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Abstract

This paper analyzes the educational wage differentials among youth graduates in Egypt using a nationally representative data set extracted from some labor market surveys. We follow the empirical framework of Mincer's estimation of the simple schooling model, extending the model by adding additional control variables. On average, college graduate are found to earn more hourly wages than their non-college counterparts. The educational attainment wage gap is found to be not uniform across youth earners' wage distribution. Using newly developed methods, we decompose the educational wage differentials among youth graduates into endowment effects, explained by differences in productivity characteristics, and discrimination effects attributable to unequal returns to covariates. We find that discrimination effects contribute more significantly to the educational wage gap than endowment effects throughout the wage distribution.

Keywords: Wage differentials, Colleges and vocational graduates, Returns to education, ELMPS, Egypt

JEL Classifications: I26, J01, J24, J31

ملخص

تحلل هذه الورقة الفروق في الأجور على أساس التعليم بين شباب الخريجين في مصر باستخدام مجموعة بيانات تمثيلية من أنحاء البلاد مستخرجة من بعض مسوحات سوق العمل. ولهذا الغرض، نحن نتبع الإطار التجريبي لشركة مينسير لتقدير نموذج التعليم البسيط، مع التوسع في النموذج بإضافة متغيرات تحكم إضافية. وتبين الورقة أنه، في المتوسط، يحصل خريجو الجامعات على أجر أكبر مقابل ساعة العمل مقارنة بنظرائهم غير الجامعيين. كما وجد أن فجوة الأجور على أساس التعليم ليست موحدة عبر توزيع أجور الشباب. باستخدام الطرق التي تم تطويرها حديثًا، نقوم بتحليل الفروق في الأجور على أساس التعليم الذي حصل عليه شباب الخريجين إلى تأثيرات الموهبة الطبيعية، موضحة من خلال الاختلافات في خصائص الإنتاجية وتأثيرات التمييز التي تعزى إلى عدم المساواة في المردود بالنسبة إلى المتغيرات المشتركة. ونجد أن آثار التمييز تساهم بدرجة أكبر في فجوة الأجور على أساس التعليم من آثار الموهبة في كافة جوانب توزيع الأجور.

1. Introduction

Within two consecutive days in September 2015, the ministry of higher education in Egypt witnessed two perplexing protests[3]. On the first day, high school students and parents demanded raising the cap on the number of newly admitted students to public universities. The following day, Ph.D. and MBA graduates staged a fire burning their diplomas in front of the ministry of higher education protesting inability to decent jobs and long lines of unemployment despite their high education degrees. Both demands reflect serious political and social discontent in the Egyptian labor market.

This paper contributes to the existing literature by investigating employed youths' wage determination for both college and non college graduates and the educational wage differentials among them. It's noteworthy that, none of the previous contributions to the literature has decomposed the educational wage differentials across the wage distribution and investigated how labor market characteristics contribute to distributional wage disparities among the youth graduates. Over the past decades, the lion's share of the literature on wage gap has focused on the gender and public-private sector wages differentials. It can be of interest and significance to evaluate the graduates' wage determination at different points of wage distribution as done in a number studies dealing with the wage differentials. Indeed the rate of return to factors such as the education (years of schooling), the experience and others may not be identical at all earnings levels.

In this paper, using a nationally representative labor market data set from the recent rounds of the Egypt Labor Market Panel Survey conducted in 2006 and 2012 (ELMPS 2006-2012), we aim to analyze the wage determination system for both graduates (college and non colleges graduates) by using OLS estimation and the unconditional quantile regressions developed by Firpo et al. (2009). To decompose the mean wage gap by educational attainment, we apply a recently-developed regression-compatible procedure by Fortin (2008). For a deeper analysis, we also combine the mean decomposition method developed by Fortin (2008) with the unconditional quantile regression elaborated by Firpo et al. (2009) in order to decompose the educational wage differentials at different quantiles. The conducted method is computationally straightforward and it permits to divide up both the two effects (endowment and discrimination effects) into the contribution of each covariate. Furthermore, to overcome small sample cells in youth groups in ELMS we complement this analysis with yet another comprehensive panel data on young Egyptians, the "Survey of Young People in Egypt" (SYPE), in order to document career trajectories of college vs. non-college graduates over the period 2009-2014.

The remainder of this paper is organized as follows. In the subsequent sections we present the background and related work about the educational attainment, earnings, and labor transitions in Egypt, mainly the differences in labor market experiences of college graduated vs. non-college graduated. In section 4, we describe the used data and the regression and decomposition methods. Section 5 gives a descriptive analysis of the real educational wage differentials among youth employed in each sector (private and public) using the ELMPS and SYPE surveys. Section 6

[3] https://dailynewsegypt.com/2015/09/11/egypts-students-protest-against-education-ministers/#disqus_thread

presents the regression, decomposition and employment transition results and the final section concludes.

2. Background of the Study

Egypt is one of many developing countries with a significant share of young and educated labor force, yet not fully exploited. Several studies on the Egyptian youths have documented the ever-increasing numbers of the working age population, especially the youth (15-34 years), representing one third of the working age population. A pattern that is triggered by the onset of the demographic transition momentum which started by late 1980s. Between 2009 and 2014, the proportion of people in the age group 15-34 has risen by 6% yearly. Statistical predictions confirm this pattern will continue for the next 20 years, at least (Fig. 1). In 2015, a little over one third of the population is under 15 years of age, compared to 30% in 2030.

Statistics on the Egyptian labor market confirm a striking division along the educational spectrum: on the one hand, over one third of them are illiterates (38%). On the other hand, 44% have at least high school diploma, of which nearly two thirds of workers are vocational school graduates, and one-third have college degrees (ILOStat, 2016). To understand this divisional structure of the labor market, we look at the education system in Egypt, in particular secondary and college education.

Secondary education in Egypt has two tracks: vocational secondary education, and general secondary education. The latter is a pre-requisite to proceed to college education, and represents 60% of secondary school population. Technical and vocational high school graduates, or Technical and vocational education training (TVET) are distributed as follows: industrial (20%), commercial (16%) and agricultural (4%). (CAPMAS, Central Agency for Public Mobilization and Statistics), Statistical yearbook, CAPMAS, Cairo, 2012). Two features separate the general secondary from TVET education tracks:

- graduates of TVET tend to join the labor market once they receive their diploma. Contrary to general secondary graduates who are expected to continue in the system and enroll in college education, thus enter the labor market at least 4 years later (depending on the program of specialization).
- the second distinction concerns the pedagogical aspect of the programs. TVET programs are usually less selective, and have a restricted curriculum compared to general secondary track. Students are less likely to take advanced instruction in math and science compared to the general education. Thus, vocational education is perceived as the track of (and for) lower aptitude students, and the labor market implicitly links good employment with college education.

A classic development economics textbook would consider this influx of youngsters a demographic dividend and an endowed force towards economic growth. Labor, a factor of production, contributes to economic growth via its quantity and quality. And while educational attainment is the standard measure for labor force quality, unemployment rate, despite the debate over its inaccuracy, is still used as a proxy to gauge the quantity element of the labor force.

Figure 2 displays how unemployment rates respond to changes in GDP of the previous year. The graph shows that despite mediocre economic growth over time, the unemployment rate in Egypt has reached unprecedented levels since 1990. Comparing the period (2011-2016) to earlier periods such as (2001-2006), figure 2 depicts a more aggressive and sharper response to changes in GDP.

In other words, the figure sketches a detachment of growth efforts from labor market goals.
Figure 3 takes a closer look at unemployment rates within three levels of education: primary, secondary and tertiary. The figure shows persistently higher levels of unemployment for college graduates compared to lower educated groups. Despite dismal prospects for college graduates, enrollment in secondary general education, a pre-requisite to college admission, has been rising and expected to rise in the future (See Figures 4 and 5).

3. Literature Review

Little research has traced the dynamics between educational attainment, earnings, and labor transitions in Egypt, especially the differences in labor market experiences of college degree holders vs. non-college degree holders. A handful of studies have documented employment transition probabilities in Egypt. One of the earlier tracing studies on graduates of vocational technical education in 2008 reported only 53% accepted offers of employment after their graduation. By 2012, 25% of them reported working in public sector and 11% in the private sector (Adams, 2010). Using a school-to-work transition of young people (ages 15-29) in 2012, Barsoum (2014) reports only one third of school graduates have secured a satisfactory employment.
Using longitudinal data on the Egyptian labor market, Assaad and Krafft (2014) examine transition probabilities across employment statuses during periods 1998-2006 and 2006-2012. They find a decline in status persistence over time. Said (2015) confirms this finding where graduates report easier access to employment in 2006 compared to 1998. Said, however, points to static status for public and private sector workers. Amer (2014) and Assaad and Krafft (2014) agree on a significant difference in mobility patterns between informal and formal employment. For example, Wahba (2009), using Egyptian LMPS 2006 find informal employment is a "stepping stone" for highly educated male workers, but a dead end for the less educated and females.
One of the main objectives of the present study is to test the tenets of the "bumping model" of G. Fields (1972). The model offers some answers to the conundrum between outputs of the education system and efficient functions of the labor market. On the demand side, an excess supply of the highly educated leads to general upgrading of the hiring standards. Employers prefer to hire the more educated in these jobs because: *i)* either they prefer to be associated with "the educated", or *ii)* they presume they are more productive than adequately matched, but less educated, workers. On the supply side, college education is perceived as a "sheep skin" effect. Returns to education are sharply divided along college- no college certification.
Workers without college diplomas face a labor market that is blind to their educational achievement. Wages for this group are determined independent of workers' education, and workers do not compete on wages they are willing to accept given their education, but rather they compete on jobs (job competition model, Thurow 1979). Therefore, the incentive to top this threshold persists. The excess supply of the highly educated who queue for lower matched jobs is first hired at the lower prevailing wage, bumping the less educated out. The result is that the expected lifetime earnings of the less educated decline while those of the higher educated are unchanged, leading to greater demand on higher education. To put it differently, the higher the supply of college educated workers in the economy, the greater the demand on higher education.
This model is in clear contradiction of the classic human capital theory (Becker, 1964), which pre-

assumes a competitive and a well-functioning labor market. In this model, the competitive labor market compensates workers at their marginal product. For a given level of labor demand, relative wages would decline if the supply of adequately matched labor exceeds its demand. The labor market then signals a saturated market of this type of labor, driving prospective graduates to major in a different field of education. But the labor market in Egypt is farther away from being competitive. Government and public-sector wages are institutionally set by the government, where education and specialization are key determinants in rank and fringe benefits. Wages in the private sector are determined by forces of supply and demand. The informal sector, working as a shock absorbent, contributes large share of low paid employment. These rigidities result in erroneous market signals (i.e. perceived future earnings) to future cohorts of new entrants into the labor market.

