Determinants of Gender Pay Gap in Kyrgyzstan

(2010-2013)

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Contents

Introduction

The gender pay gap is defined as the differences in wages of genders while having similar skills and characteristics. Globally for every dollar that a man gets, the woman earns only 77 cents. This is mostly justified by the fact that women tend to work fewer hours then men because of domestic responsibilities; thus, receiving unequal pay. However, empirical research that are discussed in the literature review proves that even if the human capital characteristics of men and women are the same, women still earn less.

Since 1991, when Kyrgyzstan became more conservative and developed stricter gender norms, women's participation in the labor market decreased. One reason for participation reduction is because childcare subsidies were eroded after the collapse of Soviet Union. (ADB, 2019). Therefore, according to the UN women, Kyrgyz women are still excluded from most of the decision makings about the country. According to the World Bank (2019), female labor participation is 44.1% which less than Central Asian countries such as Kazakhstan, Turkmenistan, and Uzbekistan.

According to United Nations Economic Commission for Europe (UNECE), the pay gap is evidenced to be 27% in 2017. Thus, I am conducting this research using Life in Kyrgyzstan Longitudinal survey in order find out what determinants affect the gender pay gap in the country. In addition, for providing a more detailed evidence of pay gap, I investigate the effecting determinants at certain quantiles of wages.

The next sections include a description of theoretical framework, literature review, data description, model and methodology by following which estimation of gender pay gap can better be understood.

Theoretical Part

In this section, theoretical frameworks are discussed in order to provide the ground for the later claims and results on gender pay gap. The most widely used approach to explain gender pay gap has been explained by the human capital theory of wage discrimination, introduced by Mincer (1958) and Polachek (1975). They argue that the skills and abilities a person gets from training, education, and experience are the main factors to decide a person's earnings. According to their traditional approach of division of labor, women tend to participate less in the labor market. This is because women are more likely to participate in part-time jobs because of their domestic liabilities, housework, and rearing children. Some women tend to leave their jobs after having children. Thus, the human capital approach implies that the higher work experience of men and lower work experience of women will even increase the earnings gap between genders.

In addition to human capital attributes, Becker (1962) also explained the effect of marriage on the division of labor in family and a person's earnings. Men tend to work more years and put more effort into work after marriage. This is because of the division of labor in the family in which men invest more in human capital while women are more invested in-home activities; thus, increasing the gender pay gap after marriage.

Moreover, Becker adds that some individuals have a taste for discrimination. This means the pay gap that is not due to lack of qualifications of women or their domestic responsibilities, it is generally acknowledged by him that it is caused by market discrimination. Men are willing to work with women in lower position, but they dislike it when women are given higher positions.

The fundamental model of human capital returns was first introduced by Mincer (1974) in which he introduced logarithm of earnings as dependent and education, experience, and squared of experience as independent variables. The model was later modified by controlling for gender, occupation, and sectors of work.

In the next section modern literatures are reviewed that base their assumption for estimation of gender pay based on the theories discussed.

Literature Review

In this section, empirical literatures are reviewed in order to describe that gender pay disparities that exist between males and females in both developed and developing countries. in the first part the findings and methodologies of literatures from developing and transitioning countries are reviewed. In the second part, developed countries are discussed and what determinants affect the wage gap in those countries. the next part discusses, the studies that have been done in Kyrgyzstan and in the last section the drawbacks of the literatures are discussed.

The same model has been used to estimate gender pay gap in the new empirical studies by emphasizing at certain determinants of gender pay gap. According to longitudinal data analysis of 2004-2016 of Vietnam Household Living Standards Surveys (VHLSS), the main determinants causing wage differentials in Vietnam are education attainment, ethnicity, economic sectors, and geographic location. After running the quantile regression for different percentiles of wage distribution, they find that wage gap is more severe at higher and lower quantiles of wages. This can be explained by the concept of “sticky floors” effect because women are more likely to work in low-paid jobs; and “glass ceiling” where women are discriminated to work at high-paid jobs (Vroman, 2003).

Baye et al. (2016) confirm that differences in educational attainment and location widens pay gap while studying gender wage differentials in Cameroon using pooled 2005 and 2010 labor force survey. However, work experience is also a main factor determining wage gap. Using an extended Mincerian-type model and quantile regression considering 25, 50, and 75 quantiles, they find that men are overpaid in Cameroon while women are underpaid generally. However, the wage gap in the 25th quantile is due to the difference in human capital characteristics; whereas, in the 50th and 75th quantiles the wage gap tends to decrease with increasing years of experience. Nevertheless, living in urban areas causes the wage gap to increase.

