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Obbey A. Elamin

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Send correspondence to:
Obbey A. Elamin
King Faisal University
obbey.elamin@outlook.com

[1] Department of Economics, King Faisal University, P.O Box 400, postal code 31982, Al Hofuf, Saudi Arabia. (Email 1: obbey.elamin@outlook.com), (Email 2: oabdelrahman@kfu.edu.sa). ORCID id: 0000 − 0002 − 2883 − 9815.

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Abstract

This research examines the impact of informal job search on wage for university graduates on the first entry to the job-market and after making some experience. Informal job search is affected by unobserved factors related to productivity, peers effects, employers, which influence wage and cause endogeneity in empirical models. We use data from the Higher Education Graduates Survey 2012 in Egypt and Jordan, and apply the generalized empirical likelihood method GEL and GMM method to control for endogeneity and correct the bias in the estimates. Our results show wage penalties in Egypt that reach 11% and 38% for informal job-search in the first two jobs after graduation, respectively, but no evidence of effect in Jordan. We recommend that universities should establish job career offices to help graduates search and find suitable jobs at their area of expertise and originate effective work experience trajectory.

Keywords: Generalised empirical likelihood, bias-correction, informal job-search, wage, university graduates.
JEL Classifications: C01, C10, C21, J31, J64

ملخص

تدرس هذه الورقة تأثير البحث غير الرسمي عن عمل على الأجور لخريجي الجامعات في أول دخول لهم لسوق العمل وبعد الحصول على قدر ما من الخبرة. يتأثر البحث عن العمل غير الرسمي بالعوامل غير المرصودة ذات الصلة بالإنتاجية ، وبأثر القرناء، وأرباب العمل ، مما يؤثر على الأجور ويتسبب في التداخل في النماذج التجريبية. نحن نستخدم بيانات من مسح خريجي التعليم العالي 2012 في مصر والأردن ، ونطبق طريقة الإحتمالية التجريبية المعممة و طريقة العزوم المعممة وذلك للسيطرة على التداخل وتصحيح التحيز في التقديرات. تبين نتائجنا أجور فجزائية فى مصر تصل إلى 11٪ و 38٪ للبحث عن عمل غير رسمي في أول وظيفتين بعد التخرج ، على التوالي ، لكن لا يوجد دليل على تأثير مماثل في الأردن. نوصي أن تنشئ الجامعات مكاتب توظيفية لمساعدة الخريجين في البحث والعثور على وظائف مناسبة في مجال خبرتهم وخلق مسار خبرة عمل فعال.

I Introduction

Job-search methods are chosen by job-seeker based on effectiveness, costs, expected productivity, non-wage income in addition to potential wage offers, Holzer (1988). In the job-market usually a fraction of job-seekers use informal job-search to improve their job finding opportunities. It is estimated that 30-60 percent of workers find their jobs through informal job-search, Horváth (2014). Bentolila et al. (2010) find that informal contacts reduce unemployment duration by about 1 to 3 months on average. Informal job-search include search through contacts from family, friends, relative and neighbours. When transfer of information between employers and job seekers is not efficient search through informal methods could be a reliable option. However, wages could be affected for individuals with short experience and individuals at the beginning of their career, among whom university fresh graduates are a substantial group.

The impact of informal job-search on job-market outcomes has been an interesting topic in labour economics for decades. Controversial results, however, are found in the literature in labour economics and microeconometrics. Informal job-search might lead to a wage premium or a wage penalty. Wage penalty means that a worker that found a job through informal contacts is offered a wage below the average wage of similar workers who used formal methods. A wage premium is the opposite case, i.e when informal contact leads to higher wage on average. Informal job-search effectiveness depends on many factors such as job-market structure, personal skills, productivity and unemployment rate. Endogeneity might occur when wage is modelled if some of these factors are omitted, see Pellizzari (2010) and Tumen (2016). In this research we empirically examine the impact of informal job-search method on real wage for university graduates by applying the generalised empirical likelihood (GEL) method to control for endogeneity. Our analysis focuses on the wage in the first two jobs after graduation in the private sector only.

We use the Higher Education Graduates Survey 2012 (HEGS 2012) data that is published by the Economic Research Forum (ERF) in Egypt. The survey covers a sample of university graduates in Egypt and Jordan, both are Arab countries in the Middle East with well established higher education systems and job market traditions. A number of demographic characteristics for the graduates in the sample and their families, part of the school and university academic history of the graduates and part of their employment history up to four jobs after graduations are all covered in the questionnaire, in addition to information about the current job characteristics. In the survey the respondents answer questions about the type of each job and how s/he found it.

Our sample show that about one-third of the university graduates who worked in wage paid jobs in the private sector first after graduation moved to new wage paid jobs after about two years. About 70% of those graduates in Egypt and 32% in Jordan found their first job through informal contacts. The interesting pattern that is captured in our sample is that we got an estimate of a wage penalty that is about 11% for informal job-search in the first job after graduation in Egypt, which should make informal search an un-plausible option when searching for the second job. For the second job after graduation, however, the percentages are slightly higher in Egypt and lower in Jordan, see Table A1. This brought our interest to investigate whether this informal job-search wage penalty exists when university graduates search for the second job and what is the size and level is this penalty? In our analysis we use real wage after dividing nominal wage by inflation rate and utilise a number of recently developed estimation methods in econometrics to estimate the model.

This research is motivated by the concern about understanding the impact of informal job-search phenomenon in university graduates job-market in the Middle East. This provides a key for understanding the quality of jobs and experience that are provided at the beginning of the career for university graduates, which affect graduates skills, productivity and work trajectory in the future. The quality of the first job could be inferred in our sample by examining what methods that graduates use move to second job, where as shown in the literature review in Section II, that informal job-search through friends and family when associated with wage penalty indicate low job-seeker productivity and skills, and is likely associated with job dissatisfaction and over-educational mismatch. When a university graduate works in a suitable position at his/her area of expertise in the first job after graduation, even with using informal job-search, as found by Carroll and Tani (2015), it is less likely to have job dissatisfaction and over-educational mismatch problems occurred or face a wage penalty.

Selection on the first job after graduation depends more on academic performance in the university and the higher education institution from which the graduate awarded his/her qualification. Selection in the second job is more likely to depends on the characteristics of the applicant, experience, productivity and many other factors related to the first job but to a less degree on the university academic performance. However, our data does not allow for examining productivity and skills as well as first job quality and characteristics, although, that we are able to observe job-search methods and wage. Using informal job-search methods through family and friends rather than through expertises in the field to find the second job, accordingly, indicates lowering bargaining position for the graduates (job-seeker) and inefficiency in the job market, which is revealed as wage penalty. This indicates also that the graduate was incorrectly matched with the first job after graduation.

We utilise advanced econometric techniques to estimate the impact of informal job-search on wage and to overcome the endogeneity bias that is caused by omitted variables problem in our model. The generalised empirical likelihood (GEL) is an econometric estimation method that is based on moment condition, that used for instrumental variables estimation which controls for endogeneity similar to the generalised method of moments (GMM). Compared with GMM method, GEL method estimates have better small sample properties and asymptotic bias that does not grow with the number of moment conditions. For our analysis GEL method has a number of advantages due to the small sample that is available to us. To enhance the quality of our estimates we apply bias correction procedures for each of the GMM and GEL estimates. We discuss the choice of the instrumental variables in Section V. Our results show that a wage penalty of about 38% exists for informal job-search in the second job in Egypt. In Jordan neither wage penalty exists in first job after graduation nor in the second job.

The wage penalty in the second job indicates that many university graduates have lowering bargaining position when negotiating wage, possibly for weaknesses in required experience, productivity, or due to peers effect. Factors such as educational mismatch and satisfaction in the first job, which are unobserved in our data, should be considered in future research for their significant impact of the decision of re-using informal job-search. We suggest that universities should establish career offices to help graduates find suitable jobs at their area of expertise and have successful work experience and successful work trajectory in terms of productivity and income. The research is organised as follows: in Section II we present a literature review on the topic, then Section III contains a description of the econometric methods that is used and the computational process. The data and the results are presented in Sections IV and V, respectively. Finally, we end with the conclusions in Section VI.

II Review of the relevant literature

The role of friends, relatives and social network is investigated by Barthauer and Kauffeld (2018), Hensvik and Skans (2016), Dustmann et al. (2015), Carroll and Tani (2015) and Hensvik and Nordström Skans (2013) among many others. Stupnytska and Zaharieva (2015) argue that informal family and friends contacts are usually used by workers with low productivity and informal contact through professional network is largely used by more productive workers. Try (2005) uses the Norwegian Graduate Surveys between the years 1995 and 2000 to study job-search methods. He argue that using informal job-search method is restricted by the so-called social capital, which is defined as "sets of resources that inhere in family relations and in community social organisations, which individuals may benefit from when they want to achieve certain goals".