4. Data and Research Methodology

4.1. Data

The analysis in this paper utilizes two sample surveys: a) Egypt Labor Market Panel Survey (ELMPS) for rounds 2006 and 2012[4]. The questionnaire for the sequential rounds (ELMPS 2006 and ELMPS 2012) is composed of three sections: in the first section, a household questionnaire addressed to the head of household provides information on basic demographic characteristics of members of the household. In the second section, an individual questionnaire addressed to everyone to obtain vital information on parental background, detailed education histories, detailed employment characteristics, job characteristics and earnings. The third section of the questionnaire is devoted entirely to the income sources of the household.

b) Furthermore another comprehensive panel data on young Egyptians is used to complement the analysis of youth employment. The SYPE surveys carried out in 2009 and 2014 by the Population Council, and Information and Decision Support Center of the Cabinet (IDSC)[5].

To ensure comparability between the two surveys, and to eliminate unobserved heterogeneity bias, the first part of the analysis using the ELMPS surveys is limited to earners and educated, "not in school" graduates in the age group 18-30 in 2006 and 2012, while in the second part we limit the sample to the educates and earners who are aged 18-30 in 2009 and become 23-35 years old in 2014. This limits the sample to individuals entering or leaving the labor market during the same time and facing the same conditions. The age restriction in the second part of the analysis is intended to track the progression of this cohort in the labor market. Since one of the research questions assess wage compression along the vertical occupational ladder, the working sample is restricted to wage employment only in public or private sector jobs (i.e. we exclude self-employed group).

[4]For details about the three sequential rounds of the ELMPS see Assaad and Krafft (2013).

[5]In 2014 the Population Council in partnership with the Central Agency for Public Mobilization and Statistics (CAPMAS) collected the second round of data for the Survey of Young People in Egypt (SYPE) following the initial 2009 SYPE wave carried out by Population Council, the Information and Decision Support Center of the Cabinet (IDSC). The common objective of the two SYPE rounds is to update the state of knowledge on adolescents and youth in Egypt aged (10-29) and identify issues of importance to youth in the country's new political environment. (Roushdy, Rania and Maia Sieverding, 2015).

4.2. Research Methodology

The analysis spans over two contours:

4.2.1. Employment transition matrix

Specifically, we examine patterns of transition probability into and out of different employment statuses by answering the following questions:

- How do college graduates vs. non-college graduates compare in terms of finding full time employment?
- How do college graduates vs. non-college graduates compare in terms of mobility between distinct types and statuses of employment?

Employment transition matrixes have been standard analytical tools in longitudinal survey data. From Maloney (1999) to Gong et al (2004) and Calderon-Madrid (2000) in Mexico, to Canavire-Bacarreza and Soria (2007) in Argentina, to eastern Europe such as Duryea et al. (2006), Lehman and Pignatti (2008), and Pages and Stampini (2009). In fact, longitudinal analysis in Argentina, Brazil and Mexico reversed the traditional cross-section findings of large asymmetries between formal and informal sectors into more symmetrical flows (Bosch and Maloney,2007).

4.2.2. Decomposition analysis

One of the objectives of this research is to determine if college education acts as social exclusion device, spreading the social and economic gap between college graduates and non-college graduates. Towards this end, wage equations for the two groups taking into account the sector of activity (public or private sector), separately, will be decomposed into a productivity effect (i.e. explained or the composition effect) and a wage structure effect (i.e. unexplained or discrimination effect). The main data used in this part of empirical analysis is extracted as mentioned above from the two recent waves of the ELMPS surveys carried out in 2006 and 2012 by the Central Agency for Public Mobilization and Statistics (CAPMAS) in cooperation with Economic Research Forum (ERF).

To estimate and decompose wage equationsfor each group, we restrict the working samples to wage earners only aged between 18 and 30. The dependant variable in these regressions is the log real hourly wage (instead of hourly wage)[6] , which is computed by dividing the monetary net earnings by the number of hours worked per year. As data is originated from different periods, all wages will be expressed in 2012 prices in order to adjust data for inflation. It is revealed that surveyed workers answered all the questions required for the estimation of the Mincerian wage equation and the basic earnings functions. Accordingly, in the first step before dealing with wage differentials between different groups, we'll follow in the empirical framework the Mincer's estimation of the simple schooling model, which links earnings to work experience and years of schooling. It is worth to note that some labor market characteristics and a set of individual features will be added to the basic Mincer's model to get an extended model that takes into account a variety of factors when estimating wages equations.

Using the basic Oaxaca and Blinder decomposition technique (Blinder, 1973; Oaxaca, 1973), wage

[6]Log real hourly wage is used in regressions instead of the hourly wage to reduce the effects of wages outliers.

difference equations will be estimated for public and private sector wage earners separately. To explain, suppose the mean log wage function for each group (4 groups) is described by the subsequent equation:

$$E(Y_G|X_G) = X_G\beta_G \qquad (1)$$

where □denotes the logarithmic real hourly wages, □is the vector of general (i.e. age, gender, education, marital status, experience, stability and residence) and labor market characteristics (i.e. occupation, sector of activity) (including the constant term), β is the vector of coefficients and G denotes the group of graduates in each sector: non-college and college graduates in public and private sectors. Then the OLS estimate of □□ assesses the impact of □ on the conditional or unconditional mean of □ for group G. It is noteworthy that the Oaxaca–Blinder decomposition has been widely used to decompose the mean wage gap between two opposite groups (initially between male and female groups) into a composition effect explained by differences in productivity features and an unexplained wage structure effect due to different returns to covariates. Accordingly, the mean log wage gap between non-college (G) and college ($\bar{G}$) graduates in public and private sectors can bewritten as follows:

$$\overline{\boldsymbol{Y}}_{\boldsymbol{G}} - \overline{\boldsymbol{Y}}_{\bar{\boldsymbol{G}}} = (\overline{\boldsymbol{X}}_{\boldsymbol{G}} - \overline{\boldsymbol{X}}_{\bar{\boldsymbol{G}}})\widehat{\boldsymbol{\beta}}_{\boldsymbol{G}} + \widehat{\boldsymbol{X}}_{\bar{\boldsymbol{G}}}(\widehat{\boldsymbol{\beta}}_{\boldsymbol{G}} - \widehat{\boldsymbol{\beta}}_{\bar{\boldsymbol{G}}}) \qquad (2)$$

Where $\hat{\beta}_G$ is the reference wage structure, and $(\bar{X}_G - \bar{X}_{\bar{G}})\,\widehat{\beta}_G$ is the composition effect and $\hat{X}_{\bar{G}}(\hat{\beta}_G - \hat{\beta}_{\bar{G}})$represents the wage structure effect (discrimination effect).

Notwithstanding its usefulness in explaining whether differences in wages between different population sub-groups are due to variations in characteristics between them or alternatively due to the wage structure, the Oaxaca-Blinder decomposition method is recently criticized for considering only the decomposition of the mean wage differences, yielding an incomplete representation of the inequality sources. Accordingly, other conventional methods have extended the decomposition beyond the mean and allow the investigation of the entire distribution, yet they all share the same weaknesses in that they entail a set of assumptions and computational issues (Fortin, Lemieux, &Firpo, 2010). In this regard, the Recentered Influence Function (RIF) regression approach recently suggested by Firpo, Fortin, and Lemieux (2009) addresses these weaknesses and provides a straightforward regression-based method for performing a detailed decomposition of some distributional statistics such as quantiles, variance, and other statistics. The RIF is the key concept of the unconditional quantile regression, the recently widely used method of decomposition in the recent literature.

For this analysis, RIF (Y, q_τ) is the function of explanatory variables:

$$\mathrm{E}\big(\mathrm{RIF}(\mathrm{Y},\mathrm{q}_\tau)|\mathrm{X}\big) = \mathrm{X}\beta_\tau \qquad (3)$$

Where q_τ is the τth quantile and β_τ is the vector of parameters associated to q_τ .Because RIF(Y,q_τ)is unobserved in practice, we use the estimated equation:

$$\widehat{RIF}(Y_G,\hat{q}_\tau) = \hat{q}_\tau + \frac{\tau - I(Y_G \le \hat{q}_\tau)}{\hat{f}_Y(\hat{q}_\tau)} \qquad (4)$$

Where $\hat{f}_Y$is the estimated marginal density function of Y and I is an indicator function.

After estimating the model in equation (3) for the 10^{th}(lowest percentile) to 90^{th}(highest percentile) quantiles of the population, we use the obtained unconditional quantile regression

estimates to decompose the different gaps into a component attributable to differences in the distribution of characteristics (composition effect) and a component due to differences in the distribution of returns (wage structure) as follows:

$$\hat{q}_{G,\tau} - \hat{q}_{\overline{G},\tau} = \overline{RIF}(Y_G, \hat{q}_{G,\tau}) - \overline{RIF}(Y_{\overline{G}}, \hat{q}_{\overline{G},\tau}) = (\overline{X}_G - \overline{X}_{\overline{G}})\hat{\beta}_{G,\tau} + \overline{X}_{\overline{G}}(\hat{\beta}_{G,\tau} - \hat{\beta}_{\overline{G},\tau}) \quad (5)$$

It is noteworthy that this RIF-based decomposition permits, after computing both the composition effect and discrimination effect throughout the wage distribution, to divide up the two effects into the contribution of each explanatory variable. Moreover, the issue resulting from the use of categorical predictors can also be straightforwardly resolved using the Yun's method (2005) of normalization.

5. Stylized Facts

5.1. SYPE Statistics

As indicated earlier, the sample is restricted to educated, "not in school" graduates and wage earners between 18 and 30 years of age (in 2009), who have been interviewed in 2014. College educated workers represent only 22% of the sample. Figure (6) is a cross section analysis of the panel sample in 2009 vs. 2014 by employment status. Individuals are sorted in one of five mutually exclusive categories: Full time employed (FT); part time employed (PT), unemployed—both actively searching and discouraged (Unemp), self-employed /employer (selfemp); and out of the labor force and not in school (OLF_NIS). The employed, both FT and PT, are workers who engage in some type of productive activity for the purpose of monetary earnings. The figure exhibits a drop in the fraction of OLF that is largely compensated by a rise in the fraction of the self-employed between 2009 and 2014, for both groups. The figure also shows significant underutilization of this educated labor force. In 2014, 52% of graduates without college degree school graduates and 45% of university graduates were either unemployed or out of the labor force.

Assaad and Kraft (2014) and Barsoum (2015) refer to this cohort as "the modern transition group". They refer to workers with at least secondary school diploma in search of formal employment. The dichotomy between the two groups of workers is evident along the economic status of their households. Approximately 30% of secondary educated graduates come from the top-richest- 40% of the wealth distribution, whereas most college educated youths come from the upper middle end of the wealth distribution (Assaad and Kraftt, 2014). But, cross section analysis hides the internal dynamics of movements between different employment statuses. For example, the higher proportion of self-employment in 2014 compared to that of 2009 could be due to new entrants into the labor market, not due to workers shifting from out of the labor force or unemployment to employment. Panel or longitudinal data analysis allows to trace the internal shifts between different employment statuses.