Moreover, confirming Becker's theory of taste for discrimination, Yasin et al (2010) conclude that pay gap in Pakistan is caused by segmenting males into high-paid occupations and female in low-paid jobs. Using Pakistan's Labor Force Survey (LFS) based on cross sectional data of 2003-2004 and running the OLS regression, it is also concluded that beside discrimination based on gender, low levels of education, illiteracy, and low professional skills cause pay gap to even widen. However, according to empirical results they obtain, it is evidenced that women are no different than men in terms of productivity, but it is the cultural constraints that hinder female labor participation and causing the pay gap. Thus, the only solution that the government can offer is to encourage equal employment opportunities and provide quality education and training for women.

Other evidence of pure discrimination has been studied by Razavi and Habibi (2014) by applying Oaxaca decomposition model and using Iran's Household Expenditure and Household Survey (HEIS) for years of 2002 and 2005. The results suggest that in both public and private sectors, the wage gap is due to discrimination. This is evidenced after finding out that for Iranian men and women, the human capital attributes were approximately similar. The research finds that female workers are even more educated than male workers in the public sector; however, there has been a 7 percent gap in yearly salary of workers in favor of men. Thus, despite the significant improvements in Iranian women's education level through the past years, they still face promotion and employment discrimination, causing the gender gap to widen.

In addition to the above mentioned developing and transitioning countries, a survey of 4000 Malasiyan working households have been conducted using stratified random sampling in 2011. The researcher uses Oaxaca decomposition method in order to investigate occupational segregation and wage differential among genders. According to the empirical results suggest that 0.244 or 91.5 percent of wage gap is due to within occupational discrimination and the rest is caused by other human capital attributes and sample selection bias. Hence, being woman in Malaysian labor market is said to have a significant yet negative effect on wages compared to being a man; thus, confirming Becker's theory of taste for discrimination (Ismail et al., 2017).

Nevertheless, some of the current empirical studies on gender wage gap of developed countries conclude that gender wage gap tends to have decreased compared to the past, but it still exists in the labor market. A longitudinal study of 9000 U.S. households through years of 1994 to 1996 and 2005 to 2008 using pool data and Oaxaca decomposition method concludes that gender pay gap at lowest quantile of wages; whereas, it has decreased by 5% at the highest quantile. The decrease in pay gap in the highest quantile of wage distribution is due to the fact that women are more invested in attaining higher education, thus, it has increased their wages. However, the decrease in wage of lowest quantile is caused by obtaining more years of work experience. Thus, human capital characteristics are the main determinants of gender pay gap (Kassenboehmer et al., 2014).

In addition, another study in the U.S. that investigates whether gender pay gap is caused by gender segregation uses the data from U.S. Current Population Survey (CPS) taking a sample of 82, 887 only working participants between 2011-2012. The method of Propensity Score Matching (PSM) is used by selecting a control group with male and female observations that have identical characteristics. This way, they are able to better investigate the wage gap based on gender segregation. After running the hackman model in order to avoid the sample selection bias, it is concluded that there is a statistically significant pay gap and high degree of gender wage segregation by sector and occupation even after using PSM method. Thus, just differences by sectors and occupation do not justify the gender pay gap, gender-based discrimination is evidenced even after taking the same numbers of gender and same occupations and sectors (Meara et al., 2017).

The base paper used for this paper is researched by Goy and Johnes (2015) using the cross-sectional data from Malaysia Population and Family Survey (MPFS) from 1994 to 2004. In order to find the evidence for gender pay, they first run OLS regression in order to find the mean difference between two genders. Then quantile regression is used to examine the wage gap at 10, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles. The earning gap tends to be higher at bottom percentiles of wage, this is known as the "sticky floor" in which wages of women tend to be lower than men at low level of wages. However, the gap decreases at medium percentile of wages and tends to increase once again at high wage percentile because of the "glass ceiling" in which women are discriminated to work at high-paid jobs; yet, the difference of wages at higher quantiles are modest. Moreover, it is summed that age, years of experience, ethnicity, location, education, and marital status are the main determinants affecting a person's earnings. However, the quantile estimation suggests are wage gap is mainly due to employers undervaluing female workers and providing them with lower wages compared to their male counterparts despite having similar characteristics.

One of the existing researches on gender pay in Kyrgyzstan is done by Kylcheva (2016). It included a pooled sample of 9446 using the Life in Kyrgyzstan (LiK) questionnaire from 2010-2012. She used both OLS and Oaxaca decomposition method in order to find the mean wage difference. In conclusion, she finds that gender pay gap is significant in Kyrgyzstan and the equal rights amendment to the Constitution did not decrease the pay gap in the country.