The strength of social capital differ between individuals and with age and depends on person's connections and the level of resources available to his/her connections. Leija et al. (2018), Cappellari and Tatsiramos (2015) and Cappellari and Tatsiramos (2010) find significant effect of employed friends on the probability of finding job. Plug et al. (2018) find that parents social capital has significant effect on children labour market input. On the other hand, contradicting with the above findings Bentolila et al. (2010) find that informal job-search increases over-educational mismatch, reduces job-satisfaction and affects both productivity and tuner. Holzer (1987) in studying the impact of informal job-search on black

American youth brought the attention that ethical and social barriers can also influence employers selection for the disadvantage of certain groups and recommend using formal methods for job-search and hiring.

Håkansson and Tovatt (2017) explain that fluctuations in the unemployment in the short run and the institutional change and the growing importance of social networks in the long run are two main factors that motivate the use of informal job-search. Calvó-Armengol and Jackson (2004) show that increasing cost of job-search can lead to drop-out from labour market and reduce employment prospectives. Informal job-search method speed-up matching with vacancies, cheaper in terms of cost and effort, provide better transform of information between employers and job-seekers and have acceptance in many communities, see Bentolila et al. (2010) and Holzer (1988). In Poland Piróg (2016) finds that graduates turned to more informal methods for finding jobs.

Transition form education to work is a turning point in life and a starting of a career for university graduates. This especial job market transition has attracted considerable attention among economists including Nilsson (2018), Olah et al. (2015), Salas-Velasco (2007), Pozzoli (2009), Adams (2007). Job-search method for university graduates is considered by many authors including Van der Klaauw et al. (2004), van der Klaauw and Van Vuuren (2010). Informal job-search is common among university graduates and usually used jointly with formal job-search methods. The advantages of informal job-search for university graduates are that it allows for better transition of information between job seekers and potential employers, which as explained by Carroll and Tani (2015), reduces over-educational job mismatch for jobs in their area of expertise. In the UK Andrews et al. (2001) show that in the labour market of youth the matching probability depends on the type of training and negatively with the size of the the number of job-seekers. Using Swedish data Kramarz and Skans (2014) find that the effect of social capital on graduates' first entry to the job-market is stronger for weak graduate position, i.e. low university results, and during high unemployment periods.

Li and Miller (2015) claim that job-search method has impact on over-educational mismatch for university graduates and state that in the Australian job-market of university graduates about 60% of the workers are incorrectly matched to their jobs. Educational mismatch as being argued by Mora (2010) and Ordine and Rose (2015) is associated with factors such as family background, personality, age, educational characteristics, which are all factor that are not disconnected from the social capital. Over-educational mismatch for university graduates, as discussed by Kler (2005), is associated with wage penalty. This discussion about the wage penalty associated with over-educational mismatch is extended in Wu and Wang (2018) and Sellami et al. (n.d.) among many others. Kalfa and Piracha (2015) empirically using Australian data, find that an over-educational mismatch is more likely to occur particularly among females. Diaz (2012) and Horváth (2014) examined the impact of informal contacts on the over-educational mismatch and supports this argument.

It is documented in the literature in labour economics that informal job-search might lead to either wage premium or wage penalty. The reasons of this wage disparity are not well understood. Pellizzari (2010) finds that wage penalties and wage premiums for jobs found through informal contacts in the European Union are equally alike to appear and depends on the efficiency of formal job-search methods. However, Pellizzari (2010) shows that informal job-search leads to better wage if it provides better channel to transmit information between job-seekers and employers and the wage differential disappear with tuner. Tumen (2016), on the other hand, assumes an existence of non-monotonicities in wage offers and recommend carefully controlling for unobserved heterogeneity in empirical models. Chen et al. (2018) on the other hand, find significant wage penalty among rural migrants in China and they explain that the penalty of informal job-search exists due to the trade-off that immigrants do between job quality and quicker entering the labour market.

Tumen (2016), additionally, shows that the fraction of job-seekers who search informally are affected by two factors, the unobserved heterogeneity in the cost of informal search and the effect of peers in the population. Informal job-search for finding job in the same neighbourhood might result in less wage offer. Zaharieva (2013) assumes that the strength of a worker's bargaining position and wage negotiation drives the informal job-search wage disparity. Peers effect, which is linked to the social capital, is more common among low wage earners and has negative effect on wage. Using data from the US and the EU, Bentolila et al. (2010)

empirically show that there is a wage discount ranges 2.5-3.5% for jobs that are found through informal contacts. Their analysis, however, does not differentiate university graduates.

In Egypt Antoninis (2006) uses data from the manufacturing sector and finds that using contacts such as friends and relatives has negative effect on wage, in contrast of using a referee individual with experience in the job field. Abdel-Mowla (2012), on the other hand, evaluates job-search behaviour among Egyptian youth and also examines the gender gap in labour market. Assaad et al. (2010) use duration model analysis to study transition from education to work for Egyptian graduates. Abdel-Mowla (2012) alarmed for a wide pessimism in the pool of job-seeker and high tendency to use informal search method due to lack of awareness about formal job-search methods. It has not come to our knowledge any similar research or relevant papers that examining informal job-search behaviour in the labour in Jordan.

III The econometric method

Our interest is to estimate the effect of using informal job-search on wage using the following linear dummy endogenous variable model model:

$$y = \alpha w + \mathbf{x}_1' \boldsymbol{\beta}_1 + u, \tag{1}$$

where y denotes the dependent variable, which is the log monthly real wage. w is a scalar represents the endogenous treatment variable which is an indicator of whether the given job, for which the real salary y is paid, is found through an informal job-search method. $\mathbf{x}_1$ is a vector of length $p-1$ that includes the intercept and exogenous independent variables. α is the coefficient that is associated with w and it is the coefficient of interest since it measures the impact of informal job-search on real wage. Let $\mathbf{x}' = [w, \mathbf{x}_1']$ and $\boldsymbol{\beta}' = [\alpha, \boldsymbol{\beta}_1']$ each be a vector of length p, containing the independent variables in the model and the coefficients, respectively. Accordingly, the model can be written as:

$$y = \mathbf{x}' \boldsymbol{\beta} + u. \tag{2}$$

Then one of the components of $\mathbf{x}$ is correlated with the error term. Using ordinary least squares (OLS) or maximum likelihood (ML) method will produce biased and inconsistent estimates. One option to reach consistent estimates is to use the two-stage least squares (2SLS) method, see Wooldridge (2010), which has a disadvantage of having finite sample problems and large standard errors. Alternatively, we can use an estimation method that relaxes some of the underlying restrictive assumptions to gain advantages in the estimates' small sample properties and asymptotic properties. In the following we present the moment based estimation method which enhance those properties for the estimates, which make them attractive of being utilised in this research.

Assume that there exists a vector of $q \geq p$ instrumental variables $\mathbf{z}$ that are correlated with $\mathbf{x}$ but not correlated with the error term, so that the following population moment conditions evaluated at the value of the true parameter vector $\boldsymbol{\beta}_0$ have an expected value $\mathbf{0}$ as follows:

$$E(\mathbf{z}(y - \mathbf{x}'\boldsymbol{\beta}_0)) \equiv E(g(\boldsymbol{\beta}_0)) = \mathbf{0}, \tag{3}$$

where $g(\boldsymbol{\beta}_0)$ denotes a $q \times 1$ vector of the population moment conditions evaluated at the true parameter vector. Accordingly, the population moment conditions are implied restrictions on functions of unknown parameters, $\boldsymbol{\beta}_0$, that can be approximated from the observed data. The moment conditions can then be used as bases for having a valid estimate for $\boldsymbol{\beta}_0$. In contrast to the estimation based on OLS, 2SLS and ML function, no complete restrictive parametric distribution assumptions are imposed. Moment based estimation methods, additionally, have less bias than 2SLS method. Comparison between these methods in the case of small samples is available in Andrews et al. (2017).

A realisation of the moment conditions from sample observations can be calculated easily at any value of the coefficient vector. Suppose for observation i in the sample, where $i = 1, 2, \cdots, n$, we can evaluate the moment conditions at a sub-optimal vector of parameter $\boldsymbol{\beta}$ as $g_i(\boldsymbol{\beta}) = \mathbf{z}_i(y_i - \mathbf{x}_i'\boldsymbol{\beta})$. For the sample let $\widehat{g}(\boldsymbol{\beta}) = n^{-1}\sum\limits_{i=1}^{n}(\mathbf{z}_i(y_i - \mathbf{x}_i'\boldsymbol{\beta}))$ be the sample equivalent of the population moment conditions at $\boldsymbol{\beta}$. A number of estimation methods in econometrics are based on moment conditions of this form, the easiest and the commonly used method in microeconometrics are the generalised method of moments (GMM) of Hansen (1982), the empirical likelihood of Owen (1988), the exponential tilting of Kitamura and Stutzer (1997) and continuously-updated GMM estimator of Hansen et al. (1996). The latter three methods are members of a wide and fast growing estimation approach known as the "**generalised empirical likelihood (GEL)**", see Imbens (2002) and Newey and Smith (2004). Additionally, they are also members and classified in a wider and more recently developed estimation approach known as an "**info-metric**" approach, which combines information theory with econometric, see Hall (2015) and Golan (2008). However, the length of literature in info-metric approach is shorter than that available in GEL approach. Accordingly, in this research we find that it is easier to interpret those estimators as generalised empirical likelihood GEL estimator as presented below.