5.2. ELMPS Statistics

The descriptive statistics of variables are reported separately by educational attainment (college and N. college) and sector of activity (public vs. private) for the two years 2006 and 2012 in Tables 1a,b and Tables 2a,b. Monthly income is the sum of monthly earnings received in all forms from the current job in 2006 and 2012 (including regular wages, bonuses, subsidies and all other

types of earnings). Following the majority of existing studies, hourly wage is computed using monthly earning and monthly working hours. Tables 1a and 1b reveal ,as expected, that college graduates earn globally more than non-colleges peers particularly in 2006. Table 1a show that college graduates earn respectively about 24.64% (=1.268–1.022) and 21.76%, more hourly wage than N. college graduates in public and private sectors. In 2012, this average wage gap is about -27.5% in public sector and about 10.5% in private sector among the two groups.

Among the graduates, the college ones are slightly older and with more years of education. The average schooling is about 15 years, which are generally required for finishing high school in Egypt. The variable *Experience*, which is available only in 2012 survey, measures experience as the years living and working in each sector. The first five variables measure the quintile of the household wealth. While the average of the fourth quintile variable for the two years is remarkably high for college groups than others, the mean of Experience is slightly greater for the second group than their college counterparts. Married is a binary variable equal to 1 if the respondent is currently married and 0 otherwise.

Additional summary statistics of the educational differences in distributions of occupations, stability of jobs, industries and regions among public and private sectors are displayed in Tables 2a and 2b. In public sector, about 94.5% of college graduates and 81.8% of non-college counterparts work in services sector in 2006, while in private sector, the two statistics decline to respectively 83.3% and 65,3%. The figure isn't significantly different in 2012. In terms of industry distribution, the primary sector of graduates is the services, hiring about 95.6% of college graduates in public sector and around 80% of non-college graduates in private sector. Finally, the bottom part of the two Tables 2a and b show that the educational differences in distribution of regions are more important in private sector in the two years.

From Table 1a, we know that on average college graduates earn 24.64% higher wages than their non-college counterparts. To further investigate the educational wage gaps, we present preliminary statistics of hourly wage for each group and sector in 2006 and 2012 by occupation, industry, sector of activity and regions in Table 3. As expected, college graduates are found to earn higher average wages in the majority of categories. Among the six regions observed, the educational wage gap is the lowest for workers living in rural upper region with non colleges' average wage being 86.85% of that for college graduates in 2006. For the same year, the educational wage differential is the largest for workers in private sector, both in absolute (hourly wage difference) and relative terms (N.college/college le wage ratio). The figure is a bit different in 2012; The lowest gap (99.61%) between the two groups of graduates is observed in Agriculture sector and the highest is observed among graduates living in Gr. Cairo (56.39%). From the table 3, we see that N.college earn less than college graduates in the two years among the three sector of activity and the majority of regions.

To better describe the educational wage disparities among graduates, we present for the two years the kernel density estimates of logarithmic hourly wages for both group working in private and public sectors in Fig. 7a,b, from which we can see the contrasted wage distributions across the two educational attainments (college and non-college). The two-sample Kolmogorov–Smirnov test rejects the null hypothesis that the logarithmic hourly wages for the two groups come from the

same distribution (p-value=0.000). Following Albrecht et al. (2003), we plot the real educational attainment log wage differential at each percentile in Fig. 2a, b. We see globally, that the aforementioned wage differential between the two groups is confirmed at different percentiles not only in average but it's worth to note that the distributional educational wage differentials are found to be uneven through-out the wage distribution (see Fig. 8a,b).

6. Empirical analysis

6.1. Transition/Mobility Matrixes

Taking advantage of the panel structure of the two surveys, table 4 shows transition matrix based on workers' flow across different employment statuses using SYPE panel survey of 2009 and 2014. As previously mentioned, individuals ages 18-30 are sorted in one of five mutually exclusive categories: Full time employed (FT); part time employed (PT), unemployed—both actively searching and discouraged (Unemp), self-employed and/or employer (self-emp); and out of the labor force and not in school (OLF_NIS). The implicit assumption in this classification is that to a prospective labor market entrant, full time employment is the ideal status to secure, followed by part time employment, then self-employment. Unemployment is the last resort before the worker decides to quit the labor market.

Shaded boxes in yellow denote no change in employment status in 2014 from 2009, blue shading (upper-right) denotes downward mobility and green (lower-left) denotes upward mobility. According to table (8), the most persistent or static status is OLF group with about 78% remaining OLF after five years. This is not surprising since over 50% of those in the age group 18-30 are married with at least one child (Amer, 2007).

At the opposite end of the matrix, over half of full time workers in 2009 remained employed full time in 2014. Of those who lost their ideal job by 2014, a litter over 17% of shifted to own employment. Notably, an average of 45% of part time or self-employed workers in 2009 were able to land a full-time job in 2014. As such, it implies that part time and self-employments are perceived as experience accumulating statuses that may eventually pay off in acquiring a full-time employment in the future. In fact, maintaining an active status in the labor market, as a part time worker or self-employed, are more rewarding in the long run compared to an unemployed, who is more likely to drop out of the labor market in 2014.

Figure (9) is a representation of the previous table comparing the experience of graduates without college diploma vs. college educated. It shows the employment status in 2014 given 2009 status. Each column reflects the distribution of employment status in 2014 given the status in 2009. Several observations emerge from this figure: Education does not seem to play a significant role in future employment shifts if the individual is full time employed or OLF in 2009. In other words, conditional on full-time employment (or OLF) in 2009, no sizeable shifts are observed for college vs. no college alike in 2014, creating gridlocks at both ends of the employment statuses spectrum. Another key difference between the two groups of graduates is observed in the unemployment category. Unemployed college graduates are twice as likely to move to full or part time jobs in 2014 compared to the unemployed, lower educated graduates. In fact, unemployment for graduates without a college degree seems to be a precursor or a last resort before quitting the labor market all together. Close to 50% of the unemployed of the latter group in 2009 quit the labor market by

2014. This is twice the proportion of the unemployed college graduates who end up leaving the labor market in 2014.

College graduates seem to have better experience in self-employment compared to lower educated graduates. Over one third of self-employed college graduates in 2009 stay self-employed five years later. On the other hand, over 50% of the self-employed graduates without college diploma shift to a full or part time work in 2014. Additionally, full or part time employment is the preferred next best alternative to self-employed without college diploma. They are twice as likely as college graduates to leave self-employment to full or part time employment. Conversely, self-employed college graduates are twice as likely to move to unemployment or out of the labor force compared to self-employed without college diploma.

Even though the OLF status is a persistent one, the likelihood to move from OLF to a full-time employment status is almost twice as large for college graduates compared to non-college graduates. The previous finding points reflects a labor market that values credential (i.e. college degree) over experience. It appears that the early entrance of those who don't pursue college degrees are less likely to find full or part time employment five years later.

Adding age to the transition matrix allows to examine changes in employment statuses by age of employment. Figure (9) presents changes in employment status over age smoothed using a restricted cubic spline of proportions of observations in each category. Overall, college graduates experience steeper trajectories compared to vocational graduates. The figure reveals that the probability of having a full-time job increases with age then declines for both groups of graduates, but it is bolder for college graduates. The likelihood of engaging in full time employment rises to age 27 for graduates without college degrees, and up to age 30 for college graduates.

Compared with lower educated groups, college graduates detached from the labor market in their early years after graduation (i.e. OLF) are more likely to join the labor market later in life. They are more likely than the comparable group to remain active participants in the labor market as they get older. This is explained by earlier findings that marriage and having children are significant deterrent facing women in this age group.

Figure 10 also displays a rising incidence of self-employment with age for both types of graduates. Two reasons may explain this trend: 1) By nature, self-employment is a risky decision to consider and securing the start-up capital is time consuming, especially when official lending venues are limited. 2) As one gets older, the likelihood of securing a full-time employment dwindles. Self-employment comes as a last refuge in one's employment life.

6.2. Regressions Results

As discussed in previous studies, graduates' wages are largely determined by market forces. Given the information in the ELMPS surveys data, we rely on the human capital model to guide us in the estimation process. We run in the first step an OLS regression with a non-college and college pooled sample, allowing the effect of each covariate to vary with the educational dummy. Then we test the joint significance of all the interaction terms. We reject the null hypothesis that the OLS coefficient estimates are the same for both genders (*p-value=0.000*). After that, we investigate the mean wage determination for each group separately. In order to keep the analysis simple, we include a covariate related to the sector of activity (public/private) in regression instead of doing

OLS regression for each sector. Table 5a, b displays the OLS regression results for each graduates group with Huber–White standard errors to correct for heteroscedasticity of unknown forms.

Occupation (skilled and semi skilled workers) and industry dummies are included in the regressions in addition to the aforementioned general characteristics' workers. Notwithstanding these variables are likely to be jointly determined with wages, we keep these arguably endogenous variables in different regressions to reflect unmeasured human capital. Indeed, Albrecht et al. (2003) reveal that these variables are useful in explaining wage differentials as accounting exercise.

The results shown in Tables 5a and 5b reveal that the relation of graduates' logarithmic hourly wages to their ages has the widely documented inverted U-shape in 2006 for the two groups college and non-college. The returns to schooling are around 8% for college graduates in 2006 and 14.2% for the same group in 2012. We attribute this persistent disparity in returns among the two groups to the different education systems. Even receiving the same years of schooling as college graduates, non-college graduates may have lower wage premiums from schooling as shown in the descriptive analysis. The return to experience, a variable that is observed only in 2012, is shown to haven't any significant impact on wage determination system.

The stability of job and the occupation dummy are all significant in the two years mainly for the college graduates. The regression results shown in tables 5a,b reveal that the wage premium to permanent employment is very high, being 44.6% and 20% respectively for college and non-college graduates in 2006 and 29.4% and 12.7% respectively for college and non-college graduates in 2012. In accordance with previous studies, the coefficient estimates of the gender variable is found to be highly and positively correlated at conventional levels to wage in 2006 and 2012 confirming that a gender wage gap persist in the two groups during the considered period. The results show furthermore that the wage premium to public sector in 2012 is significantly high being 18.6% for college graduates and 11.2% for non-college graduates while being negative and equal to 18.1% for college graduates in 2006. An explanation for this finding is that college workers are more rewarded in public enterprises and government than in private sector.