Although the afore-mentioned literatures provide a ground for my research, there are some drawbacks of the literatures when used in Kyrgyzstan's case. The usage of Oaxaca decomposition method by many of the literatures generate the problem of the index number in which the reference group in the model effects the results. In addition, the Oaxaca method only evaluates the average wage difference which does not provide detail information about wage gap across quantiles. The literature that researched on gender pay gap in Kyrgyzstan by Klycheva (2016), uses the same method. In addition, this literature also uses lesser number of observations and narrower time period.

Thus, in order to better estimate the gender pay gap in Kyrgyzstan, I am going to use the new estimation method called Quantile Regression which will provide detailed information about wage distribution at certain quantiles of wage rather than considering just the average. In addition, the time period od 2010-2013 are considered by making a panel data of all these four years which provides more efficiency, variability, contains more information about the same individuals across the time period. This way, we will better find out what determinants are causing the gap and in which quantiles of wage distribution there is a higher gap. Since the study is very new to Kyrgyzstan, the results can provide a ground for further policies in order to improve the condition of women.

In the next section, the dataset of Life in Kyrgyzstan (LiK) is discussed in details and then the methods of data cleaning, model and methodology selection are explained in the subsequent sections.

Data Description

In this part, the dataset used for the research is explained first. Second, the main advantages and drawbacks of the data are clarified in order to better understand what to expect from the results. Later, the method of data cleaning of each variable is elucidated and descriptive statistics are provided.

is The Life in Kyrgyzstan (LiK) longitudinal survey is used to investigate the gender pay gap in Kyrgyzstan. LiK was carried out annually from 2010-2013 tracking the same households of over 3000 and individuals of over 8000 each year. The first wave of data collection in 2010 included 8160 individual observations and 3000 households. In the second wave in 2011, only 7,364 observations or 90.2 percent of 2010 observations were interviewed and 702 new observations were added. In the third wave in 2012, 8,177 individual observations and 2,816 households were interviewed in which 7,630 observations were from the second wave. The fourth wave in 2013, 7681 individuals and 2,584 households were interviewed 97.6 percent of which comprised of the observations that were in the third wave.

The data was collected once a year around October-November each year in all Oblasts of Kyrgyzstan, and Bishkek and Osh cities. The 3000 households were selected by a two-stage random sampling and was conducted by the National Statistical Committee (NSC) of the Kyrgyz Republic.

The survey contains an extensive array of topics such as demographics, education, health, employment, migration, remittances, shocks, assets, expenditures, subjective well-being, social networks and so on. There are four types of questionnaires; household, individual, community and control which were answered by the most informative household member or household head, individuals over 18 years of age, community heads respectively.

The main benefits of using LiK for this research is that it traces the same individuals and households throughout all four years. This way, I can better find out about the dynamics and changing patterns of the individual's characteristics. In addition, since each individuals and households are given separate IDs which makes it easier for researchers to conduct both household and individual level research in a wide array of topics.

However, LiK also includes some drawbacks; since it only covers 3000 households, the data cannot represent characteristics of Kyrgyzstan's population as a whole. In addition, there some variables that are included in some years, but are removed from the rest; therefore, this decreases the scope of variables that could have been used in the model to even strengthen the results.

In order to finalize the variables for my model, a series of data cleaning have been undertaken. The same as the empirical literatures, I am using the basic Mincerian type model which includes logarithm of earnings as dependent variable and experience, experience squared, and education as independent variables. Besides, I have also added age, age squared, gender, marital status, ethnicities, number of children, health, occupation, sectors, location, and oblasts. The wage variable is divided into three types; daily, weekly, and monthly in the individual questionnaire. Since the National Statistical Committee (NSC) of the Kyrgyz Republic earnings monthly, I have changed the daily and weekly earnings to monthly earning by first by multiplying daily wages by 22 since on average Kyrgyz workers work 22 days a month, and dividing weekly wages by 5 since there are five working days in a week and then multiplying it by 22 to get the subsequent monthly wages.

The variable education is taken from the question about the highest level of education a person has obtained. The answers vary from being illiterate to PhD, and then 8 dummy variables are created. In the model, the dummy variable “illiterate” is removed from the model in order to avoid perfect collinearity among the educational categories.

