnings will be remarkably less than the worker in the same age range and working in an appropriate job.

Similar to the VV model estimated earlier, a higher marginal effect (in absolute terms) indicates a higher level of underutilization for a given educational degree in the workforce. By using modal values, Table 1 reports the number of people who have surplus education for each educational degree. Although it yields an aggregated value omitting individual attributes, such as gender, age, and so on, it is possible to measure the cost of overall underutilization of over schooling by using the results of Table 1 and 7. This cost reflects an overall wage loss incurred between 2009 and 2012 with 2012 prices. For example, in our data's time period, on average there are 5.1 million workers per year employed in jobs (defined by industry and occupation) that require 5 years of education. More than half of this group is over-educated. Related cost of this underutilization measured by the wage loss can be shown as follows:

Table 8: Weighted estimates of the underutilization cost between 2009-2012 for workers working in jobs that require 5 years of schooling (elementary school) with 2012 prices – VV Method

					<-----------------TL------------------>			
Attained (Actual) Education	Num. of workers in jobs with REM=5 (x1000)	Educ. mismatch status	Marginal wage effect %	Cum. wage effect %	Average hourly wage for matched workers	Hourly wage loss	Total wage loss in 1 hour (x1000)	Annual wage loss in 4 years (millions)
Illiterate	63	Deficit Ed.						
Literate - no schooling	212	Deficit Ed.						
Elementary school	2398	Matched						
Middle school	1244	OEMD(8)	11.00	11.00	2.02	0.22	276	569
HS- - general	460	OEMD(11)	9.90	20.90	3.83	0.80	368	765
HS- - vocational	611	OEMD(13)	23.30	44.20	5.42	2.40	1466	3050
University and above	120	OEMD(15)	5.90	50.10	11.17	5.60	6700	1398
Total	**5106**						**11,109**	**5782**

Notes: (1) Number of workers and average wages reflect population values calculated by population weights given in the surveys. (2) We assume that workers work 52 weeks in a year, 5 days a week, and 8 hours in a day on average. (3) HS denotes High School.

The first column taken from Table 1 shows that less than 50 percent of the workers have schooling that matches the required elementary level education and as stated before, most workers have an educational surplus in varying degrees. Marginal wage effects are from Table 7 and average hourly wages for workers who work in jobs that match their education are calculated from the data. Hourly wage losses reflect the loss that the worker would have earned if she had worked in job that requires her education. For example, workers with a university degree working in a job requiring a university degree earn 11.17 TL per hour. A worker with the same degree, on the other hand, working in a job that requires an elementary level schooling earns 50.10 percent less. Hence, an hourly wage loss for 120 thousand workers with a university degree working in a job that only requires 5 years of education is calculated as 5.6 TL per hour.

As mentioned before, Table 8 is not intended to give an exact cost of underutilization in terms of wage loss. Achieving that is beyond the scope this paper and needs more detailed simulations that take the individual attributes and their wage effects into account. However, Table 8 provides a rough approximation that shows the magnitude of the problem. The cost of underutilization per year between 2009 and 2012 is about 5.78 billion TL or around 2.89 billion USD with 2012 prices only for workers with educational surplus working in jobs that require 5 years of schooling. The same calculations can easily be done for other workers working in jobs that require more schooling years. Although this exercise excludes the cost of under-education, using a similar calculation method it can also be computed easily. Table 8 uses the results estimated by the VV model given in Table 7. In order to see the sensitivity of the results to the estimation method used, we calculated the same aggregate cost by using the DH estimation coefficients. Table 9 reports the cost of underutilization based on the results estimated by the DH-REM coefficients given in the sixth of Table 3.

Table 9: Weighted estimates of the underutilization cost between 2009-2012 for workers working in jobs that require 5 years of schooling (elementary school) with 2012 prices – DH Method

					<---------------------	TL	-------------------->	
Attained (Actual) Education	Num. of workers in jobs with REM=5 (x1000)	Total wage effect of over educ.	Wage effects of RE if matched	Wage penalty	Average hourly wage for matched workers	Hourly wage loss	Total wage loss in 1 hour (x1000)	Annual wage loss (millions)
Illiterate	63							
Literate without schooling	212							
Elementary school	2398							
Middle school	1244	0.43	0.58	0.14	2.02	0.29	362	753
HS - general	460	0.50	0.79	0.29	3.83	1.11	510	1060
HS - vocational	611	0.55	0.94	0.38	5.42	2.08	1271	2644
University and above	120	0.60	1.08	0.48	11.17	5.36	642	1335
Total	**5106**						**11,296**	**5792**

Notes: (1) Number of workers and average wages reflect population values calculated based on the population weights given in the surveys. (2) We assume that workers work 52 weeks in a year, 5 days a week, and 8 hours in a day on average. (3) HS denotes High School.