We report the unconditional quantile regression estimates separately by educational attainment at the 10th, 50th and 90th percentiles for the two years 2006 and 2012 in Tables 6a,b with asymptotic standard errors. Similarly to the OLS regression, the coefficient estimates from RIF–OLS regressions are explained as the marginal effects of covariates on the corresponding unconditional quantiles of log hourly wages. As aforementioned, the RIF–OLS regressions could provide a more adequate and deep description of wage determination for each educational attainment than OLS regressions. The unconditional quantile regression results shown in the two tables 6a,b reveal some different estimated returns to characteristics between college and non-college graduates at different quantiles. For instance, from the OLS regression (table 5b), the return to one more year of education in 2012 is found to be no significant for the two groups, while it's found to be around 1.66% for college graduates and 1% for non college in the same year according to the quantile regression shown in Table 5b. The schooling return is found to increase significantly for the same year from 12.1% at the median to 25% at the 90th percentile for the college graduates. The 14.2% estimated

from OLS regression apparently conceals the heterogeneity in returns to schooling at different points of college graduate's wage distribution. For the non-college graduates, the schooling returns is found to be non significant at different quintiles for the two years. This leads to conclude as expected that college graduates may benefit more from their schooling than their non-college peers.

An another example that shows the advantage of unconditional quantile regression in uncovering heterogeneous effects, is underlined thereafter. We examine in this respect the impact of working in the public sector on wages differentials. while the OLS estimation show that the public sector pays around 20% more wages to college graduates in 2012, the quantile regression results for the same year show that the mean wage premium to public sector for college and non-college graduates is largely driven up by the low payoff for graduates at the 10th percentile of wage distribution in 2012 (25.2% for college graduates and 20.8% for non college ones). At the median the relative premium in 2012 is 16.4% for college and 10.4% for non colleges graduates, approximately near the value of OLs regression results.

6.3. Decomposition Results

In this sub-section, we further investigate the college and non-college wage structure and the resulting non-college/college wage gaps by using the decomposition technique described above. Specifically, the distributional education wage differentials is decomposed along the entire wage distribution into endowment effects explained by differences in productivity characteristics and discrimination effects. The decomposition results at the mean and at each quantile are presented in Tables 7a and b. The approximation errors obtained are all insignificant and small in magnitude, indicating that the conducted RIF-based decompositions provide very good approximations to the raw educational wage differentials among youth graduates.

Before delving into the non-college/college wage gap decomposition at selected quantiles, a decomposition of this gap for the two years is done at the mean following the Oaxaca–Blinder procedure. The results of this decomposition, shown in Tables 6a, b, reveals some important findings. First, on average, college graduates earn 27.7% more wages than their non-college counterparts in 2006 and 19.8% in 2012 indicating a decreasing average wage gap between the two groups over time. The Oaxaca–Blinder decomposition results reveal that the composition effect explained by differences in productivity characteristics presents -21.37% of the mean wage gap in 2006 and about -44.64% in 2012, while the discrimination effect explains 121.30% of the mean wage gap in 2006 and 144.44% in 2012, so most of the mean wage differential is due to discrimination effect rather than the differences in characteristics between the two groups. Furthermore, these results show that the discrimination against non-college graduates has intensified over time in Egypt's urban labor market.

The detailed decomposition results at selected quantiles displayed in Table 8a and b reveal some important findings. First, the wage differentials are found to be much larger at higher deciles than at the bottom and middle parts of wage distribution for the two years. The overall wage gap at the 90th percentile is 47.8% in 2006 and decreases slightly to 42.9% in 2012, while the gap at the median is 23.7% in 2006 and 16.1% in 2012. Second, the results show that discrimination effect (unexplained) is found to contribute more to the wage differential than endowment effect (explained) at every

quantile of the wage distribution for the two years mainly in 2006. This means that for this year after netting out the effects of educational difference in characteristics, a substantial part of raw educational wage differentials still exist at each quantile of the wage distribution. Table 7a shows in addition an increasing tendency of the significant discrimination effects in 2006, while in 2012 the discrimination effects follow a U-shape and tend to be larger at very low and very high deciles of graduates' wage distribution (see Table 7b).

Furthermore Tables 8a, b provides a detailed decomposition results of endowment and discrimination effects at considered quantiles. The effect of each group of variables is obtained by summing up the contributions of all the related variables generated or not from some categorical variables. A positive or negative sign suggests that the relevant variable contributes respectively positively or negatively to the corresponding endowment or discrimination effect. As clearly illuminated in Table 7a, the factors that primarily and significantly drive up the discrimination effects in 2006 at the bottom of the wage distribution are the general characteristics of youth workers. In 2012, the figure is somewhat different. Indeed the general characteristics are found to haven't significant contribution to the discrimination effects but contribute to the endowment effect at the middle of the wage distribution by 66.50%.

7. Conclusion

Using a nationally representative labor surveys data, we investigate the determinants of educational wage gaps among graduated youth job earners using OLS and unconditional quantile regressions. We find that OLS regressions cannot provide an adequate and deep description of wage determination. For a better and deeper analysis of such wage differentials, we use the unconditional quantile regression which reveal substantial gender differences in the coefficient estimates on labor market characteristics at different quantiles of the graduates' wage distributions. Using decomposition techniques, we decompose the educational wage differentials among college and non-college graduates in Egypt into endowment effects, explained by differences in productivity characteristics, and discrimination effects, attributable to unequal returns to covariates. We stress a few main findings: (a) The average educational wage gap is 27.7% in 2006 and 19.8% in 2012 among college and non college graduates. However, (b) the educational wage gap is not uniform across the graduates' wage distribution. (c) We find also that discrimination effects contribute more significantly to the educational wage gap than endowment effects throughout the wage distribution.

In addition, we propose to complement the current analysis with examining the patterns of transitional probabilities using yet another comprehensive panel data on young Egyptians, the "Survey of Young People in Egypt " for the years of 2009 and 2014. The main finding of this analysis reveal that college graduates detached from the labor market in their early years after graduation (i.e. OLF) are more likely to join the labor market later in life. They are found to be more likely than the comparable group to remain active participants in the labor market as they get older. This is explained by earlier findings that marriage and having children are significant deterrent facing women in this age group. Results show further a rising incidence of self-employment with age for both types of graduates. Two reasons may explain this trend: 1) By nature, self-employment is a risky decision to consider and securing the start-up capital is time

consuming, especially when official lending venues are limited. 2) As one gets older, the likelihood of securing a full-time employment dwindles. Self-employment comes as a last refuge in one's employment life.

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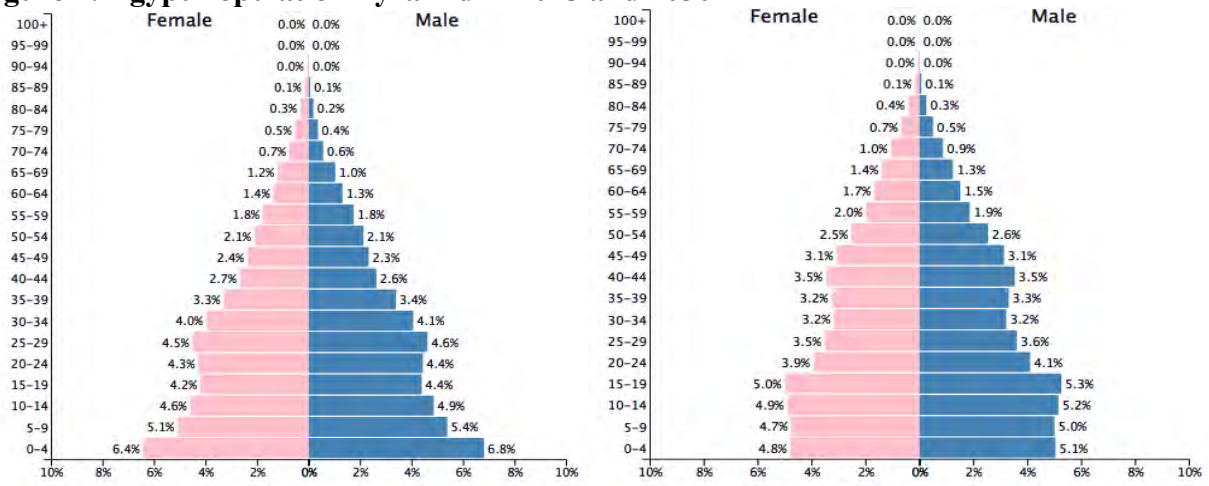
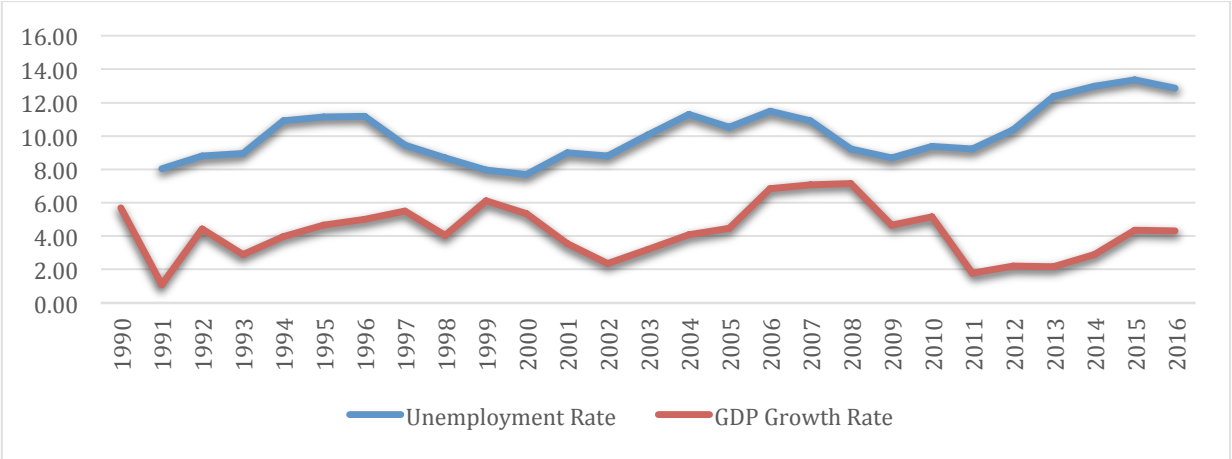
Figure 1: Egypt Population Pyramid in 2015 and 2030