One of the main drawbacks of LiK questionnaire is that, the years of work experience is not recorded in the individual questionnaire. Thus, I made the new variable from the question in the individual questionnaire that asks about a person’s employment or study status since 1989. For 2010 observations, I have added all the years in which a person was active into the labor force and dropped the observations that were not born, at school, unemployed, or interned in order to receive the years of experience only the observations that worked and gained experience. Then for the subsequent years of 2011-2012, I have added one more year for each if the person was active in the labor force. Other literatures such as Klycheva (2016) and Baye et al. (2016) faced the same problem of unavailability of data. However, they used an approach of subtracting years of schooling and 7 more years, at which people go to school from. Their approach overestimates the years of experience because in some years after school and university, they person might not work, or a woman might be at a maternity leave, or simply cannot find the job. Counting the inactive years of work would make the results incorrect. Therefore, the method that I have used better estimates the years of experience. After making the panel data, the maximum years of experience is 25 meaning that the person has been working sin 1989 each year and the minimum of 0.0833 by taking only the observations with active years of working.

Moreover, the ages of observations are taken the minimum 18 which is the official age to work in Kyrgyzstan for all kinds of jobs and maximum age of 58 for women, and 63 for men which the retirement age according to OECD Development Pathways (2018). The gender variable is a dummy variable which takes the value of 1 for men and 0 otherwise taking both genders above the ages of 18 and below the retirement age. The strongly balanced data shows the number of observations to be 31, 031 after sorting the data by age.

Marital status is also considered to be one of the main determinants affecting wage and affecting negatively if the individual is a woman (Becker, 1962). It is a dummy variable that takes the value of 1 if the person is married or lives together, and 0 if a person is divorced, single, widowed, or separated. Since Kyrgyzstan is culturally diverse country, the effect of ethnicities are crucial to be examined. Four categories of ethnicities are made which includes Kyrgyz, Uzbek, Russian, and other ethnicities variable (containing Dungan, Uighur, Tajik, Kazakh, and other). In order to avoid perfect collinearity, the normative category which is Kyrgyz is excluded from the model. This way, we can better find out whether these ethnicities cause wage to decrease compared to being Kyrgyz.

The health variable is taken from the question whether a person has any chronic illness. It is a dummy variable that takes the value of 1 if a person is ill and 0 otherwise. Moreover, the occupation variable is a categorical variable including 10 occupational dummies from being an unskilled worker to professional. The dummy variable of unskilled worker is removed from the model to avoid perfect collinearity. In the LiK questionnaire, there are 16 categories; thus, in order to avoid having many dummies, I have divided sectors into four categories (Pettinger, 2019). The primary sector includes fishing, mining, and agriculture; secondary sector includes manufacturing, construction, utilities, and social and personal services. The tertiary sector includes transport and communication, trade and repair, finance, hotels and restaurants, real estate, renting and businesses activities, health and social work, public administration, and education; while, the others sector include private households with employed persons and extra-territorial organizations. To avoid perfect collinearity, I have used the normative approach of choosing the reference category in which I choose the most basic category to be removed from the regression. For sectors too, I have excluded the primary sector and compared the effects of other sectors with this sector in order to find out whether working in other sectors increase wages.

The last variables are Oblasts and Location which are taken from the control datasets of LiK. Oblasts include all seven oblasts of Kyrgyzstan and Bishkek and Osh cities. The base category is taken to be Issyk-Kul because in this province the lowest wages are received. The Location variable is a dummy which takes the value of one if the person lives in a city and zero otherwise.

Methodology and Model Specification

This paper uses Conditional Quantile Regression (CQR) in order to estimate the gender pay gap in Kyrgyzstan. I hypothesize that gender is the main determinant in deciding earnings besides education, sectors, occupation, and location and that gender pay gap exist in Kyrgyzstan. The CQR is an intuitive way of investigating wage gap across quantiles of wage distribution. Since wages are highly dispersed, using the simple OLS approach will not provide us with more detailed representation of pay gap across quantiles of wage distribution. In addition, OLS estimation only provide us with mean difference of wages comparing male and female earnings throughout the years of 2010-2013. Moreover, the effect of explanatory variables on wages are also held constant across pay distribution. However, running Quantile regression provide us with more detailed information about the dynamics of explanatory variables across different percentiles of wages. CQR is also less robust and sensitive to the outliers, heteroscedasticity, and normality assumption compared to OLS (Hong Vo et al., 2019).

The model of Quantile Regression was first introduced by Koenker and Basset (1978) followed by Buchinsky (1998). Using the basic Mincerian model of wages by taking logarithm of wages as dependent variable conditional on independent variables at certain quantiles of wage distribution.