Generalised method of moments estimator

The Generalized Method of Moment (GMM) estimator is defined as:

$$\widehat{\boldsymbol{\beta}}_{GMM} = agumin_{\boldsymbol{\beta} \in \boldsymbol{B}} \widehat{g}(\boldsymbol{\beta})' M_N \widehat{g}(\boldsymbol{\beta}). \tag{4}$$

where M_N is a $q \times q$ weighting matrix that is assumed to be positive semi-definite and converges in probability to a positive definite matrix of constants M. The GMM estimator finds the optimum choice of the weighting matrix, M_N, that leads to obtain an optimal $\boldsymbol{\beta}$ estimate, denoted as $\widehat{\boldsymbol{\beta}}_{GMM}$. However, the choice of M_N affects the asymptotic variance of the estimate, see Hall (2015), and leads to minimum asymptotic variance. GMM estimates equals 2SLS estimates when $M_N = (n^{-1} \sum_{i=1}^{n} (\mathbf{z}_i \mathbf{z}_i'))^{-1}$ under conditional homoscedasticity of u_i on z_i.

It is preferred, however, in applied econometrics to use the two-step GMM method of Hansen (1982), where in the first-step a sub-optimal weighting matrix is used to facilitate the second step estimation. A better option, although, computationally more tedious to use is the so-called continuously-updated GMM, which is similar to the two-step GMM except that in the second step the estimator of the coefficient vector is achieved after iteratively updating W_N and re-minimising the objective function until no obvious difference in value of the estimates is seen, i.e. until convergence. A common choice is to estimate the weighting matrix from the sample moment condition using the formula:

$$M_N = \left[n^{-1} \sum_{i=1}^{n} g_i(\boldsymbol{\beta}) g_i(\boldsymbol{\beta})' \right]^{-1}. \tag{5}$$

So, in the two-step GMM and the continuously-updated GMM the weighting matrix M_N in the second step (each iteration) is updated using the moment condition from the former step (iteration). In this research we use the continuously-updated GMM for which we use the abbreviation GMM for brevity.

The first-order conditions for the minimisation of the GMM objective function is that

$$\left[\frac{\partial g_i(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}'} \right]' M_N \widehat{g}(\boldsymbol{\beta}) \mid_{\beta=\beta_{GMM}} \equiv G_i' M_N \widehat{g}(\boldsymbol{\beta}) \mid_{\beta=\beta_{GMM}} = \mathbf{0}, \tag{6}$$

which is what implied by the population moment conditions. At the GMM estimate we have $\widehat{G}_i = \frac{\partial g_i(\widehat{\beta}_{GMM})}{\partial \widehat{\beta}_{GMM}'}$ a $q \times p$ matrix of the first order derivatives. In the over-identification case the GMM is considered as a function in the identifying restriction part, which is the part that uses the information in the sample.

Let $\widehat{G} = n^{-1} \sum_{i=1}^{n} \widehat{G}_i$, $S = n^{-1} \sum_{i=1}^{n} (\mathbf{z}_i \mathbf{z}_i')$ and M_N be the optimal weighting matrix after convergence in the second step. The GMM estimated coefficients have a covariance matrix estimate that is given as:

$$\mathbf{Var}(\widehat{\boldsymbol{\beta}}_{\mathbf{GMM}}) = n^{-1} \left(\widehat{G}' M_N \widehat{G} \right)^{-1} \widehat{G}' M_N S M_N \widehat{G} \left(\widehat{G}' M_N \widehat{G} \right)^{-1} \tag{7}$$

The disadvantages of the GMM method are its limited distributional approximation and weak finite sample properties of its estimates. Imbens (2002) finds that GMM asymptotic bias increases linearly with additional moment conditions, i.e. when adding instrumental variables in the model. GMM bias estimate, as driven by Newey and Smith (2004), takes the following formula:

$$\widehat{Bias}(\widehat{\boldsymbol{\beta}}_{GMM}) = n^{-1} \begin{bmatrix} -\widehat{H} \left(\widehat{a} + \sum_{i=1}^{n} \widehat{G}_i \widehat{\psi}_i^{\beta} / n \right) - \widehat{\Sigma} \sum_{i=1}^{n} \widehat{G}_i' \widehat{P} \widehat{g}_i / n \\ -\sum_{i=1}^{n} \widehat{\psi}_i^{\beta} \widehat{g}_i' \widehat{P} \widehat{g}_i / n - \widehat{H} \sum_{j=1}^{p} \widehat{\Omega}_{\beta_j} \left(\widehat{H}_W - \widehat{H} \right)' e_j \end{bmatrix}, \tag{8}$$

where $\widehat{\Omega} = n^{-1}\sum\limits_{i=1}^{n} g_i(\boldsymbol{\beta})g_i(\boldsymbol{\beta})' \mid_{\beta=\beta_{GMM}}$, $\widehat{\Omega}_{\beta_j} = \frac{\partial \widehat{\Omega}}{\partial \beta_j}$, $\widehat{\Sigma} = \left(\widehat{G}'\widehat{\Omega}^{-1}\widehat{G}\right)^{-1}$, $\widehat{H} = \widehat{\Sigma}\widehat{G}'\widehat{\Omega}^{-1}$, $\widehat{\psi}_i^{\boldsymbol{\beta}} = -\widehat{H}\widehat{g}_i$, $\widehat{P} = \widehat{\Omega}^{-1} - \widehat{\Omega}^{-1}\widehat{G}\widehat{\Sigma}\widehat{G}'\widehat{\Omega}^{-1}$ and finally $\widehat{H}_W = \left[\widehat{G}'\widehat{W}^{-1}\widehat{G}\right]^{-1}\widehat{G}'\widehat{W}^{-1}$ and e_j is a unit vector. $\widehat{a}$ is a $q \times 1$ vector of zeros since for each element $\widehat{a}_j$ we have that:

$$\begin{aligned} \widehat{a}_j &= 0.5tr\left(\widehat{\Sigma}n^{-1}\sum_{i=1}^{n}\frac{\partial^2 g_{ij}(\widehat{\boldsymbol{\beta}}_{GMM})}{\partial\boldsymbol{\beta}\partial\boldsymbol{\beta}'}\right), \qquad j = 1, 2, 3, ..., q \qquad (9) \\ &= 0.5tr(\widehat{\Sigma}.0) = 0. \end{aligned}$$

The bias corrected GMM estimate is accordingly equals $\widehat{\boldsymbol{\beta}}^{c}_{GMM} = \widehat{\boldsymbol{\beta}}_{GMM} - \widehat{Bias}(\widehat{\boldsymbol{\beta}}_{GMM})$.

Generalised empirical likelihood estimators

Empirical likelihood (EL) is a term coined by Art Owen in his seminal paper Owen (1988) to describe an estimation method that combines between the advantages of nonparametric methods and maximum likelihood method. The main advantage of the EL method is that no distributional assumptions are imposed in the likelihood function. In return, EL method uses nonparametric specification to approximate the unknown data distribution function, accordingly, it is known also as the nonparametric maximum likelihood (NPML) method. The development of EL method for regression analysis is provided in Owen (1991) and Chen and Van Keilegom (2009) and for moment conditions models in Owen (1990), Bravo (2007) and Kitamura (2007).

Bravo (2007) lists some of the advantages of EL method compared with conventional fully parametric estimation methods in econometrics such as maximum likelihood and least squares. EL shape of confidence regions is determined by the data and obey range restrictions of the estimates, for example non-negative variance, confidence range for probability estimates in the $[0, 1]$ and correlation confidence intervals in the $[-1, +1]$ range. This in addition to that EL method estimates have less second order bias despite that its first order asymptotics are similar to that for GMM method, see also Newey and Smith (2004) for more details.

The approach followed in EL estimation method, and later in GEL class of estimators, is to search for an estimator for $\boldsymbol{\beta}$ after modifying the sample empirical distribution function weights, n^{-1}, that is given for each observation in the sample to new weights denoted as π_i under the conditions that $\sum_{i=1}^{n} \pi_i = 1$ and $\pi_i \geq 0$. A crucial assumption about empirical likelihood weights is that no ties exists in π_i, that is for any two different observations in the sample, denote them i and j, we have $\pi_i \neq \pi_j$. The estimate of $\boldsymbol{\beta}$ and the set of the probability weights $\pi_1, \pi_2, \cdots, \pi_n$ are given by maximising the empirical log-likelihood objective function that is given as:

$$l_{NPML} = \sum_{i=1}^{n} log(\pi_i), \tag{10}$$

subject to $\sum_{i=1}^{n} \pi_i g_i(\boldsymbol{\beta}) = \mathbf{0}$ and the conditions above. This optimisation problem incorporates maximising over $p + n$ parameters which might appear tedious computationally. To reduce the computation cost it is suggested to use a profile empirical likelihood function by keeping $\boldsymbol{\beta}$ fixed at a given value and maximise over $\pi_1, \pi_2, \cdots, \pi_n$. However, Since the optimisation is constrained, using the Lagrangian is straight forward as presented below in the context of GEL framework.