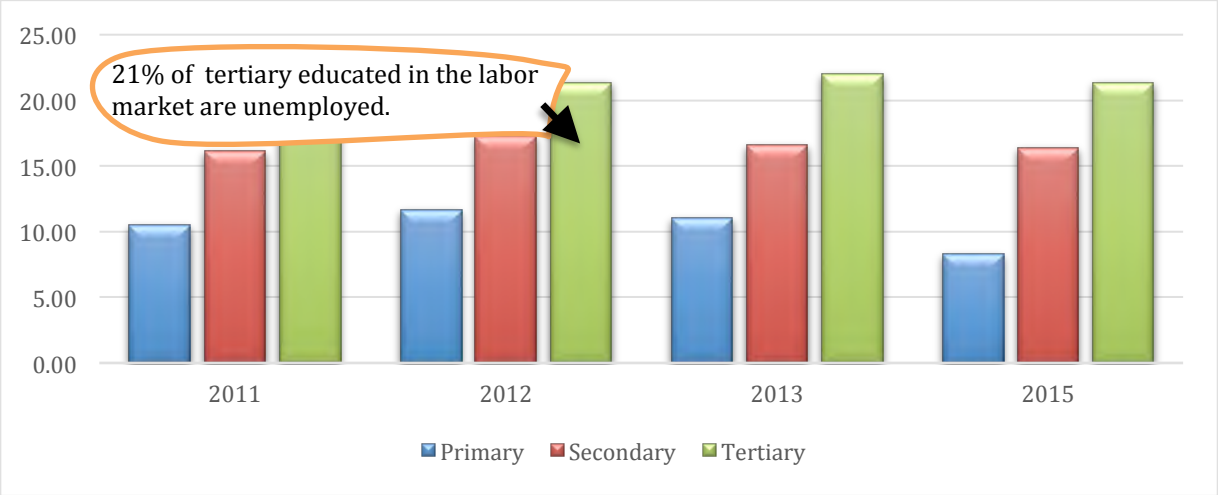
Source: https://www.populationpyramid.net/egypt/2030/

Figure 2: GDP Growth Rates and Unemployment Rates--one year lag (unemp)



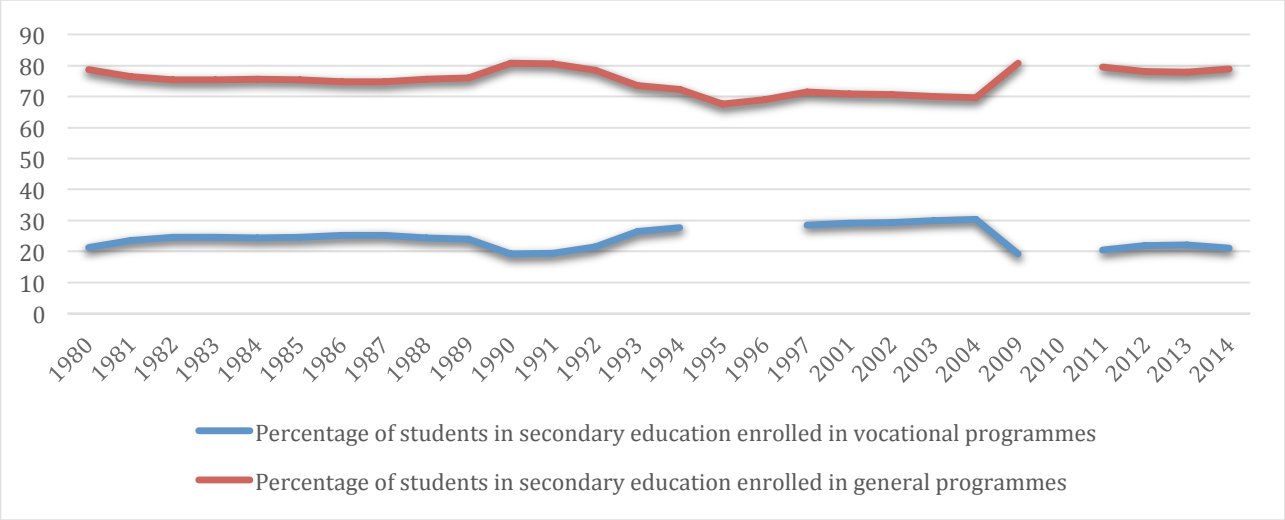
Source: IMF; World Economic Outlook (WEO) Database, April 2017 and World Development Indicators (WDI)

Figure 3: Unemployment as % of the Labor Force at Each Level of Education



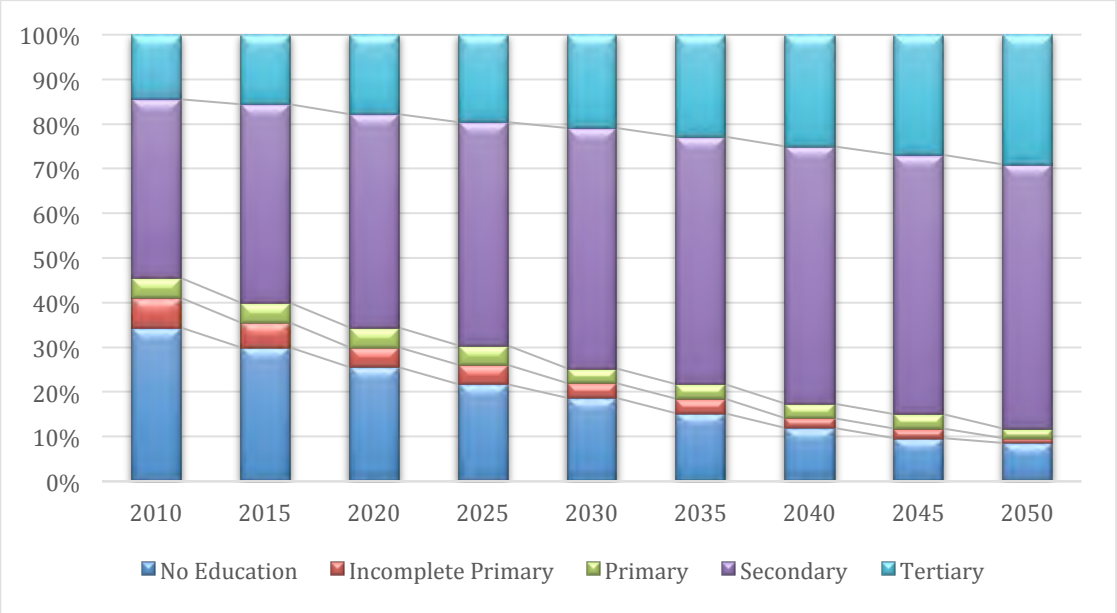
Source: WDI. Note: Secondary level represents lower and upper secondary education

Figure 4: Enrollment in Secondary General Vs. Vocational Education (%)



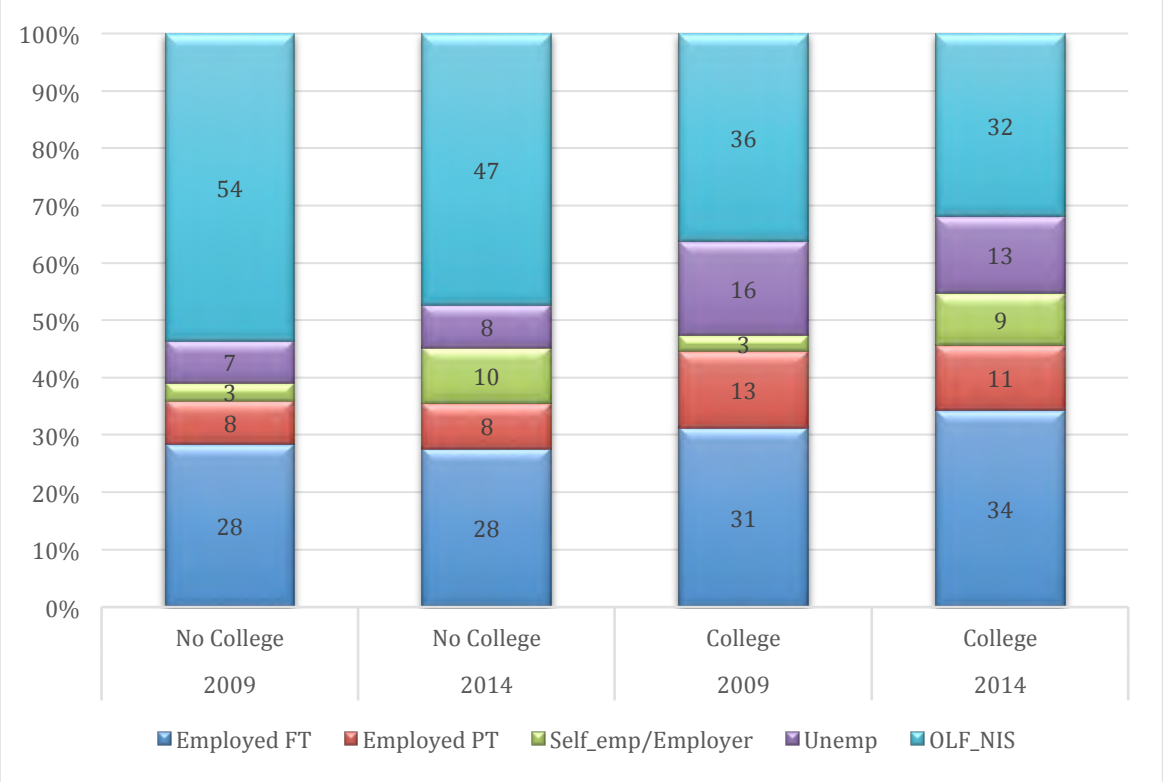
Source: UNESCO Statistics

Figure 5: Projection: % of Population 15+ By Level of Education



Source: World Bank Education Statistics.

Figure 6: Employment Status, ages 18-30, by Education, Cross section



Source: SYPE. Authors' calculations.