In order to compare the detailed results of Quantile Regression with OLS, we first run an OLS regression which is borrowed from Goy and Johnes (2015):

$$LnW_{ij} = X_{ij}B + u_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

In the above model LnW_{ij} represents logarithm of wages foo ith individual and j represents the gender of the person. X represents all the explanatory variables and B denotes the coefficient estimates of independent variables. The u_{ij} denotes the unobserved characteristics and error term that are not included in the model.

In general, one of the most common factors in such kind of wage equations that is excluded is the ability of a person. The most common solutions of the literatures solve this issue is to add instrumental variable such as IQ score in order to avoid possible endogeneity. There is other solution in which the fixed effects is run in order to receive consistent estimate of the endogenous variable. However, such kind of endogeneity problem can only occur if ability is corelated with the variable of interest. In the model investigating gender pay gap, the variable of interest is gender, and gender is not corelated with ability because men and women do not differ in terms of their cognitive abilities. Thus, in the regression, the unobserved variable of ability does not cause endogeneity issues. Thus, running the random effects in this case is plausible because I am also looking to also find the effect of time invariant variables besides time variant variables.

The extended OLS model looks like the following regression after I have made my panel and added the new variables of occupation, sectors, and Oblast compared to the base paper from Goy and Johnes (2015):

LnW_{ij}= Gender+Age+ Age_sqr+ Experience+ Exp_sqr+ Uzbek+Russian+ Other_ethnicities+ Marital+ Children+ Health+ Primary + Basic+ Primary_tec+ Secondary_tec+ Secondary_general+ University+ Secondary_sector+ Tertiary_sector+ Other_sectors+ Doccup2+ Doccup3+ Doccup4+ Doccup5+ Doccup6+ Doccup7+ Doccup8+ Doccup9+ Doccup10+ Djalalabad+ Naryn+ Batken+ Talas+ Chui+ Osh+ Bishkek+ Osh_city+ Location+ u_{ij}……………………………………………………………………………………………(2)

After running the above regression and random effects, the primary results from running the OLS suggest the variable of interest which is gender is indeed significant at all conventional levels meaning that being a man does have a positive effect on wages compared to being a woman (refer to table 2 in the Appendix). In addition, being married has a positive effect on wages at all conventional levels if the individual is male (Appendix, Table 3). However, the effect of marital status is negative for women at 5% significance level shown in Table 4. Having health issues tend to have insignificant effect on wages meaning of women that health issues listed do not restrict the Kyrgyz women from earning wages and participating into the labor market. However, the health issues negatively affect the male and decreases their wage and it is significant at 5%.

Being in other occupational positions compared to being an unskilled worker increases wages. Moreover, as hypothesized earlier, living in other oblasts compared to living in Issyk-kul increase wages, they are statistically significant at all conventional levels for both male and female. Furthermore, living in the city increases wages and it is statistically significant at all conventional levels for men and at 5% significance level for women.

Running the OLS regression, we conclude that gender does affect a person's earnings in Kyrgyzstan which is consistent with the result received in my base paper. The results conclude that there is an evidence of gender pay gap in Kyrgyzstan. However, there might be the case that women only work at subordinate positions and low-paid jobs compared to men. In order to find the evidence of wage gap at certain levels of wages, I run the Quantile Regression. According to norm for using Quantile regression, the quantiles of 25th, 50th, and 75th are use to estimate the pay gap; however, Goy and Johnes (2015) used quantiles of 10th, 25th, 50th, 75th, and 90th. However, such quantiles are used when wages are highly dispersed among quantiles. For Kyrgyzstan, usning the quantiles of 20th, 40th, and 60th is plausible. This is because the observations tend of to have similar wages, yet we have fewer observations that are over 75th quantile, thus, using the method of Goy and Johnes would provide inconsistent results in terms of Kyrgyzstan.

In order to run the quantile regression, the following regression is used which borrowed from Goy and Johnes (2015) and extending the model according to the availability of data:

$$LnW_{ij} = X_{ij}B_{\theta} + u_{ij\theta} \text{ With } Quant_{\theta}(LnW_{ij} | X_{ij}) = X_{ij}B_{\theta} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In the above model, the dependent variable is logarithm of wages and independent variable are human capital and individual characteristics. The θ determines quantiles of wage distribution which in our case are 20th, 40th, and 60th. Since it is proven that the error term is not corelated with the variable of interest, $Quant_{\theta}(u_{ij\theta} | X_{ij})=0$ is satisfied. OLS estimators tend to minimize the sum of squared residuals; however, in the Quantile regression as quantiles vary from 20% to 60%, it permits the effect of different covariates to alter among wage distributions Goy and Johnes (2015). Thus, the quantile regression will provide with more details about the wage gap in different quantiles of wage compared to OLS that only provide us with mean difference.