The second column gives the wage effect of the over-education by using the coefficients of REM and OEM in Table 3. For example, for workers with a middle school degree, it is the sum of (0.072 x 5 years) and (0.024 x 3 years), which is 0.43. The next column calculates the wage effect if these workers would work in matching jobs, which is 0.58 for the middle school-degree holders (0.072 x 8 years). The forth column shows the difference between two values given in the second and the third columns, which corresponds to the wage penalty for overeducated workers who work in jobs that require 5 years of education. The process for the rest of the table is similar to Table 8. As seen in the final column, the annual cost calculated by the DH method is almost the same as reported in Table 8.

These calculations show us the extent of the underutilization cost, which is originated from educational mismatch. One should note here again that this cost is just for over-education in jobs requiring 5 years of elementary school education. If it is calculated for all required levels of education, clearly, the total cost will be much higher. In order to reduce these costs, systematic and well-planned education and labor market policies are necessary.

5 Conclusions

This study aims to understand the possible consequences of educational mismatch in Turkish Economy. First, we explored educational mismatch levels in Turkey for nine different occupation areas in different regions and for different industries using four recent household surveys from 2009 to 2012, which include more than one million observations. Using this data, we also analyzed the effects of educational mismatch on wages in Turkish labor market by using the ORU models. Sixty percent of the population works in such jobs that require elementary school education and almost 48 percent of them are overeducated. We observe from VV estimation that, being overeducated result in a 32.8 percent wage loss. Undereducated worker's wage is 15.7 percent higher than the worker with equivalent actual education working in a matched job. Wage loss of over-educated workers substantially increases with higher age. Regional analysis indicates that in Istanbul is the region with highest benefits and losses for over and under education. Among the industries we observed highest wage effects of educational mismatch in manufacturing. Finally, using the wage coefficients obtained using different ORU models, we estimated the cost of underutilization and productivity loss due to educational mismatch. This cost is quite substantial for Turkish economy.

Clearly, well-planned educational policies are necessary to reduce this cost. Our results can be considered as important evidences that jobs and human resources are not matching well especially in regional base. We observed that sixty percent of the labor force is working in jobs requiring elementary school education. This is an indicator that structure of Turkish economy mostly contains jobs requiring unskilled workers. In order to reduce the productivity loss due to over education, governments can consider long term demand side policies that could result in a structural change in the economy towards increasing higher skilled worker need. On the other hand, by determining specific labor force needs of different regions and industries in Turkish economy, government authorities, can develop well-planned educational policies for the supply side. For instance, manufacturing is the most crowded industry and our analysis indicates that wage effects and thus productivity loss of educational mismatch are also highest in this industry. A sophisticated analysis of the labor force needs in manufacturing, and planning educational system accordingly seems crucially important for reducing the cost of mismatch and catching up a faster growth for Turkish Economy.

Appendix:

Table A1: Distribution of workers across occupations and industries – (2009-2012)

	Occupation										
Industry	1	2	3	4	5	6	7	8	9	Total	%
1	27	68	32	31	45	193	78	60	286	820	0.40
2	25	65	47	101	87	2	472	535	641	1,975	0.97
3	1,969	1,589	6,010	3,894	2,401	70	25,417	22,943	10,904	75,197	37.01
4	55	81	320	139	48	2	331	126	147	1,249	0.61
5	27	28	37	28	11	3	89	198	225	646	0.32
6	363	585	762	892	263	6	5,354	2,337	2,048	12,610	6.21
7	2,650	583	3,756	4,694	15,816	29	5,666	3,077	3,883	40,154	19.76
8	405	124	620	1,501	620	1	199	5,441	1,499	10,410	5.12
9	800	103	217	947	9,346	40	1,257	358	2,864	15,932	7.84
10	346	571	605	623	231	0	509	79	130	3,094	1.52
11	687	217	675	1,932	210	1	14	37	145	3,918	1.93
12	44	15	297	110	97	55	25	10	1,002	1,655	0.81
13	270	1,086	983	1,947	132	5	220	136	199	4,978	2.45
14	287	124	520	1,441	4,067	272	465	732	6,876	14,784	7.28
16	231	2,211	333	372	227	16	27	45	477	3,939	1.94
17	142	884	1,180	1,044	709	2	117	209	545	4,832	2.38
18	87	52	198	198	222	10	44	27	189	1,027	0.51
19	89	54	135	226	2,919	27	920	185	514	5,069	2.50
20	1	0	1	0	232	38	1	23	578	874	0.43
Total	8,505	8,440	16,728	20,120	37,683	772	41,205	36,558	33,152	203,163	100.00
%	4.19	4.15	8.23	9.90	18.55	0.38	20.28	17.99	16.32	100.00	

Note: For details of industry and occupation categories see Table 4 below.