Figure 7a: Kernel density estimates of log wage distributions by educational attainment in 2006

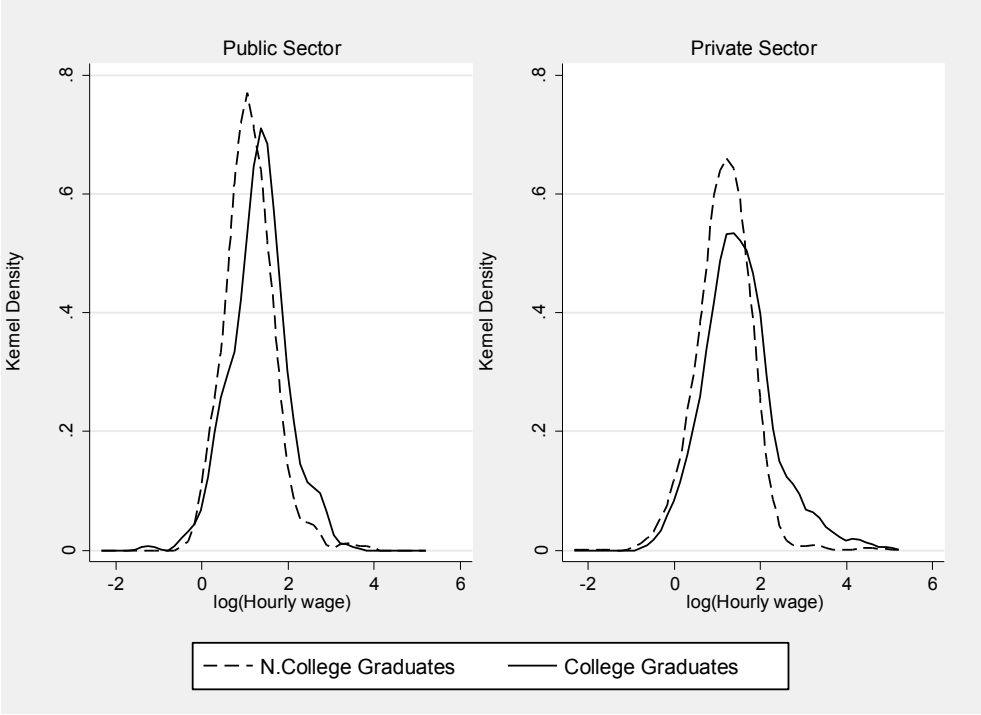


Figure 7b: Kernel density estimates of log wage distributions by educational attainment in 2012

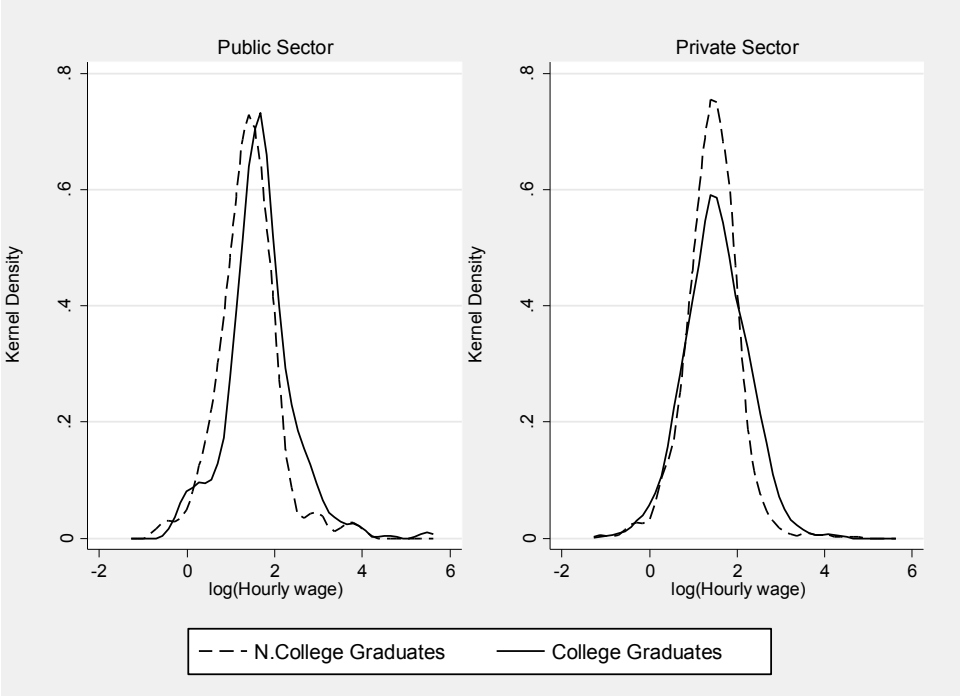


Figure 8a: Real educational attainment log wage gap by percentile in 2006

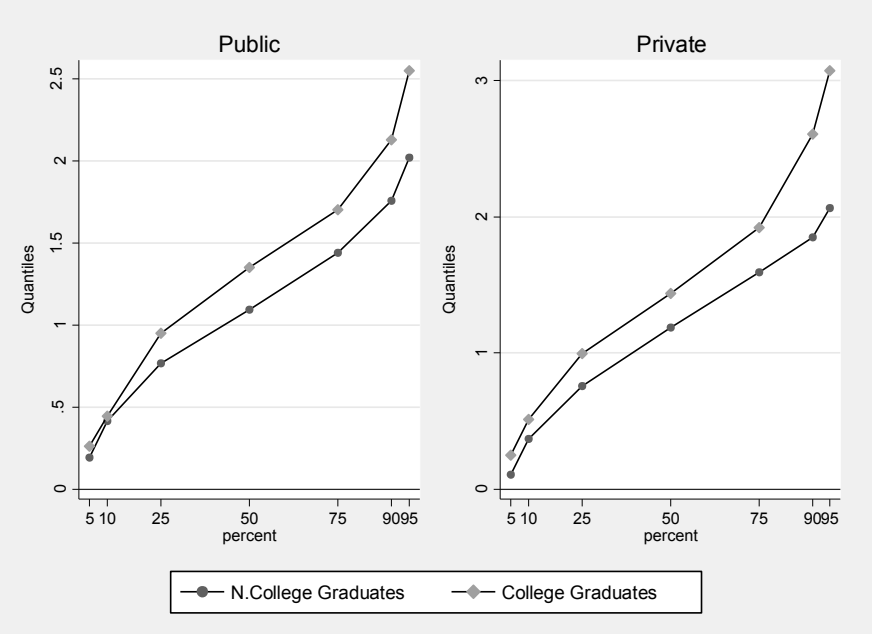


Figure 8b: Real educational attainment log wage gap by percentile in 2012

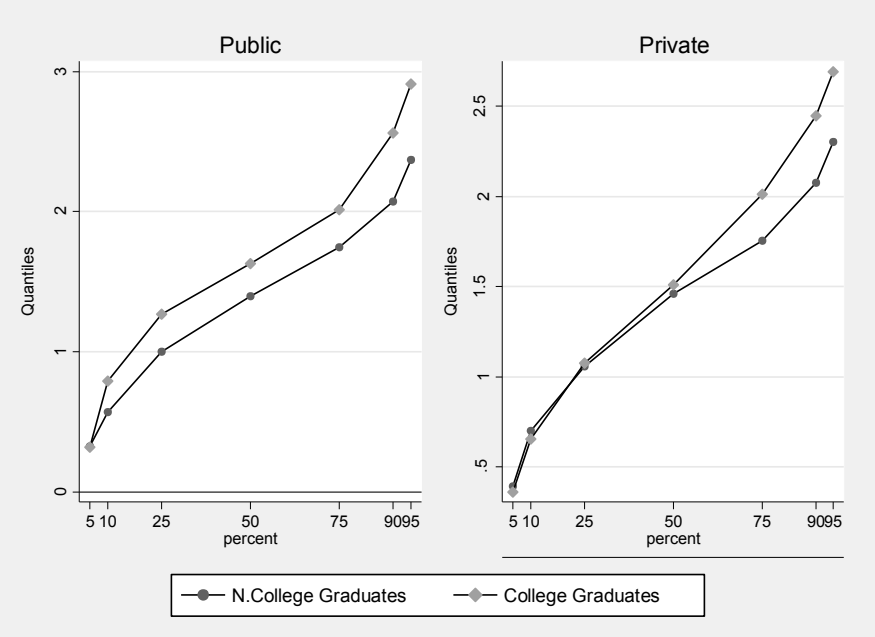
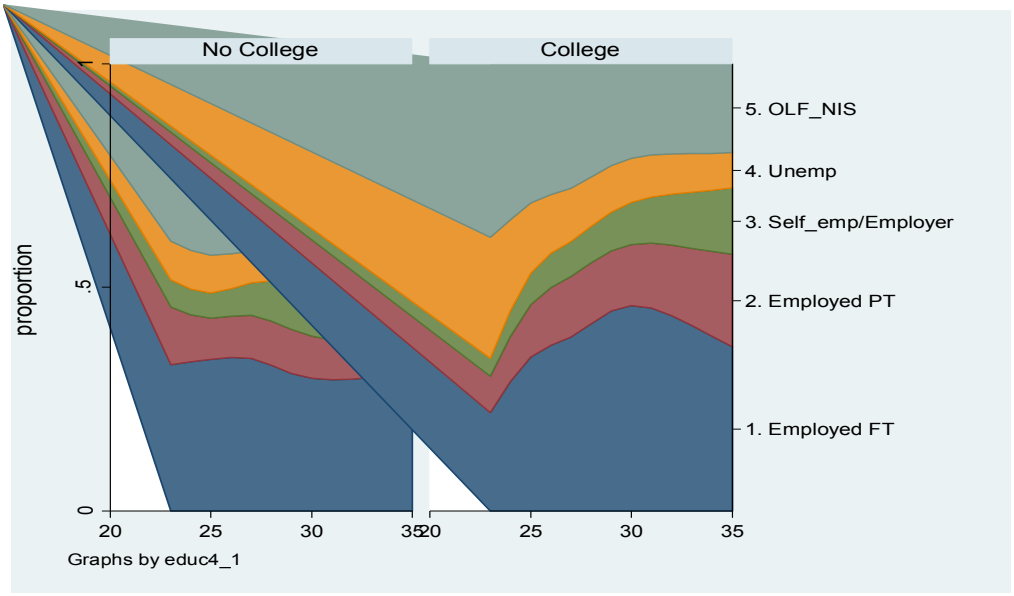


Figure 9: Transition Matrix: Employment Status in 2014 given Status in 2009

Source: SYPE. Authors' calculations.

Figure 10: Ownership among College and N.College graduates in 2014



Source: SYPE. Authors' calculations.