In the next steps, Quantile Regression will be run at certain quantiles of wage difference in order to find out what determinants affect the wage gap at certain quantiles and which quantiles tend to higher wage difference.

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Appendix

Variable	Obs	Mean	Std. Dev.	Min	Max
hhid	49,040	6961.929	4198.204	2001	21150
pid	49,040	3.150897	1.992642	1	14
idpp	49,040	696196	419820.3	200101	2115005
year	49,040	2011.5	1.118045	2010	2013
gender	47,027	.4996917	.5000052	0	1
age	47,027	30.71984	19.69987	0	105
kyrgyz	47,027	.6980245	.4591196	0	1
uzbek	47,027	.133753	.3403903	0	1
russian	47,027	.0703	.2556547	0	1
other_ethn~s	47,027	.0979225	.297213	0	1
marital	35,844	.609865	.4877872	0	1
children	47,027	2.164841	1.569429	0	9
working_age	29,018	35.69174	12.32579	18	62
health	29,966	.2766135	.4473311	0	1
illiterate	33,204	.0091856	.095402	0	1
primary	33,204	.018552	.1349383	0	1
basic	33,204	.108511	.3110294	0	1
secondary_~n	33,204	.5582761	.4965998	0	1
primary_tec	33,204	.0359896	.1862671	0	1
secondary_~c	33,204	.1112215	.314411	0	1
university	33,204	.157993	.3647399	0	1
kandidate	33,204	.0002711	.0164617	0	1
primary_se~r	16,221	.3525677	.4777842	0	1
secondary_~r	16,279	.1927637	.3944812	0	1
tertiary_s~r	16,279	.4438848	.4968564	0	1
other_sect~s	16,280	.0121007	.1093391	0	1
doccup1	16,280	.0244472	.1544376	0	1
doccup2	16,280	.0972359	.2962878	0	1
doccup3	16,280	.0718673	.258276	0	1
doccup4	16,280	.0447174	.2066892	0	1
doccup5	16,280	.1149263	.3189428	0	1
doccup6	16,280	.0530098	.22406	0	1
doccup7	16,280	.119656	.3245688	0	1
doccup8	16,280	.0115479	.1068422	0	1
doccup9	16,280	.4590295	.4983339	0	1
doccup10	16,280	.0035627	.0595834	0	1
wage	26,138	4080.278	9056.459	0	692100
additional~e	26,138	121.2657	1287.207	0	85000
experience	29,251	12.09768	8.105358	.0833333	25
location	47,026	.3287968	.469781	0	1
Issykkul	47,027	.0815914	.2737441	0	1
Djalalabad	47,027	.1835329	.3871069	0	1
Naryn	47,027	.0423161	.2013115	0	1
Batken	47,027	.0897144	.2857752	0	1
Osh	47,027	.2237438	.4167568	0	1
Talas	47,027	.0481426	.2140697	0	1
Chui	47,027	.1485742	.3556721	0	1
Bishkek	47,027	.1360708	.3428673	0	1
Osh_city	47,027	.0463138	.2101661	0	1
log_wage	13,659	8.668369	.7690593	3.401197	13.44749
exp_sqr	29,251	212.0484	207.6814	.0069444	625
age_sqr	29,018	1425.82	933.0599	324	3844

Table 1. Descriptive statistics of independent variables across 4 years.