Table A2: Required education years – Realized Matches Method – (2009-2012)

	Occupation									
Industry	1	2	3	4	5	6	7	8	9	Total
1	14.15	14.94	12.53	12.84	7.13	6.78	7.51	7.45	6.32	8.13
2	12.52	15.00	12.60	10.97	8.33	8.00	7.51	6.75	6.73	7.70
3	13.17	14.89	11.49	11.58	8.54	7.19	7.47	7.71	7.24	8.38
4	13.91	14.90	13.53	12.53	10.44	9.00	11.27	9.80	10.65	12.09
5	9.81	15.00	11.49	11.86	7.55	7.67	7.88	7.21	5.92	7.75
6	12.69	14.93	12.64	11.42	8.36	8.67	7.43	7.27	6.61	8.38
7	11.82	14.84	11.43	11.31	9.36	5.93	7.20	7.47	6.84	9.33
8	12.50	14.95	11.71	11.12	8.81	5.00	8.79	7.02	7.56	8.41
9	11.06	14.15	11.32	11.14	7.47	6.25	6.88	7.49	6.43	7.73
10	13.50	14.56	13.13	12.01	10.86	n/a	9.19	9.42	8.36	12.10
11	14.63	14.96	13.64	14.05	11.48	5.00	9.29	8.54	7.61	13.68
12	13.16	14.47	10.60	10.77	9.44	5.35	7.28	8.00	5.97	7.60

13	14.10	14.91	12.74	12.36	9.95	6.20	8.50	8.07	7.55	12.54
14	12.53	14.81	12.70	12.14	10.75	6.44	8.27	7.72	6.75	8.85
16	14.45	14.97	13.02	12.46	8.34	7.88	8.89	7.93	6.59	12.99
17	14.20	14.93	13.66	12.03	8.33	3.00	9.01	7.67	6.82	11.63
18	11.86	11.81	11.20	10.20	8.67	7.00	8.59	7.26	6.85	9.49
19	11.58	14.31	12.06	11.38	7.80	6.93	8.91	7.56	6.57	8.27
20	5.00	n/a	8.00	n/a	6.12	6.18	5.00	5.61	5.75	5.86
Total	12.65	14.87	12.00	11.85	8.82	6.55	7.52	7.55	6.90	8.98

Table A3: Required education years – Realized Matches Method – (2009-2012)

	Occupations									
Regions	1	2	3	4	5	6	7	8	9	Total
1	13.06	14.94	11.85	11.87	8.67	6.37	7.05	6.70	6.33	9.02
2	12.23	14.80	11.61	12.12	9.01	6.63	8.33	8.21	7.28	9.11
3	13.05	14.89	12.24	12.15	8.82	6.57	7.38	7.53	7.05	9.06
4	12.69	14.86	11.76	11.81	9.13	6.19	8.22	8.52	7.32	9.28
5	13.31	14.98	12.84	12.05	9.31	6.68	7.68	7.85	7.26	9.75
6	12.32	14.79	11.99	11.98	8.80	6.63	7.34	7.57	6.76	8.87
7	12.06	14.46	12.29	11.96	9.25	7.11	7.96	7.89	7.57	9.04
8	12.37	14.82	11.96	11.60	8.99	7.00	7.99	7.95	7.35	9.00
9	11.13	14.72	12.54	11.87	9.63	9.15	7.98	7.56	7.66	9.24
10	11.74	14.39	12.29	11.71	9.17	6.96	8.18	7.76	7.24	9.05
11	11.52	14.99	12.01	11.26	8.39	6.74	7.23	7.71	6.72	8.41
12	9.79	14.57	11.37	11.16	7.89	5.27	6.79	6.55	6.13	7.60
Total	12.65	14.87	12.00	11.85	8.82	6.55	7.52	7.55	6.90	8.98

Table A4: Summary of selective variables by gender – (2009-2012)

		Male	Female	Total	%
Number of Workers		165,715	43,674	209,389	100.00
Average Hourly Wage		4.48	4.63	4.52	
Education					
	Illiterate	1,158	577	1,735	0.83
	Literate without schooling	4,003	1,423	5,426	2.59
	Elementary school	59,817	10,870	70,687	33.76
	Middle school	36,198	6,265	42,463	20.28
	High school - general	19,980	6,907	26,887	12.84
	High school - vocational	25,311	5,928	31,239	14.92
	University and above	19,248	11,704	30,952	14.78
Rural		22,827	4,295	27,122	12.95
Urban		142,888	39,379	182,267	87.05
Firm's size					

	Less than 10	60,115	12,817	72,932	34.83
	10-24	21,331	6,283	27,614	13.19
	25-49	29,466	8,939	38,405	18.34
	50-249	35,737	10,430	46,167	22.05
	250-499	8,712	2,447	11,159	5.33
	500+	10,354	2,758	13,112	6.26
Age groups					
	15-19	10,387	3,378	13,765	6.57
	20-24	17,516	8,070	25,586	12.22
	25-29	31,931	9,138	41,069	19.61
	30-34	32,474	7,902	40,376	19.28
	35-39	26,693	6,390	33,083	15.80
	40-44	20,755	4,736	25,491	12.17
	45-49	14,523	2,525	17,048	8.14
	50-54	6,706	1,086	7,792	3.72
	55-59	3,389	351	3,740	1.79
	60+	1,341	98	1,439	0.69

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