The GEL estimator of the coefficient vector $\boldsymbol{\beta}$ is given as:

$$\widehat{\boldsymbol{\beta}}_{GEL} = arg \quad \underset{\boldsymbol{\beta} \in \boldsymbol{B}}{min} \underset{\lambda \in \widehat{\boldsymbol{\Lambda}}_{\boldsymbol{n}}(\boldsymbol{B})}{sup} \quad \sum_{i=1}^{n} \rho\left(\lambda' g_i(\boldsymbol{\beta})\right) \tag{11}$$

where $-\infty < \lambda' g_i(\boldsymbol{\beta}) < 1$, the function $\rho(v) = \ln(1 - v)$ for EL estimate and $\rho(v) = -e^v$ for ET estimate. Both are normalised so that $\partial^j \rho(v)/\partial v^j = -1$ for $j = 1, 2$. If $\rho(v)$ is quadratic function we reach the continuously-updated GMM estimator of Hansen et al. (1996), see Kitamura (2007) for more information. The solution of the objective function in Eq 11 is a saddle point optimisation in which the p coefficients in $\boldsymbol{\beta}$ are found to minimise the objective function for give λ, and then an updated values of the q Lagrange multipliers are found so that to maximise the objective function for given $\boldsymbol{\beta}$. The first is denoted as the outer routine and the latter is denoted as the inner routine. Computationally, the optimisation routines iterate between updating these two estimates until convergence. The optimal empirical likelihood weights are then computed using the formula in Eq 14 below. Empirically, this procedure is very sensitive to the choice of starting values and computationally difficult to manage.

In this research we find that the duality of the function in Eq 11 is easier to manage computationally. The duality problem takes the following form:

$$\widetilde{\boldsymbol{\beta}}_{GEL} = \underset{\beta \in \boldsymbol{B}, \pi_1, \pi_2, \cdots, \pi_n}{argmin} \sum_{i=1}^{n} h\left(\pi_i\right), \qquad \text{subject to:} \tag{12}$$

$$\sum_{i=1}^{n} \pi_i g_i(\boldsymbol{\beta}) = \mathbf{0}, \qquad \sum_{i=1}^{n} \pi_i = 1, \quad \text{and} \quad \pi_i \geq 0,$$

where, $h\left(\pi\right) = -ln(\pi)$ for EL estimator and $h\left(\pi\right) = \pi ln(\pi)$ for ET estimator, are convex functions that can directly be optimised using conventional software.

For estimating the GEL models in this research we utilise the package `alabama` in the computer package software R, the codes for the estimation process and tests are developed by the author. We utilised the function `constrOptim.nl` which applies the so-called Augmented Lagrangian Adaptive Barrier Minimization Algorithm in which a constrained optimisation problem is replaced by a series of non-constrained optimisations, see Lange (2004), but with mining the Lagrange multiplier. This procedure reduced the computation cost for the objective function in Eq 12 and allowed us to mitigate the difficulties that associated with time and the starting values. However, following this procedure came with a cost that the Lagrange multiplier vector is not produced due to the optimisation penalty, and accordingly to perform LM test an additional step is needed.

For a given coefficient vector $\widetilde{\boldsymbol{\beta}}_{GEL}$ that is estimated using the duality GEL in Eq 12 let $\widetilde{g}_i = g_i(\widetilde{\boldsymbol{\beta}}_{GEL})$ be the moment condition evaluated at the duality estimate. We estimate the associated Lagrange multipliers as follows:

$$\widetilde{\lambda} = arg \underset{\lambda \in \widetilde{\boldsymbol{\Lambda}}_{\boldsymbol{n}}(\widetilde{\boldsymbol{\beta}}_{\boldsymbol{GEL}})}{max} \quad n^{-1} \sum_{i=1}^{n} \rho\left(\lambda' \widetilde{g}_i\right). \tag{13}$$

This is equivalent to the inner routine in Eq 11. The starting values of λ need to be carefully chosen for EL and ET methods separately, see Newey and Smith (2004) for more details.

The weights are updated using the formula:

$$\widetilde{\pi}_i = \frac{\rho_1\left(\widetilde{\lambda}'\widetilde{g}_i\right)}{\sum\limits_{i=1}^{n}\rho_1\left(\widetilde{\lambda}'\widetilde{g}_i\right)} \tag{14}$$

Our empirical results show no difference in the values of $\widetilde{\pi}_i$ and the calculated values of Wald test and LR test before and after applying the maximisation problem in Eq 13, i.e. no update accrues in the values of $\widetilde{\pi}_i$ after applying the optimisation in Eq 14.

Newey and Smith (2004) show that the bias in the GET estimator of $\widetilde{\boldsymbol{\beta}}$ does not grow with the number of moment conditions and has a general formula that is given as:

$$\widehat{Bias}(\widetilde{\boldsymbol{\beta}}_{GEL}) = n^{-1}\left[-\widetilde{H}\left(\widetilde{a} + \sum_{i=1}^{n}\widetilde{\pi}_i\widetilde{G}_i\widetilde{\psi}_i^{\beta}\right) - \left(1+\frac{\rho_3}{2}\right)\sum_{i=1}^{n}\widetilde{\pi}_i\widetilde{\psi}_i^{\beta}\widetilde{g}_i'\widetilde{P}\widetilde{g}_i\right], \tag{15}$$

where $\widetilde{G}_i = \frac{\partial g_i(\beta)}{\partial \beta'} \mid_{\beta=\widetilde{\beta}_{GEL}}$, $\widetilde{\Omega} = n^{-1}\sum\limits_{i=1}^{n} g_i(\boldsymbol{\beta})g_i(\boldsymbol{\beta})' \mid_{\beta=\widetilde{\beta}_{GEL}}$, $\widetilde{\Omega}_{\beta_j} = \frac{\partial\widetilde{\Omega}}{\partial\beta_j}$, $\widetilde{\Sigma} = \left(\widetilde{G}'\widetilde{\Omega}^{-1}\widetilde{G}\right)^{-1}$, $\widetilde{H} = \widetilde{\Sigma}\widetilde{G}'\widetilde{\Omega}^{-1}$, $\widetilde{\psi}_i^{\beta} = -\widetilde{H}\widetilde{g}_i$, $\widetilde{P} = \widetilde{\Omega}^{-1} - \widetilde{\Omega}^{-1}\widetilde{G}\widetilde{\Sigma}\widetilde{G}'\widetilde{\Omega}^{-1}$ and $\rho_3 = 2$ to eliminate the second moment bias in GEL estimators. $\widetilde{a}_j = 0$ as in the above. The bias corrected GEL estimate is accordingly equals $\widetilde{\boldsymbol{\beta}}_{GEL}^{c} = \widetilde{\boldsymbol{\beta}}_{GEL} - \widehat{Bias}(\widetilde{\boldsymbol{\beta}}_{GEL})$.

IV The data

The Higher Education Graduates Survey 2012 (HEGS 2012) is conducted by the Economic Research Forum (ERF) - a regional organisation that is based in Cairo, Egypt - with association with Cairo Demographic Centre and the Department of Statistics at The Hashemite Kingdom of Jordan. A random sample of university graduates in the disciplines of accounting, business administration, and information sciences is taken from graduates the each country. The sample design focuses on those disciplines due to the high heterogeneity in the job-market outcome of all university graduates. The respondents age between 25 to 40 years old and the sample was restricted to graduates in the fifteen years preceding the survey. For each respondent information about; socio-economic status, household characteristics, education history, work experience, employment history and mobility is collected. The number of respondents in Egypt is 1710 and in Jordan is 1873 individuals.

Table 1 presents the summary statistics for the variables that are used in the model for the individuals covered in the sample. The percentage of males is slightly lower in the sample of Jordan. The average graduation grade is highly different, where in Egypt the average grade is 66.58 with only 45% of the graduates in the sample with at least good classification. Compared with Jordan the average graduation grade is 72.14 with 74.8% of the graduates in the sample having at least good classification. The major difference between graduates in Egypt and Jordan is in the proportion of those graduated from universities that use English language as medium of instruction, where 82.1% of the graduates in Jordan completed their undergraduate degree in English compared with only 15.7% in Egypt.