log_wage	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.3244585	.0175041	18.54	0.000	.290151	.3587659
uzbek	.0417153	.0268602	1.55	0.120	-.0109298	.0943604
russian	.0097653	.0289096	0.34	0.736	-.0468964	.066427
other_ethnicities	.1401663	.028397	4.94	0.000	.0845092	.1958234
marital	.0379355	.0188216	2.02	0.044	.0010458	.0748252
children	.025146	.0056409	4.46	0.000	.01409	.0362021
health	-.0170991	.0165292	-1.03	0.301	-.0494959	.0152976
primary	-.5177434	.2232675	-2.32	0.020	-.9553396	-.0801472
basic	-.2899205	.2046673	-1.42	0.157	-.6910612	.1112201
secondary_gen	-.2358789	.2032734	-1.16	0.246	-.6342874	.1625295
primary_tec	-.2907566	.2054706	-1.42	0.157	-.6934716	.1119584
secondary_tec	-.2619551	.2042324	-1.28	0.200	-.6622432	.138333
university	-.1063746	.2041763	-0.52	0.602	-.5065528	.2938036
secondary_sector	.3228493	.0224447	14.38	0.000	.2788586	.3668401
tertiary_sector	.3596963	.021145	17.01	0.000	.3182528	.4011398
other_sectors	.2579238	.0550546	4.68	0.000	.1500187	.3658289
doccup1	.3616943	.0403512	8.96	0.000	.2826074	.4407811
doccup2	.1717766	.0271385	6.33	0.000	.1185861	.2249672
doccup3	.0869181	.0261642	3.32	0.001	.0356373	.138199
doccup4	.0125968	.0309112	0.41	0.684	-.047988	.0731816
doccup5	.1379727	.021799	6.33	0.000	.0952474	.1806981
doccup6	.1389764	.0306139	4.54	0.000	.0789743	.1989786
doccup7	.1276972	.0213515	5.98	0.000	.0858489	.1695455
doccup8	.1345616	.0520676	2.58	0.010	.032511	.2366122
doccup10	.2217217	.097084	2.28	0.022	.0314406	.4120028
experience	-.0147649	.004021	-3.67	0.000	-.0226459	-.0068838
location	.1287475	.023962	5.37	0.000	.0817828	.1757122
Djalalabad	.303673	.0357457	8.50	0.000	.2336127	.3737334
Naryn	.3741409	.0465849	8.03	0.000	.2828361	.4654457
Batken	.3630225	.0405641	8.95	0.000	.2835184	.4425267
Osh	.2319213	.0344193	6.74	0.000	.1644606	.299382
Talas	.6169589	.0469379	13.14	0.000	.5249622	.7089556
Chui	.4994413	.0350228	14.26	0.000	.4307979	.5680846
Bishkek	.5309317	.0380725	13.95	0.000	.456311	.6055525
Osh_city	.331566	.0490484	6.76	0.000	.2354328	.4276991
exp_sqr	.00091	.0001559	5.84	0.000	.0006044	.0012157
age_sqr	-.0000376	.000013	-2.89	0.004	-.0000631	-.0000121
_cons	7.846197	.2068446	37.93	0.000	7.440789	8.251605
sigma_u	.43035302					
sigma_e	.52073665					
rho	.40581889	(fraction of variance due to u_i)				

Table 2. general OLS regression not controlled for gender.

log_wage	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
uzbek	.0767838	.0327681	2.34	0.019	.0125595	.1410082
russian	.076934	.0398982	1.93	0.054	-.001265	.1551331
other_ethnicities	.2292687	.0349749	6.56	0.000	.1607192	.2978182
marital	.1539455	.0267185	5.76	0.000	.1015782	.2063127
children	.0351899	.0069231	5.08	0.000	.021621	.0487588
health	-.0448621	.0217381	-2.06	0.039	-.0874679	-.0022563
primary	-.3961569	.2381511	-1.66	0.096	-.8629245	.0706106
basic	-.2757139	.2139505	-1.29	0.198	-.6950492	.1436214
secondary_gen	-.1710315	.2122718	-0.81	0.420	-.5870766	.2450137
primary_tec	-.2588229	.2149352	-1.20	0.229	-.6800883	.1624424
secondary_tec	-.2234082	.2138459	-1.04	0.296	-.6425386	.1957221
university	-.0429536	.2138842	-0.20	0.841	-.4621589	.3762517
secondary_sector	.3099732	.0259093	11.96	0.000	.2591918	.3607545
tertiary_sector	.3371271	.0256375	13.15	0.000	.2868785	.3873757
other_sectors	.2656173	.0673907	3.94	0.000	.1335341	.3977006
doccup1	.3385238	.0475369	7.12	0.000	.2453531	.4316945
doccup2	.1511172	.0380225	3.97	0.000	.0765945	.2256398
doccup3	.0202907	.0363289	0.56	0.576	-.0509125	.091494
doccup4	.0619097	.0439533	1.41	0.159	-.0242372	.1480566
doccup5	.1168142	.0282157	4.14	0.000	.0615125	.172116
doccup6	.1586741	.0341625	4.64	0.000	.0917168	.2256314
doccup7	.1009704	.0254968	3.96	0.000	.0509977	.1509431
doccup8	.1620174	.064566	2.51	0.012	.0354705	.2885644
doccup10	.2330369	.1023588	2.28	0.023	.0324174	.4336564
experience	-.0281177	.0053448	-5.26	0.000	-.0385933	-.0176421
location	.1432702	.0301931	4.75	0.000	.0840929	.2024475
Djalalabad	.347588	.0448346	7.75	0.000	.2597137	.4354622
Naryn	.4426411	.0565587	7.83	0.000	.331788	.5534941
Batken	.5025489	.0494968	10.15	0.000	.4055368	.5995609
Osh	.2913562	.0430523	6.77	0.000	.2069752	.3757373
Talas	.7413846	.0604407	12.27	0.000	.622923	.8598463
Chui	.6018943	.0443178	13.58	0.000	.515033	.6887557
Bishkek	.5711162	.0498734	11.45	0.000	.4733662	.6688663
Osh_city	.4171176	.062711	6.65	0.000	.2942063	.5400289
exp_sqr	.0013137	.0002024	6.49	0.000	.000917	.0017105
age_sqr	-.0000589	.0000164	-3.59	0.000	-.000091	-.0000267
_cons	8.052462	.2168104	37.14	0.000	7.627521	8.477402
sigma_u	.4181749					
sigma_e	.53348628					
rho	.38058471	(fraction of variance due to u_i)				