Table 1a: Summary statistics by region and educational attainment in 2006

	Public					Private				
	College Graduates		N.College Graduates		Normalized Difference	College Graduates		N.College Graduates		Normalized Difference
	Mean	Variance	Mean	Variance		Mean	Variance	Mean	Variance	
Household wealth										
1st Quintile	0.040	0.038	0.107	0.096	-0.184	0.031	0.030	0.208	0.165	-0.401
2nd Quintile	0.082	0.076	0.203	0.162	-0.247	0.093	0.085	0.258	0.192	-0.315
3rd Quintile	0.143	0.123	0.269	0.197	-0.224	0.115	0.102	0.259	0.192	-0.267
4th Quintile	0.225	0.175	0.259	0.192	-0.056	0.300	0.211	0.172	0.142	0.216
5th Quintile	0.511	0.251	0.163	0.137	0.559	0.461	0.249	0.102	0.092	0.614
Hourly wage [1]	4.410	11.950	3.154	2.908	0.326	6.417	145.854	3.962	20.219	0.190
Log hourly wage	1.268	0.433	1.022	0.255	0.297	1.376	0.702	1.158	0.401	0.207
Age	26.693	6.738	26.011	9.813	0.168	25.985	6.233	24.148	12.279	0.427
Male	1.502	0.251	1.315	0.216	0.273	1.238	0.182	1.111	0.099	0.240
Married	3.116	1.041	3.176	1.049	-0.042	2.718	0.917	2.667	0.888	0.038
Education	15.599	1.040	11.192	2.968	2.201	15.337	0.467	10.163	4.684	2.280
Urban	1.283	0.203	1.424	0.245	-0.211	1.183	0.150	1.459	0.248	-0.438

1: adjusted for inflation (constant 2012 CPI) and for gepgraphical variation of standards of living

Source: Authors' calculations from ELMPS 2006

Table 1b: Summary statistics by region and educational attainment in 2012

	Public					Private				
	College Graduates		N.College Graduates		Normalized Difference	College Graduates		N.College Graduates		Normalized Difference
	Mean	Variance	Mean	Variance		Mean	Variance	Mean	Variance	
Household wealth										
1st Quintile	0.023	0.023	0.128	0.112	-0.285	0.048	0.046	0.235	0.180	-0.393
2nd Quintile	0.113	0.101	0.180	0.148	-0.133	0.081	0.075	0.282	0.202	-0.380
3rd Quintile	0.149	0.127	0.237	0.181	-0.158	0.177	0.146	0.223	0.173	-0.081
4th Quintile	0.258	0.192	0.294	0.208	-0.057	0.225	0.175	0.180	0.147	0.081
5th Quintile	0.456	0.249	0.161	0.136	0.475	0.468	0.249	0.081	0.074	0.679
Hourly wage [1]	7.979	290.302	5.252	34.412	0.151	6.023	32.838	5.108	30.329	0.115
Log hourly wage	1.667	0.590	1.392	0.449	0.269	1.526	0.515	1.421	0.373	0.111
Age	26.784	4.903	26.714	7.526	0.020	26.313	5.730	24.901	11.365	0.342
Male	1.592	0.242	1.281	0.203	0.467	1.186	0.152	1.050	0.048	0.303
Married	3.328	0.920	3.474	0.835	-0.110	2.804	0.961	2.959	1.025	-0.110
Education	15.271	0.497	11.230	2.136	2.491	15.129	0.151	10.131	4.226	2.389
Experience	4.529	7.563	7.721	14.884	-0.674	4.359	9.438	7.913	18.415	-0.673
Urban	1.420	0.244	1.529	0.250	-0.154	1.347	0.227	1.594	0.241	-0.361

1: adjusted for inflation (constant 2012 CPI) and for geographical variation of standards of living

Source: Authors' calculations from ELMPS 2012

Table 2a: Labor market characteristics by sector and educational attainment in 2006

	Public					Private				
	College Graduates		N.College Graduates		Normalized Difference	College Graduates		N.College Graduates		Normalized Difference
	Mean	Variance	Mean	Variance		Mean	Variance	Mean	Variance	
Stability										
Permanent	0.781	0.171	0.819	0.149	-0.066	0.675	0.220	0.575	0.245	0.147
Temporary	0.216	0.170	0.176	0.145	0.071	0.288	0.206	0.205	0.163	0.137
Seasonal	0.000	0.000	0.000	0.000	.	0.003	0.003	0.005	0.005	-0.026
Intermittent	0.003	0.003	0.005	0.005	-0.025	0.034	0.033	0.215	0.169	-0.403
Occupation										
Skilled workers	0.997	0.003	0.995	0.005	0.025	0.966	0.033	0.785	0.169	0.403
S.Skilled workers	0.003	0.003	0.005	0.005	-0.025	0.034	0.033	0.215	0.169	-0.403
Sector of activity										
Agriculture	0.006	0.006	0.019	0.018	-0.081	0.031	0.030	0.100	0.090	-0.200
Industry	0.049	0.046	0.163	0.137	-0.267	0.136	0.118	0.247	0.186	-0.200
Services	0.945	0.052	0.818	0.149	0.283	0.833	0.140	0.653	0.227	0.297
Regions										
Gr. Cairo	0.173	0.144	0.173	0.144	0.000	0.372	0.234	0.159	0.134	0.349
Alx, Sz C.	0.146	0.125	0.112	0.100	0.072	0.158	0.133	0.123	0.108	0.071
Urb. Lwr.	0.140	0.121	0.144	0.124	-0.008	0.155	0.131	0.134	0.116	0.042
Urb. Upp.	0.258	0.192	0.147	0.125	0.198	0.133	0.116	0.124	0.109	0.018
Rur. Lwr.	0.167	0.140	0.259	0.192	-0.159	0.115	0.102	0.247	0.186	-0.248
Rur. Upp.	0.116	0.102	0.165	0.138	-0.102	0.068	0.064	0.212	0.167	-0.299

Source: Authors' calculations from ELMPS 2006

Table 2b: Labor market characteristics by sector and educational attainment in 2012

	Public					Private				
	College Graduates		N.College Graduates		Normalized Difference	College Graduates		N.College Graduates		Normalized Difference
	Mean	Variance	Mean	Variance		Mean	Variance	Mean	Variance	
Stability										
Permanent	0.832	0.140	0.846	0.130	-0.028	0.612	0.238	0.374	0.234	0.345
Temporary	0.166	0.139	0.146	0.125	0.039	0.276	0.200	0.155	0.131	0.210
Seasonal	0.000	0.000	0.000	0.000	.	0.002	0.002	0.008	0.008	-0.058
Intermittent	0.002	0.002	0.008	0.008	-0.057	0.111	0.099	0.463	0.249	-0.597
Occupation										
Skilled workers	0.998	0.002	0.992	0.008	0.057	0.889	0.099	0.537	0.249	0.597
S.Skilled workers	0.002	0.002	0.008	0.008	-0.057	0.111	0.099	0.463	0.249	-0.597
Sector of activity										
Agriculture	0.000	0.000	0.003	0.003	-0.051	0.050	0.048	0.157	0.132	-0.252
Industry	0.441	0.042	0.112	0.100	-0.180	0.165	0.138	0.193	0.156	-0.051
Services	0.956	0.042	0.885	0.102	0.186	0.785	0.169	0.651	0.227	0.213
Regions										
Gr. Cairo	0.084	0.077	0.112	0.100	-0.066	0.278	0.201	0.093	0.084	0.347
Alx, Sz C.	0.113	0.101	0.107	0.096	0.015	0.138	0.119	0.078	0.072	0.136
Urb. Lwr.	0.170	0.142	0.107	0.096	0.130	0.121	0.107	0.101	0.091	0.045
Urb. Upp.	0.212	0.168	0.148	0.127	0.118	0.121	0.107	0.136	0.118	-0.032
Rur. Lwr.	0.256	0.191	0.320	0.218	-0.100	0.234	0.180	0.304	0.212	-0.113
Rur. Upp.	0.164	0.137	0.206	0.164	-0.076	0.109	0.097	0.288	0.205	-0.326

Source: Authors' calculations from ELMPS 2012

Table 3: Descriptive average N.College Graduates/College Graduates wage gap

	2006						2012					
	College Graduates (G)		N.College Graduates ($\bar{G}$)		G-$\bar{G}$	$\bar{G}$/G (%)	College Graduates (G)		N.College Graduates ($\bar{G}$)		G-$\bar{G}$	$\bar{G}$/G (%)
	N	Mean	N	Mean			N	Mean	N	Mean		
Sector												
Public	328	4.705	374	3.692	1.013	78.46	475	7.979	384	5.252	2.728	65.82
Private	321	7.005	1454	4.062	2.943	57.98	478	6.023	2160	5.108	0.915	84.80
Occupation												
Skilled workers	637	5.802	1515	3.742	2.06	64.49	899	7.041	1541	4.888	2.15	69.43
S.Skilled workers	12	8.010	314	5.164	2.847	64.46	54	6.293	1003	5.501	0.792	87.41
Sector of activity												
Agriculture	11	4.979	153	3.401	1.578	68.31	24	5.247	340	5.226	0.021	99.61
Industry	60	5.748	420	3.928	1.819	68.35	99	7.215	459	5.035	2.181	69.78
Services	578	5.869	1255	4.077	1.792	69.47	830	7.023	1745	5.136	1.887	73.13
Regions												
Gr. Cairo	177	6.994	298	4.596	2.399	65.71	173	8.058	243	4.544	3.514	56.39
Alx, Sz C.	98	6.138	221	4.278	1.860	69.70	119	7.610	210	4.804	2.806	63.12
Urb. Lwr.	96	5.749	249	3.721	2.028	64.73	139	7.022	259	4.542	2.480	64.68
Urb. Upp.	127	5.192	235	3.667	1.525	70.62	158	6.283	350	5.636	0.647	89.70
Rur. Lwr.	92	5.142	456	3.787	1.355	73.65	234	6.628	781	4.989	1.639	75.28
Rur. Upp.	59	4.543	370	3.945	0.598	86.85	130	6.539	701	5.550	0.989	84.88

Source: Authors' calculations based on ELMPS 2006 and 2012

Table 4: Transition Matrix in 2014

		2014						
		Employed FT	Employed PT	Selfemp-Emplyr	Unemp	OLF_NIS		n
	Employed FT	57.1	13.8	17.4	3.3	8.4	100	1,365
	Employed PT	47.0	20.3	17.3	4.4	11.0	100	428
	Selfemp/Emplyr	43.9	10.8	31.8	4.7	8.8	100	148
2009	Unemp	31.8	9.0	7.6	15.2	36.4	100	368
	OLF_NIS	8.1	4.3	3.0	7.1	77.5	100	2,581
	Total	28.1	8.9	9.5	6.3	47.2	100	
	n	1,372	436	465	309	2,308		4,890

Source: SYPE. Authors' calculations.