The proportions of graduates who worked in wage paid jobs in the first position after graduation are 52% and 59.5% in Egypt and Jordan, respectively. Other job types include self-employed, family business, housewife, voluntary work and other options. The proportion of graduates who moved from a first wage paid job to a second wage paid job are 20% and 21% in Egypt and Jordan, respectively. This counts about 38.4% and 36% of workers in first wage paid jobs. The average duration for a university graduate in the sample to a first wage paid job is 3.6 month in Egypt and 6.7 month in Jordan. However, the average duration between starting the first job and starting the second job is 26.8 month in Egypt compared with 36.1 in Jordan. The distributions of the percentages of job moves from position to another and the average age at the first job are almost similar in the two countries. The major differences are in the duration between the starting of the first two jobs. The data does not allow for measuring the duration of the unemployment spell, if any, before starting the second job. In Jordan the proportion of graduates who used informal job-search method is less than half the proportion in Egypt but difference in real salary seems wider in Egypt than in Jordan.

Table 1: Summary Statistics

		Egypt		Jordan	
		Mean	**SD**	**Mean**	**SD**
Sample	n	1710		1539	
	Male	0.747	0.435	0.674	0.469
	Age	28.935	4.225	30.327	4.379
	married	0.476	0.500	0.481	0.500
	G. grade	66.580	8.645	72.137	7.146
	Good	0.449	0.498	0.748	0.434
	English	0.157	0.364	0.821	0.384
	Wage paid job				
	1^{st}	0.519	0.500	0.595	0.491
	2^{nd}	0.199	0.400	0.214	0.411
	3^{rd}	0.067	0.250	0.051	0.221
	4^{th}	0.018	0.133	0.011	0.105
	Private 1	0.443	0.497	0.398	0.490
	Private 2| Private 1	0.318	0.466	0.304	0.460
First Job[1]	n	757		612	
	Male	0.790	0.408	0.712	0.453
	Age	22.589	1.879	22.529	2.235
	Duration	3.695	5.389	6.706	11.768
	l(salary 1)|	6.296	0.692	5.740	0.538
	Informal search 1	0.694	0.461	0.296	0.457
	movers	0.406	0.491	0.402	0.491
	l(salary 1)|informal 1	6.255	0.673	5.778	0.586
Second Job[1]	n	241		186	
	Male	0.896	0.306	0.780	0.416
	Age	24.639	2.420	25.527	2.769
	Duration	26.810	21.753	36.124	29.611
	log real salary 2	6.663	0.718	6.033	0.610
	Informal search 2	0.714	0.453	0.253	0.436
	movers	0.407	0.492	0.269	0.445
	l(salary 2)|informal 1	6.603	0.700	5.999	0.633
	l(salary 2)|informal 1 & 2	6.641	0.673	5.999	0.648

[1] Private sector only.

V The results

Table 2 reports the coefficients of the ordinary least squares regression and the two-stage least squares regression that are estimated for Equation 2. Panel A reports the coefficients that are estimated for the first wage paid job after graduation and Panel B presents the estimated coefficients for the second wage paid job after graduation. The number of sample observations after removing the observations with missing values in any of the covariates or the instrumental variables are presented in the last row of each panel. The results in Panel A indicate that being employed through informal job contact has wage penalty in Egypt only, with no enough evidence that the endogeneity problem exists in the model. Wu-Huasman test is applied for the 2SLS method estimates in Panel A, in addition to the control function approach test, see Wooldridge (2010), which both show that the non-existence of endogeneity problem hypothesis has been accepted.

Based on the endogeneity tests we conclude that the coefficients that are listed for the OLS regressions in Panel A for Egypt and Jordan are valid. Informal job-search, accordingly, has a wage penalty of about 11% on average in Egypt, and has no significant effect on wage in Jordan. Other significant variables in the model are, academic grade, male and firm size, are having positive effect on real wage. However, return of good grade is higher in Jordan and gender discrimination is lower. Additionally, work during university study has negative effect on real wage after graduation in Jordan but has insignificant effect in Egypt. The model shows that the elasticity between the wage in the second job and end salary in the first job is 0.41 only.

In contrast to the models that are reported in Panel A, the tests of no endogeneity problem are rejected in Panel B for Egypt. For Jordan, however, there is no enough evidence that finding the second job after graduation in the private sector through informal job-search method impacts real wage. This latter result about Jordan is consistent with the finding about the first job that is reported in Panel A. For Egypt the endogeneity tests indicate that the decision to use informal search method to find a second job is correlated with the unobserved confounders that impact also the error term. Example of some of the unobserved confounders that might affect our model for the second job after graduation in Egypt are cognitive skills, ability, bargaining position, first job characteristics, job market characteristics and many other variables. Although, that the OLS coefficient is positive and insignificant the 2SLS coefficient is -0.462 and significant at 5% level of significance. This indicates that if a graduate, after making some experience in the first job after graduation decided to move to a second job and used informal job-search method, s/he will probably face very high wage penalty compared with a similar graduated who didn't use informal job-search method. This penalty, as being estimated by the 2SLS, reach on average a 37% less wage.

The 2SLS produce estimates that are consistent but biased in the same direction of the biased OLS estimates, see Murray (2006). Accordingly, we suspect that the effect of informal job-search that is reported in Table 2 under-estimates the true effect. For examining this argument we use the GMM method and the GEL method and perform the bias correction procedure as described above. The simulation studies of Newey et al. (2005) and Andrews et al. (2017) emphasis that EL estimates have the lowest asymptotic bias among the three moment based estimators that are used in this research. The GEL method estimates generally have better second order asymptotic properties and higher reliability in small samples than the 2SLS method.

However, all used method are sensitive to the choice of the instrumental variables. Using weak or too many instruments can cause more bias in the results and have sever consequences to our model. So, we managed to make the number of instrumental variables small and carefully choose the variables that serve as IV's in the model based on the suggestions from the econometric theory and the empirical model that we estimate. After searching for valid and strong instruments in our data and the World Bank Data, we reached at 5 sets of instrumental variables that are used and examined in the following tables.

In all sets the main and the strongest IV variable is a dummy that indicates whether the informal job-search method was used to find the first job after graduation. We find that using informal job-search to find the first job after graduation can serve as valid instrument as it is, logically, has no impact on the second job wage. On the other hand, using the informal job-search in the first job increases the likelihood of using informal job-search to find the second job by about 35

Table 2: OLS regression and two-stage least squares estimates of the return to informal job-search for the first and second jobs after graduation

	Egypt				**Jordan**			
Panel A: First job after graduation[1]								
	OLS		2SLS[3]		OLS		2SLS[3]	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Informal search 1	-0.120**	(0.054)	0.207	(0.425)	0.072	(0.046)	0.183	(0.274)
Good	0.106**	(0.049)	0.105**	(0.051)	0.218***	(0.050)	0.186***	(0.066)
Male	0.475***	(0.066)	0.464***	(0.071)	0.169***	(0.048)	0.175***	(0.050)
Age 1	0.010	(0.014)	0.007	(0.016)	0.002	(0.009)	-0.002	(0.012)
English	0.087	(0.063)	0.114	(0.076)	0.039	(0.053)	0.030	(0.057)
No. of employees 1	0.058***	(0.007)	0.061***	(0.008)	0.042***	(0.009)	0.039***	(0.010)
Training	0.069	(0.054)	0.087	(0.062)	-0.089	(0.145)	-0.225	(0.158)
Work during study	-0.009	(0.036)	-0.025	(0.038)	-0.159	(0.054)***	-0.126	(0.070)*
Intercept	5.468***	(0.351)	5.343***	(0.410)	5.214	(0.229)	5.290***	(0.298)
F (p-value)	17.25	(0.000)			8.03	(0.000)		
R-squared	0.155				0.084			
End.test (p-value)			0.69	(0.408)			0.09	(0.763)
t_{v1} (p-value)			-1.12	0.265			-0.30	0.765
Durbin (score)[1]			0.69	0.408			0.04	0.835
Wu-Hausman[1]			0.69	0.411			0.04	0.836
n	712		712		612		612	
Panel B: Second paid job after graduation[2]								
	OLS		2SLS[4]		OLS		2SLS[4]	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Informal search 2	0.026	(0.084)	-0.462**	(0.207)	0.072	(0.088)	-0.240	(0.217)
Good	0.209***	(0..079)	0.240***	(0.085)	0.121*	(0.079)	0.118*	(0.079)
Male	0.627***	(0.129)	0.607***	(0.161)	0.300***	(0.088)	0.321***	(0.094)
Age 2	-0.011	(0.021)	-0.002	(0.021)	0.032***	(0.018)	0.034***	(0.018)
English	-0.088	(0.101)	-0.109	(0.105)	0.039	(0.081)	0.016	(0.082)
End salary 1	0.385***	(0.0598)	0.413***	(0.066)	0.377***	(0.105)	0.382***	(0.106)
Duration 12	0.159**	(0.070)	0.114*	(0.066)	0.061	(0.086)	-0.048	(0.106)
Private 1	-0.550***	(0.179)	-0.611***	(0.187)	-0.022	(0.139)	-0.100	(0.149)
Intercept	3.870***	(0.555)	4.030***	(0.608)	2.522***	(0.548)	2.662	(0.585)
F	11.76		9.18		11.43		8.52	
F (p-value)	0.000		0.000		0.000		0.000	
R-squared	0.278		0.195		0.291		0.220	
End.test (p-value)			7.68	(0.006)			2.34	(0.126)
t_{v1} (p-value)			3.05	(0.003)			1.67	(0.097)
n	224		224		206		206	

[1] The variables: *Age 1* is age at the start of first job, *No. of employees 1* is log the number of employees in the workplace in the first job, *Training* is whether the graduate attended any job training course during university, *Work during study* is whether the graduate worked for income during university study.