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Table 3. OLS regression result if the individual is male.

log_wage	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
uzbek	-.0285813	.0459471	-0.62	0.534	-.118636	.0614734
russian	-.0600225	.0412956	-1.45	0.146	-.1409603	.0209153
other_ethnicities	-.054899	.0475411	-1.15	0.248	-.1480779	.0382798
marital	-.0536916	.0269462	-1.99	0.046	-.1065053	-.000878
children	.0027271	.009674	0.28	0.778	-.0162337	.0216878
health	.0194037	.0251008	0.77	0.440	-.0297931	.0686004
primary	-.9596835	.7042472	-1.36	0.173	-2.339983	.4206156
basic	-.4125435	.6848641	-0.60	0.547	-1.754853	.9297655
secondary_gen	-.4823836	.682568	-0.71	0.480	-1.820192	.8554252
primary_tec	-.4350066	.6854484	-0.63	0.526	-1.778461	.9084476
secondary_tec	-.482269	.682982	-0.71	0.480	-1.820889	.8563511
university	-.3664845	.6829298	-0.54	0.592	-1.705002	.9720333
secondary_sector	.3601825	.0458098	7.86	0.000	.270397	.449968
tertiary_sector	.4039169	.0388358	10.40	0.000	.3278	.4800337
other_sectors	.2685752	.0969012	2.77	0.006	.0786524	.458498
doccup1	.4260772	.0773695	5.51	0.000	.2744357	.5777187
doccup2	.1868355	.0398045	4.69	0.000	.1088201	.2648509
doccup3	.13163	.0387032	3.40	0.001	.0557732	.2074868
doccup4	-.0255171	.0440674	-0.58	0.563	-.1118877	.0608534
doccup5	.1576988	.0343852	4.59	0.000	.090305	.2250926
doccup6	-.0258165	.073339	-0.35	0.725	-.1695583	.1179252
doccup7	.161162	.0399192	4.04	0.000	.0829218	.2394022
doccup8	.0691132	.0870514	0.79	0.427	-.1015044	.2397308
doccup10	.141814	.3673848	0.39	0.699	-.5782469	.8618749
experience	-.0035127	.0062702	-0.56	0.575	-.015802	.0087765
location	.0836142	.0386514	2.16	0.031	.0078588	.1593696
Djalalabad	.2559447	.057752	4.43	0.000	.1427529	.3691366
Naryn	.2789574	.0805349	3.46	0.001	.1211118	.436803
Batken	.0987234	.0697498	1.42	0.157	-.0379837	.2354305
Osh	.1516912	.0559751	2.71	0.007	.0419819	.2614004
Talas	.4422483	.0730482	6.05	0.000	.2990763	.5854202
Chui	.3410037	.0558265	6.11	0.000	.2315858	.4504217
Bishkek	.4744262	.0579487	8.19	0.000	.3608487	.5880036
Osh_city	.2025924	.0769662	2.63	0.008	.0517414	.3534434
exp_sqr	.0004843	.0002507	1.93	0.053	-7.17e-06	.0009757
age_sqr	1.78e-06	.0000214	0.08	0.934	-.0000402	.0000438
_cons	8.16452	.6857595	11.91	0.000	6.820456	9.508584
sigma_u	.4393185					
sigma_e	.48963424					
rho	.44599449	(fraction of variance due to u_i)				

Table 4. OLS regression result if the individual is female.

besides marital status, sectors, occupation, and location.