Table 5a: OLS regressions results in 2006

VARIABLES	log of Rhwg_Aduj_06 (G)	log of Rhwg_Aduj_06 ($\bar{G}$)
Age	0.502**	0.176***
	(0.224)	(0.0590)
Age squared /100	-0.914**	-0.324***
	(0.428)	(0.121)
Sex	0.290***	0.450***
	(0.0544)	(0.0459)
Married	0.278***	0.136***
	(0.0583)	(0.0344)
Years of School	0.0789**	0.00553
	(0.0306)	(0.00655)
Stability=permanent	0.446***	0.200***
	(0.0682)	(0.0359)
Urban/Rural	-0.288***	0.00752
	(0.0580)	(0.0281)
Public/Private	-0.181***	0.0211
	(0.0574)	(0.0379)
Skilled/S.Skilled	0.541***	0.423***
	(0.187)	(0.0466)
Sector=Agriculture	-0.0906	-0.159***
	(0.138)	(0.0465)
Sector=Industry = o,	-	-
Sector =Services	0.00813	-0.0396
	(0.0786)	(0.0332)
Constant	-6.775**	-1.365*
	(3.001)	(0.724)
Observations	649	1,827
R-squared	0.249	0.162

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

Table 5b: OLS regressions results in 2012

VARIABLES	log of Rhwg_Aduj_12 (G)	log of Rhwg_Aduj_12 ($\overline{G}$)
Age	0.320	0.155***
	(0.224)	(0.0535)
Age squared /100	-0.574	-0.303***
	(0.425)	(0.109)
Sex	0.189***	0.224***
	(0.0536)	(0.0569)
Married	0.0687	0.129***
	(0.0515)	(0.0283)
Years of School	0.142***	0.00814
	(0.0468)	(0.00668)
Work experience	0.0159	0.00339
	(0.0109)	(0.00411)
Stability=permanent	0.294***	0.127***
	(0.0585)	(0.0390)
Urban/Rural	-0.174***	0.0317
	(0.0518)	(0.0260)
Public/Private	0.186***	0.112**
	(0.0566)	(0.0440)
Skilled/S.Skilled	0.489***	0.417***
	(0.0956)	(0.0388)
Sector=Agriculture	-0.254*	
	(0.139)	
Sector=Industry = o,	-	
Sector =Services	-0.116	0.0413
	(0.0804)	(0.0358)
Sector=Agriculture		-
Sector=Industry = o,		0.120***
		(0.0457)
Constant	-5.279*	-1.218*
	(3.041)	(0.665)
Observations	920	2,484
R-squared	0.109	0.099

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

Table 6a. Quantile regression in 2006

	College Graduates			N.College Graduates		
VARIABLES	rif_10	rif_50	rif_90	rif_10	rif_50	rif_90
Age	1.261***	-0.0835	0.690	0.425***	0.0384	0.0891
	(0.382)	(0.228)	(0.656)	(0.121)	(0.0641)	(0.0991)
Age squared /100	-2.313***	0.201	-1.343	-0.815***	-0.0480	-0.165
	(0.721)	(0.440)	(1.268)	(0.243)	(0.133)	(0.211)
Sex	0.183**	0.247***	0.303*	1.018***	0.288***	0.0879
	(0.0931)	(0.0608)	(0.161)	(0.109)	(0.0378)	(0.0648)
Married	0.170**	0.200***	0.562***	0.226***	0.144***	0.00240
	(0.0838)	(0.0618)	(0.176)	(0.0608)	(0.0394)	(0.0700)
Years of School	0.0567***	0.0504	0.0801	0.00882	0.00499	0.0169
	(0.0212)	(0.0333)	(0.115)	(0.0119)	(0.00793)	(0.0105)
Stability =permanent	0.675***	0.401***	0.407**	0.399***	0.181***	0.0620
	(0.128)	(0.0614)	(0.162)	(0.0893)	(0.0379)	(0.0508)
Urban/Rural	-0.157*	-0.235***	-0.502***	0.0784	0.0214	-0.0878*
	(0.0939)	(0.0622)	(0.155)	(0.0565)	(0.0335)	(0.0501)
Public/Private	-0.0998	-0.0403	-0.473***	0.254***	-0.114***	0.0796
	(0.0888)	(0.0579)	(0.173)	(0.0814)	(0.0428)	(0.0787)
Occupation	0.472	0.525***	1.050	0.769***	0.387***	0.137*
	(0.291)	(0.180)	(0.858)	(0.0887)	(0.0551)	(0.0829)
SECT_06==Agriculture	-0.152	-0.155	0.117	-0.122	-0.268***	-0.161**
	(0.266)	(0.192)	(0.663)	(0.0980)	(0.0656)	(0.0712)
SECT_06==Industry	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)
SECT_06==Services	-0.118	-0.193**	0.382	-0.224***	0.0436	-0.0880
	(0.0952)	(0.0901)	(0.271)	(0.0650)	(0.0397)	(0.0661)
Constant	-17.84***	1.304	-8.382	-5.242***	0.153	0.516
	(5.100)	(3.068)	(9.166)	(1.533)	(0.775)	(1.147)
Observations	649	649	649	1,827	1,827	1,827
R-squared	0.182	0.174	0.061	0.171	0.094	0.010

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

Table 6b. Quantile regression in 2012

	College Graduates			N.College Graduates		
VARIABLES	rif_10	rif_50	rif_90	rif_10	rif_50	rif_90
Age	0.765*	-0.0178	0.502	0.237**	0.0814	0.103*
	(0.435)	(0.215)	(0.360)	(0.118)	(0.0548)	(0.0619)
Age squared /100	-1.431*	0.0334	-0.926	-0.473**	-0.149	-0.213*
	(0.821)	(0.407)	(0.696)	(0.236)	(0.112)	(0.129)
Sex	0.187*	0.138***	0.229**	0.691***	0.135***	0.0390
	(0.0995)	(0.0507)	(0.0952)	(0.141)	(0.0429)	(0.0651)
Married	0.126	0.0727	-0.0388	0.280***	0.118***	-0.00249
	(0.0960)	(0.0491)	(0.0920)	(0.0593)	(0.0300)	(0.0371)
Years of School	0.00437	0.121***	0.250**	0.0198	0.00256	0.000520
	(0.0735)	(0.0354)	(0.0982)	(0.0145)	(0.00706)	(0.00809)
Work experience	0.0104	0.0166*	0.0172	0.00667	-0.000870	0.00886*
	(0.0186)	(0.00938)	(0.0191)	(0.00887)	(0.00435)	(0.00493)
Stability=permanent	0.390***	0.202***	0.283***	0.166*	0.111***	0.00684
	(0.132)	(0.0549)	(0.0793)	(0.0968)	(0.0339)	(0.0430)
Urban/Rural	-0.221**	-0.0891*	-0.119	0.121**	0.0406	0.0143
	(0.0955)	(0.0468)	(0.0870)	(0.0565)	(0.0268)	(0.0338)
Public/Private	0.255**	0.164***	0.154	0.208**	0.104***	0.0531
	(0.107)	(0.0517)	(0.102)	(0.0953)	(0.0403)	(0.0560)
Occupation	0.727***	0.452***	0.171	0.596***	0.464***	0.00932
	(0.163)	(0.115)	(0.174)	(0.0922)	(0.0373)	(0.0463)
Sector=Agriculture	0.142	-0.214	-0.0975	0	0	0
	(0.156)	(0.175)	(0.306)	(0)	(0)	(0)
Sector=Industry	0	0	0	0.164*	0.133***	0.0116
	(0)	(0)	(0)	(0.0898)	(0.0508)	(0.0636)
Sector=Services	-0.169	-0.0861	-0.141	-0.0503	0.0860**	0.0315
	(0.138)	(0.0708)	(0.156)	(0.0668)	(0.0422)	(0.0501)
Constant	-10.07*	-0.434	-7.965*	-2.982**	-0.450	0.807
	(5.936)	(2.882)	(4.686)	(1.480)	(0.676)	(0.762)
Observations	920	920	920	2,484	2,484	2,484
R-squared	0.054	0.071	0.040	0.079	0.092	0.004

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

Table 7a: Oaxaca decomposition results in 2006

VARIABLES	Overall	Explained	Unexplained
group_1	1.139***		
	(0.0148)		
group_2	1.416***		
	(0.0299)		
difference	-0.277***		
	(0.0334)		
explained	0.0592*		
	(0.0357)		
unexplained	-0.336***		
	(0.0455)		
G.characteristics		-0.00312	-5.583*
		(0.0364)	(3.033)
Occupation		0.0649***	-0.120
		(0.00839)	(0.210)
Sector		-0.00255	-0.00499
		(0.00624)	(0.0717)
Constant			5.372*
			(3.034)
Observations	2,476	2,476	2,476

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7b: Oaxaca decomposition results in 2012

VARIABLES	overall	explained	Unexplained
group_1	1.416***		
	(0.0125)		
group_2	1.614***		
	(0.0247)		
difference	-0.198***		
	(0.0277)		
explained	0.0884***		
	(0.0318)		
unexplained	-0.286***		
	(0.0411)		
G.characteristics		-0.0462	-4.398
		(0.0344)	(3.168)
Occupation		0.135***	-0.0428
		(0.0134)	(0.127)
Constant			4.155
			(3.168)
Observations	3,404	3,404	3,404

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8a. Quantile decomposition results in 2006

		10th			50th			90th	
VARIABLES	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained
group_1	0.380***			1.151***			1.857***		
	(0.0251)			(0.0179)			(0.0210)		
group_2	0.507***			1.388***			2.335***		
	(0.0442)			(0.0303)			(0.0831)		
Difference	-0.127**			-0.237***			-0.478***		
	(0.0508)			(0.0352)			(0.0857)		
Explained	0.0684			0.0736*			0.0318		
	(0.0609)			(0.0432)			(0.0517)		
unexplained	-0.195***			-0.311***			-0.510***		
	(0.0756)			(0.0531)			(0.0992)		
G.characteristics		-0.0549	-13.29***		0.0166	2.741		0.0199	-1.859
		(0.0621)	(4.689)		(0.0441)	(3.232)		(0.0531)	(9.191)
Sector		0.0416***	-0.0391		-0.0181**	0.165**		-0.0184*	0.0816
		(0.0110)	(0.108)		(0.00771)	(0.0747)		(0.00954)	(0.209)
Occupation		0.0817***	0.0534		0.0750***	-0.0395		0.0304***	-0.810
		(0.0135)	(0.327)		(0.0102)	(0.225)		(0.0111)	(0.641)
Constant			13.08***			-3.177			2.078
			(4.686)			(3.230)			(9.185)
Observations	2,481	2,481	2,481	2,481	2,481	2,481	2,481	2,481	2,481

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8b. Quantile decomposition results in 2012

		10th			50th			90th	
VARIABLES	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained
group_1	0.674***			1.435***			2.075***		
	(0.0274)			(0.0131)			(0.0184)		
group_2	0.741***			1.596***			2.505***		
	(0.0441)			(0.0230)			(0.0438)		
Difference	-0.0673			-0.161***			-0.429***		
	(0.0519)			(0.0265)			(0.0475)		
Explained	0.252***			0.0955***			0.00717		
	(0.0710)			(0.0331)			(0.0480)		
unexplained	-0.320***			-0.256***			-0.437***		
	(0.0866)			(0.0415)			(0.0674)		
G.characteristics		0.0306	-6.389		-0.0635*	-1.571		-0.0675	-7.564
		(0.0775)	(5.887)		(0.0360)	(3.030)		(0.0527)	(5.785)
Sector		0.0242**	0.0597		0.00210	-0.0227		-0.0132*	0.0862
		(0.0118)	(0.109)		(0.00550)	(0.0560)		(0.00800)	(0.106)
Occupation		0.197***	-0.114		0.157***	0.0152		0.0878***	0.0937
		(0.0293)	(0.253)		(0.0144)	(0.129)		(0.0198)	(0.244)
Constant			6.124			1.322			6.948
			(5.889)			(3.031)			(5.787)
Observations	3,406	3,406	3,406	3,406	3,406	3,406	3,406	3,406	3,406

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1