[2] *Age 2* is age at the start of second job, *End salary 1* log real salary *Duration 12* the period between the start of job 1 and job 2, *Private 1* is whether the first job was in the private sector.

[3] Instrumental variables used are: house ownership dummy, father work in private sector, log duration in months of the unemployment spell between graduation and starting the first job.

[4] Instrumental variables used are: a dummy of whether the first job was through found informal search, whether group tutoring was used during university study, whether the father is self-employed.

[5] Robust standard errors are reported for all coefficients.

percentage point, see the results of the reduced form 2SLS regression in Table A2. Using informal job-search in the two jobs might indicate weak skills and low bargaining position. The strong correlation between using the informal job-search variables in the first and second jobs render the correlation between this instrumental variable and the error term not to be magnified in the model. This latter correlation might exist due to the common unobserved confounders that affect the wage in the second job propensity to depend more on informal job-search. Then informal job-search in the first job serve as valid and strong instrument in the model as shown by the results of the first regression in Table A2, the robust weak IVs tests in Table A3 and the over-identification restrictions in Tables A3 to A6.

Other IV variables are as follows: in IV1 set we add whether the father is self-employed and log the unemployment spell before the first job, i.e. the duration spell after graduation and before working in the first job. IV1 set is the same set that is used in the models in Table 2 and is treated as a benchmark model for being the set with average validity and strength for its variables relative to other sets, based on the values of the over-identification tests and robust weak-IV tests results. In IV2 set we substituted the first unemployment duration variable by the secondary school grades grade variable. In IV3 set we add the country annual unemployment rate to the IV variables in the set IV1. In the set IV4 we use informal job-search in the first job dummy and the secondary school dummy only. The last set, IV5, contains all the IV variables that are used in the above sets.

The coefficients of the instrumental variables in the reduced form 2SLS regression are reported in Table A2. Father self-employment and secondary school grade decrease the propensity to use informal job-search by about 25 and 47 percentage points, respectively, and both are moderately significant. Having a longer unemployment spell after graduations increases the propensity to use informal job-search by about 8 percentage points only. All the instrument in the reduced form regression, except annual unemployment rate, have impact on the endogenous variable. Additionally, F test statistics for collectively excluding the instruments that are reported in Table A2 are high and significant for all IV set. Additionally, the over-identification test results show that all the IV sets are valid. However, weak instruments test that is reported in Table A3 show that IV3 and IV5 failed the test at 5% level of significant and for 10% of OLS relative bias, see Olea and Pflueger (2013) for details about the test structure and statistics. The effect that is estimated using IV3 and IV5 sets is lower than the estimated effect when other sets are used. This agrees with the patten that is explained by Murray (2017), where weak instruments increase the bias of the 2SLS estimates in the direction of the OLS estimates.

The coefficient of informal job-search variable that are estimated using the moment based method in Section III with robust standard error and the over-identification test results are reported in Tables 3 and 4. Table 3 presents the estimates before correcting the bias with the first panel presents the 2SLS estimates. For IV1 and IV4 the over-identification test results are very close although that the robust test of weak instruments in Table A3 show very different degree of strength of the IV variables, with IV4 set extremely stronger than IV1 set. For IV2 and IV4, which are the two sets that are highly accepted based on the over-identification tests and the robust weak IV's test, both the GMM and the 2SLS estimates are very close.

The effect that is estimated using the EL and ET method exceeds that is estimated by the 2SLS and GMM methods. As shown and examined by Andrews et al. (2017), GEL bias for linear mode has an opposite sign to the 2SLS bias. Accordingly, in contrast to the estimates by 2SLS, we believe that EL and ET estimates slightly over-estimate the informal job-search. The bias corrected coefficients that are reported in Table 4 show that EL and ET estimates are very close particularly for IV2 set and IV4 set. The informal job-search coefficient is estimated about -0.48, which is equivalent to a 38% wage penalty. The robust standard error show that the effect is significant at 5% level of significance. Over-identification tests shows the the moment condition is reached by IV2 set better, accordingly we believe the effect that is estimated using IV2 set by the EL method be might by the closer to the true effect.

Table 3: GMM and GEL estimates of the impact of informal job-search on real wage[1,2,3]

	IV1	IV2	IV3	IV4	IV5
2SLS					
$\widehat{\alpha}$	-0.462**	-0.478**	-0.446**	-0.4759	-0.407**
$se(\widehat{\alpha})$	(0.207)	(0.218)	(0.207)	(0.247)	(0.196)
Hansen J statistic	1.34	0.49	3.46	0.49	4.42
Hansen J p-value	0.511	0.782	0.326	0.485	0.353
GMM model					
$\widehat{\alpha}$	−0.418**	−0.485**	−0.441**	−0.485**	−0.390**
$se(\widehat{\alpha})$	(0.200)	(0.218)	(0.202)	(0.247)	(0.191)
Hansen J	1.39	0.49	3.46	0.49	4.4
Hansen J p-value	0.500	0.784	0.325	0.486	0.351
EL model					
$\widehat{\alpha}$	−0.445**	−0.503**	−0.499**	−0.502**	−0.470**
$se(\widehat{\alpha})$	(0.204)	(0.222)	(0.204)	(0.250)	(0.199)
LM test statistics	1.45	0.47	3.73	0.47	4.89
	0.485	0.791	0.292	0.493	0.299
Wald test statistics	1.45	0.47	3.73	0.47	4.89
	0.485	0.791	0.292	0.493	0.299
LR test statistics	1.43	0.48	3.68	0.48	4.77
	0.489	0.788	0.298	0.49	0.311
ET model					
$\widehat{\alpha}$	−0.449**	−0.496**	−0.500**	−0.492**	−0.465**
$se(\widehat{\alpha})$	(0.204)	(0.220)	(0.205)	(0.248)	(0.196)
LM test statistics	1.39	0.49	3.47	0.44	4.43
	0.499	0.784	0.325	0.509	0.351
Wald test statistics	1.47	0.48	3.77	0.48	5.14
	0.479	0.788	0.288	0.489	0.273
LR test statistics	1.44	0.48	3.66	0.43	4.89
	0.486	0.787	0.301	0.511	0.299
over-id res.	2	2	3	1	4

[1] Robust standard errors in parentheses.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.

Table 4: Bias-corrected GMM and GEL estimates of the impact of informal job-search on real wage[1,2,3]

BC-GMM	IV1	IV2	IV3	IV4	IV5
$\widehat{\alpha}$	-0.442^{**}	-0.512^{**}	-0.480^{**}	-0.494^{**}	-0.438^{**}
$se(\widehat{\alpha})$	(0.201)	(0.220)	(0.204)	(0.248)	(0.194)
Hansen J stat	1.45	0.52	3.54	0.500	4.53
Hansen J p-value	0.484	0.769	0.316	0.481	0.339
BC-EL					
$\widehat{\alpha}$	-0.432^{**}	-0.482^{**}	-0.485^{**}	-0.484^{*}	-0.457^{**}
$se(\widehat{\alpha})$	(0.203)	(0.220)	(0.202)	(0.249)	(0.198)
LM test statistics	1.43	0.46	3.7	0.46	4.83
	0.489	0.793	0.296	0.496	0.305
Wald test statistics	1.46	0.48	3.78	0.48	4.9
	0.482	0.786	0.286	0.487	0.297
LR test statistics	1.43	0.48	3.68	0.48	4.77
	0.489	0.788	0.298	0.490	0.311
BC- ET					
$\widehat{\alpha}$	-0.440^{**}	-0.484^{**}	-0.492^{**}	-0.479^{*}	-0.461^{**}
$se(\widehat{\alpha})$	(0.203)	(0.219)	(0.204)	(0.247)	(0.196)
LM test statistics	1.38	0.48	3.45	0.43	4.42
	0.503	0.786	0.327	0.511	0.353
Wald test statistics	1.48	0.49	3.79	0.49	5.16
	0.478	0.781	0.285	0.483	0.271
LR test statistics	1.44	0.48	3.66	0.43	4.89
	0.486	0.787	0.301	0.511	0.299
over-id res.	2	2	3	1	4

[1] Robust standard errors in parentheses.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.

VI Conclusions

This research examined the impact of using informal job-search method on wage for university graduates in the disciplines of accounting, business administration, and information sciences in Egypt and Jordan. We used data from Higher Education Graduates Survey in 2012 and examined the effect using dummy endogenous variable model. The generalised empirical likelihood method is used to estimate the model and a bias correction procedure is applied to enhance the quality of the estimates. Our result demonstrate that using informal job-search method to find the first job after graduation has negative effect on real wage in Egypt but has no effect on real wage in Jordan. University graduates in the sample from Egypt who found their first job through informal contacts paid a penalty of about 11% less wage than similar graduates who found their jobs through formal contacts. For the first job the decision to use informal job-search method is exogenous to wage and the effect is captured directly using the ordinary least squares method.

For the second job after graduation, however, the decision to use informal job-search is endogenous to wage, which makes the ordinary least squares method estimates biased and inconsistent. For university graduates in Egypt using informal job-search methods and finding the second job through friends and relatives contacts is correlated with unobserved factors in the model such as productivity, skills, personal and employer characteristics and job-market structure that also affect wage. After using the generalised empirical likelihood estimation method and applying a bias correction procedure, we find that the wage penalty of using the informal job-search for the second job reaches 38%.

The findings in this research are interesting for labour economists, and do not contradict with the findings of Antoninis (2006) in the study of workers in the manufacturing sector in Egypt. These findings show that most university graduates are relatively worst-off in the job market after the first job. It seems that many university graduates have lowering bargaining position when negotiating wage, possibly for weaknesses in required experience, productivity, or peers effect. Factors such as educational mismatch and satisfaction in the first job, which are not observed in our data, have significant impact of the decision to use informal job-search through non-referee individual with experience in the job field. It is crucial for universities to have career offices to help graduates to be allocated in suitable jobs at their area of expertise and have successful work trajectory in terms of productivity and income.

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Appendix A

Table A1: Percentages of formal and informal job-search use for university graduates in the sample in Egypt and Jordan[1]

		Egypt				**Gordon**			
	Jobs	First	Second	Third	Fourth	First	Second	Third	Fourth
All	Formal job-search	27.94	29.61	33.25	32.88	70.97	71.28	69.06	71.79
	Informal job-search	60	61.8	52.22	47.26	26.95	25.62	23.4	23.08
	Self-employed	11.47	7.93	13.05	18.49	1.46	1.71	0.38	0
	Other	0.59	0.66	1.48	1.37	0.62	1.39	7.17	5.13
	Total	100	100	100	100	100	100	100.01	100
	Number of obs[2]	1020	1047	406	146	961	933	265	78
Private sector[3]	Formal job-search	28.98	26.45	30.11	32.95	67.34	67.14	58.55	60.98
	Informal job-search	70.5	73.27	68.4	65.91	32.5	32.5	33.55	31.71
	Other	0.52	0.28	1.49	1.14	0.16	0.36	7.89	7.32
	Total	100	100	100	100	100	100	99.99	100.01
	Number of obs[2]	773	726	269	88	643	560	152	41

[1] The percentages are taken from the number in the bottom raw.
[2] Number of observations is the number of the valid answers for relevant question in the survey.
[3] Percentages do not include those who are self-employed.

Table A2: Two-stage least squares reduced form 2SLS regression results[1,2,3]

	(1) IV1	(2) IV2	(3) IV3	(4) IV4	(5) IV5
Good	0.0543	0.0448	0.0538	0.0366	0.0473
	(0.058)	(0.059)	(0.058)	(0.060)	(0.058)
Male	-0.1030	-0.1251	-0.1030	-0.1515	-0.1162
	(0.113)	(0.112)	(0.114)	(0.112)	(0.113)
Age	0.7343	0.6083	0.7818	0.8672	0.2735
	(1.445)	(1.441)	(1.455)	(1.439)	(1.464)
English	-0.0089	0.0102	-0.0084	-0.0054	0.0022
	(0.069)	(0.070)	(0.069)	(0.076)	(0.070)
End salary 1	0.0778*	0.0786*	0.0773*	0.0856*	0.0715*
	(0.044)	(0.045)	(0.044)	(0.045)	(0.044)
Duration 12	-0.0548	-0.0554	-0.0567	-0.0718	-0.0540
	(0.054)	(0.051)	(0.054)	(0.051)	(0.055)
Private 1	-0.1112	-0.1375	-0.1066	-0.1588	-0.1172
	(0.126)	(0.124)	(0.130)	(0.123)	(0.124)
Informal search 1	0.3589***	0.3771***	0.3582***	0.3785***	0.3712***
	(0.070)	(0.068)	(0.070)	(0.069)	(0.068)
Father self-empolyed	-0.2492*	-0.2840**	-0.2455*		-0.2566**
	(0.135)	(0.125)	(0.135)		(0.125)
Duration 01	0.0852**		0.0852**		0.0846**
	(0.041)		(0.041)		(0.040)
Secondary school grade		-0.4815**		-0.4605**	-0.4778**
		(0.214)		(0.210)	(0.212)
Unemployment			0.0100		0.0094
			(0.030)		(0.030)
Intercept	0.0365	2.2913**	-0.0685	2.1739**	2.1739**
	(0.387)	(1.051)	(0.499)	(1.040)	(1.072)
R^2	0.186	0.189	0.187	0.167	0.206
adj. R^2	0.148	0.151	0.145	0.132	0.161
RSS	37.1921	37.0547	37.1712	38.0686	36.2991
Model df	213	213	212	214	211
F	4.60	5.40	4.23	4.89	5.07
Excluded instruments test	13.05	15.00	9.87	18.24	10.17
p-value	0.000	0.000	0.000	0.000	0.000

[1] Robust standard errors in parentheses.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.

Table A3: Two-stage least squares estimates[1,2,3]

	IV1	IV2	IV3	IV4	IV5
Informal search 2	-0.4621*	-0.4775*	-0.4457*	-0.4759	-0.4070*
	(0.207)	(0.218)	(0.207)	(0.247)	(0.196)
Good	0.2395**	0.2405**	0.2385**	0.2404**	0.2361**
	(0.085)	(0.086)	(0.085)	(0.086)	(0.084)
Male	0.6070***	0.6063***	0.6076***	0.6064***	0.6092***
	(0.161)	(0.161)	(0.160)	(0.161)	(0.159)
Age	-0.2155	-0.1885	-0.2441	-0.1914	-0.3116
	(2.130)	(2.147)	(2.120)	(2.139)	(2.099)
English	-0.1090	-0.1097	-0.1083	-0.1096	-0.1066
	(0.105)	(0.105)	(0.104)	(0.106)	(0.103)
End salary 1	0.4127***	0.4135***	0.4118***	0.4134***	0.4096***
	(0.066)	(0.067)	(0.066)	(0.067)	(0.066)
Duration 12	0.1142	0.1129	0.1155	0.1130	0.1188
	(0.067)	(0.067)	(0.066)	(0.068)	(0.066)
Private 1	-0.6113**	-0.6132**	-0.6092**	-0.6130**	-0.6043**
	(0.187)	(0.188)	(0.186)	(0.188)	(0.184)
Intercept	4.0304***	4.0354***	4.0250***	4.0349***	4.0123***
	(0.608)	(0.608)	(0.607)	(0.611)	(0.600)
R^2	0.196	0.189	0.203	0.190	0.219
adj. R^2	0.166	0.159	0.173	0.159	0.190
F	9.18	9.03	9.20	8.94	9.21
Hansen J statistic	1.34	0.49	3.46	0.49	4.42
Hansen J p-value	0.511	0.782	0.326	0.485	0.353
Endogeneity test	7.68	7.05	7.08	6.49	6.15
Endogeneity test p-value	0.006	0.008	0.008	0.011	0.014
Effective F statistic[4]	12.278	13.235	9.387	17.595	9.069
Effective F Critical Values $\tau = 5\%$	16.922	17.137	20.325	10.335	21.922
Effective F Critical Values $\tau = 10\%$	10.633	10.756	12.285	7.208	12.999
over-id res	2	2	3	1	4

[1] Robust standard errors are reported for all coefficients.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.
[4] Montiel-Pflueger robust weak instrument test.

Table A4: GMM method estimates[1,2,3]

	IV1	IV2	IV3	IV4	IV5
Informal search 2	−0.4180**	−0.4853**	−0.4411**	−0.4849**	−0.3902**
	(0.2004)	(0.2176)	(0.2017)	(0.2471)	(0.1911)
Good	0.2269***	0.2410***	0.2291***	0.2410***	0.2263***
	(0.0832)	(0.0859)	(0.0838)	(0.0864)	(0.0827)
Male	0.6227***	0.5999***	0.6144***	0.5999***	0.6042***
	(0.1588)	(0.1613)	(0.1593)	(0.1614)	(0.1580)
Age	−0.0004	−0.0003	0.0016	−0.0003	0.0029
	(0.0209)	(0.0214)	(0.0209)	(0.0214)	(0.0206)
English	−0.1182	−0.1085	−0.1199	−0.1084	−0.1130
	(0.1023)	(0.1050)	(0.1031)	(0.1063)	(0.1011)
Duration 12	0.1154*	0.1110*	0.0938	0.1110	0.0939
	(0.0657)	(0.0673)	(0.0645)	(0.0680)	(0.0636)
End salary 1	0.4072***	0.4189***	0.4144***	0.4188***	0.4180***
	(0.0649)	(0.0664)	(0.0650)	(0.0667)	(0.0645)
Private 1	−0.6322***	−0.6248***	−0.6769***	−0.6247***	−0.6893***
	(0.1843)	(0.1879)	(0.1846)	(0.1881)	(0.1824)
Intercept	3.9982***	3.9894***	4.0331***	3.9891***	3.9637***
	(0.5994)	(0.6042)	(0.5974)	(0.6094)	(0.5882)
BC-GMM					
Informal search 2	−0.4415**	−0.5125**	−0.4802**	−0.4944**	−0.4381**
	(0.2011)	(0.2196)	(0.2036)	(0.2477)	(0.1937)
Good	0.2344***	0.2513***	0.2411***	0.2476***	0.2428***
	(0.0837)	(0.0865)	(0.0846)	(0.0866)	(0.0837)
Male	0.6342***	0.6033***	0.6324***	0.6015***	0.6220***
	(0.1588)	(0.1616)	(0.1597)	(0.1614)	(0.1583)
Age	−0.0024	−0.0008	0.0013	−0.0002	0.0035
	(0.0210)	(0.0216)	(0.0212)	(0.0214)	(0.0209)
English	−0.1352	−0.1212	−0.1393	−0.1128	−0.1320
	(0.1030)	(0.1059)	(0.1044)	(0.1065)	(0.1025)
Duration 12	0.1168*	0.1096	0.0932	0.1096	0.0926
	(0.0663)	(0.0680)	(0.0654)	(0.0683)	(0.0646)
End salary 1	0.4026***	0.4222***	0.4131***	0.4193***	0.4202***
	(0.0649)	(0.0667)	(0.0651)	(0.0668)	(0.0647)
Private 1	−0.6362***	−0.6262***	−0.6798***	−0.6271***	−0.6951***
	(0.1855)	(0.1897)	(0.1870)	(0.1886)	(0.1852)
Intercept	4.0849***	3.9998***	4.0647***	3.9935***	3.9584***
	(0.6001)	(0.6068)	(0.6004)	(0.6099)	(0.5919)

[1] Robust standard errors are reported for all coefficients.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.

Table A5: EL method estimates[1,2,3]

	IV1	IV2	IV3	IV4	IV5
Informal search 2	−0.4454**	−0.5031**	−0.4987**	−0.5018**	−0.4702**
	(0.2036)	(0.2219)	(0.2036)	(0.2501)	(0.1986)
Good	0.2352***	0.2447***	0.2401***	0.2448***	0.2442***
	(0.0840)	(0.0868)	(0.0861)	(0.0873)	(0.0863)
Male	0.6352***	0.6008***	0.6260***	0.5996***	0.6352***
	(0.1607)	(0.1613)	(0.1615)	(0.1613)	(0.1605)
Age	−0.0000	0.0003	−0.0005	0.0002	0.0057
	(0.0210)	(0.0215)	(0.0215)	(0.0215)	(0.0215)
English	−0.1243	−0.1094	−0.1275	−0.1090	−0.1247
	(0.1035)	(0.1052)	(0.1059)	(0.1064)	(0.1041)
Duration 12	0.1169*	0.1099	0.0922	0.1097	0.0900
	(0.0662)	(0.0677)	(0.0659)	(0.0684)	(0.0657)
End salary 1	0.4079***	0.4213***	0.4121***	0.4211***	0.4227***
	(0.0651)	(0.0666)	(0.0664)	(0.0670)	(0.0661)
Private 1	−0.6341***	−0.6252***	−0.6864***	−0.6262***	−0.6853***
	(0.1813)	(0.1873)	(0.1823)	(0.1873)	(0.1819)
Intercept	3.9884***	3.9732***	4.1415***	3.9783***	3.8966***
	(0.5964)	(0.6051)	(0.6006)	(0.6096)	(0.5953)
BC-EL					
Informal search 2	−0.4319**	−0.4824**	−0.4855**	−0.4842*	−0.4569**
	(0.2026)	(0.2202)	(0.2025)	(0.2486)	(0.1975)
Good	0.2352***	0.2437***	0.2408***	0.2450***	0.2446***
	(0.0837)	(0.0863)	(0.0858)	(0.0869)	(0.0860)
Male	0.6357***	0.6035***	0.6264***	0.6024***	0.6359***
	(0.1603)	(0.1607)	(0.1611)	(0.1607)	(0.1601)
Age	−0.0009	−0.0007	−0.0011	−0.0008	0.0049
	(0.0209)	(0.0213)	(0.0213)	(0.0213)	(0.0213)
English	−0.1262	−0.1124	−0.1296	−0.1125	−0.1266
	(0.1029)	(0.1043)	(0.1053)	(0.1056)	(0.1035)
Duration 12	0.1164*	0.1105	0.0911	0.1103	0.0893
	(0.0659)	(0.0672)	(0.0655)	(0.0680)	(0.0654)
End salary 1	0.4043***	0.4179***	0.4082***	0.4172***	0.4193***
	(0.0650)	(0.0663)	(0.0663)	(0.0666)	(0.0659)
Private 1	−0.6326***	−0.6253***	−0.6849***	−0.6261***	−0.6844***
	(0.1803)	(0.1859)	(0.1813)	(0.1861)	(0.1810)
Intercept	4.0216***	4.0010***	4.1720***	4.0110***	3.9284***
	(0.5943)	(0.6016)	(0.5986)	(0.6066)	(0.5931)

[1] Robust standard errors are reported for all coefficients.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.

Table A6: ET method estimates[1,2,3]

	IV1	IV2	IV3	IV4	IV5
ET					
Informal search 2	−0.4488**	−0.4959**	−0.5002**	−0.4923**	−0.4648**
	(0.2044)	(0.2203)	(0.2047)	(0.2478)	(0.1964)
Good	0.2361***	0.2431***	0.2426***	0.2431***	0.2418***
	(0.0840)	(0.0864)	(0.0862)	(0.0868)	(0.0857)
Male	0.6319***	0.6002***	0.6275***	0.5995***	0.6222***
	(0.1607)	(0.1610)	(0.1617)	(0.1608)	(0.1597)
Age	0.0007	−0.0001	0.0037	0.0000	0.0053
	(0.0211)	(0.0214)	(0.0215)	(0.0214)	(0.0213)
English	−0.1215	−0.1084	−0.1266	−0.1075	−0.1242
	(0.1034)	(0.1048)	(0.1059)	(0.1059)	(0.1036)
Duration 12	0.1163*	0.1103	0.0906	0.1103	0.0895
	(0.0662)	(0.0674)	(0.0657)	(0.0681)	(0.0651)
End salary 1	0.4111***	0.4193***	0.4187***	0.4193***	0.4222***
	(0.0653)	(0.0664)	(0.0663)	(0.0666)	(0.0658)
Private 1	−0.6366***	−0.6247***	−0.6838***	−0.6272***	−0.6932***
	(0.1815)	(0.1862)	(0.1821)	(0.1862)	(0.1789)
Intercept	3.9579***	3.9902***	3.9977***	3.9878***	3.9287***
	(0.5974)	(0.6030)	(0.6019)	(0.6073)	(0.5926)
BC-ET					
Informal search 2	−0.4404**	−0.4842**	−0.4925**	−0.4788*	−0.4606**
	(0.2035)	(0.2192)	(0.2037)	(0.2467)	(0.1958)
Good	0.2381***	0.2461***	0.2458***	0.2456***	0.2472***
	(0.0838)	(0.0862)	(0.0860)	(0.0865)	(0.0856)
Male	0.6363***	0.6023***	0.6333***	0.6012***	0.6287***
	(0.1602)	(0.1604)	(0.1612)	(0.1603)	(0.1594)
Age	−0.0008	−0.0013	0.0022	−0.0007	0.0040
	(0.0210)	(0.0213)	(0.0214)	(0.0213)	(0.0213)
English	−0.1312	−0.1168	−0.1375	−0.1108	−0.1346
	(0.1029)	(0.1042)	(0.1054)	(0.1053)	(0.1032)
Duration 12	0.1172*	0.1110*	0.0919	0.1106	0.0910
	(0.0660)	(0.0672)	(0.0655)	(0.0678)	(0.0650)
End salary 1	0.4076***	0.4194***	0.4153***	0.4177***	0.4209***
	(0.0651)	(0.0662)	(0.0661)	(0.0664)	(0.0657)
Private 1	−0.6345***	−0.6255***	−0.6815***	−0.6283***	−0.6915***
	(0.1809)	(0.1856)	(0.1815)	(0.1853)	(0.1786)
Intercept	4.0044***	4.0079***	4.0373***	4.0025***	3.9517***
	(0.5956)	(0.6005)	(0.6002)	(0.6050)	(0.5913)

[1] Robust standard errors are reported for all coefficients.
[2] Number of observations 224.
[3] *p<0.1; **p<0.05; ***p<0.01.