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Estimating the effect of vocational training programs on employment and wage: The case of Tunisia

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Abstract

The aim of this paper is to estimate the impact of vocational training programs offered in Tunisia on employment and wage of individuals. The data we use come from a study carried out in Tunisia in 2001 by the Ministry of Vocational Training and Employment on the graduates of the national vocational training. We use different econometric approaches as well as a parametric selection model to estimate the effect of these programs. The results show that the participation of individuals in training programs in Tunisia increases their probability to find a job and their monthly wage.

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1. INTRODUCTION

Middle East and North Africa (MENA) countries have some of the highest youth unemployment rates in the world. On the other hand, employment programs in these countries have been always criticised for their inefficiency and vocational training has often been blamed for its bad quality. Yet, there is very little evidence on the effects of these kinds of programs. For example, Salehi-Isfahani et al. (2009) claim that returns to vocational education in MENA countries is small in relations to returns to high school education and pretend that this is a sign of the inefficiency of the vocational training in these countries.

Tunisian employment and vocational training programs were developed gradually over several years and have undergone several reforms since the 1990s, following especially international commitments signed by Tunisia. Two types of training programs are offered in Tunisia; in-service training which is generally offered to graduates of higher education and who are already employed, and initial vocational training which is received by young people after dropping out of the general education system. Our paper focuses on the second type of these programs (the initial vocational training programs).

Despite the development and the diversity of the vocational training policies in Tunisia, there has been a lack of serious evaluations of these programs. All the studies made provide summary and general results, far from the causal scientific evaluation carried out in developed countries such as US and France. Hence, the contribution of our paper, in which we evaluate the effects of Tunisian Vocational Training Programs on employment and wage.

Several studies on the evaluation of public policies, especially those of employment policies have been conducted during these last years. In practice, evaluating a given policy is not easy to achieve, because in addition to the questions about the efficiency of the policy studied, other questions raised about the choice of the method to be used. This method must enable us to identify the effects caused by the studied policy.

The majority of the evaluation studies has been performed on non-experimental data such as those we use in our paper (see, for example, Angrist and Krueger 1991, Bonnal et al.1997, Heckman et al.1997 ,1998, Heckman and Smith 1998, Dehejia and Wahba 1999, 2002, Fougère et al.2001). In comparison with experimental data, estimating the impact of a given policy on the basis of non-experimental data is not easy to achieve because of the problems of endogeneity and selection bias present in such data. Any evaluation process should carefully take into account these problems.

A problem of selection bias exists when people's participation in the training program is the result of a decision taken by those most eligible. This decision depends on both observable characteristics (such as place of residence, education level, age,...) and unobservable ones (such as willingness to work, individual ability,...). Then, the assignment of individuals to the program is by self-selection and not by random assignment. From an econometric point of view, this corresponds to a problem of endogeneity of the variable of interest (training) in the outcome equations that we want to study (employment and wage here) (see Heckman 1978 and Heckman and Hotz 1989).

In the literature, several methods have been proposed to deal with the problem of selection bias. Rubin (1977) and Rosenbaum and Rubin (1983) propose in this context the matching method. Dehejia and Wahba (1999, 2002) and Heckman et al.(1997, 1998) use this method to evaluate American training programs. Note, however, that this non parametric method takes into account only the phenomena of selection on observables. Heckman (1976) suggests using instrumental variables to correct this problem. This method was subsequently used in several studies (see for example Angrist and Krueger 1991, Card 1993, Imbens and Angrist 1994, Heckman and Smith 1998, Heckman and Vytlacil 2000). However, the difficulty in using this method lies in choosing the appropriate instrumental variable.

Another way to deal with the problem of self-selectivity is the use of parametric selection models. In such models, we simultaneously estimate the equations of treatment and observed outcomes by making parametric assumptions on the joint distribution of error terms of these equations (see Lee 1978, Maddala 1983). The parametric selection model with normal disturbances is the most commonly used in literature. It is the approach we adopt in our paper. The advantage of this model is that it takes into account the phenomena of selection on observables and unobservables. It allows dependency between the various disturbances of the equations conditionally on observable characteristics. Fougère et al.(2001) use this model to evaluate the impact of training sponsored by employers on employees mobility and wage in France.

For our empirical framework, we use a non-experimental micro-data from a study conducted in 2001 by the Tunisian Ministry of Vocational Training and Employment. This study has focused on the graduates of initial vocational training in 1998. In total the survey covered a sample of 1,002 individuals and provided a number of relevant information concerning the characteristics of individuals, their situation on the labor market and the characteristics of their job at the time of the study.

Using the information from this survey, we estimate the impact of programs on the employment and the wage of individuals. We begin our analysis by some preliminary estimations in order to explore the main features in our data. This will help us to understand and interpret the results of the complete model that will be estimated earlier.

The estimation results show that the participation of individuals in training programs significantly increases their probability to find a job and their monthly wage.

Section 2 puts the light on the main contextual and institutional aspects of vocational training in Tunisia, then gives some descriptive statistics of the data. Section 3 presents the results of preliminary estimations. Section 4, describes our model. Section 5 discusses the estimation results and section 6 concludes the paper.

2. INSTITUTIONAL ASPECTS AND DATA

2.1. Overview of Tunisian Training Programs

The Tunisian Vocational Training device was developed gradually over a period of thirty years. It is composed of Vocational Middle Education, Vocational High Education and the Vocational College. These three levels are respectively attested by CAP[1], BTP[2] and BTS[3] degrees. Before college, the General or Regular Education System in Tunisia is organized as follows: 9 years of Basic Education (Including 6 years in Primary School and 3 years in Middle-High School) and 4 years of High School Education. The CAP degree is a training offered to students who have completed basic education. The BTP degree concerns students who have completed the two first years of high school or laureates of a CAP degree. The BTS degree offers a course to applicants with a high school degree or laureates of a BTP degree. All these vocational training programs are two years lasting.

[1] "Certificat d'Aptitude Professionnelle".

[2] "Brevet de Technicien Professionnel".

[3] "Brevet de Technicien Superieur".

Vocational training in Tunisia is freely provided by the public sector, mainly by The Tunisian Agency of Vocational Training (ATFP). Other initial training are organized by different operators but are not sanctioned by the degrees mentioned above. They are commonly called non-degree programs and attested by apprenticeship certificate.

The number of individuals pursuing the training programs has increased significantly during the two last decades. Although admission is determined after examination of applications and results of tests conducted for the purpose, the programs are not highly selective and the demand does not fulfill all the offered seats in a given training.

During the training the individuals receive skills specific to the special field[4] of the training as well as general teachings. General teachings are essentially languages, computer skills, quality standards, health and safety at work and labor law. The level of deepening in these teachings differs between the CAP, BTP and BTS degrees, but students acquire at least fundamentals of these subjects.

2.2. Data and Descriptive Statistics

The data used in this paper come from the survey of vocational training programs graduates conducted by the Ministry of Vocational Training and Employment in Tunisia in 2001. The data file is in two samples. Participants sample contains 499 individuals who were graduated from a vocational training program in 1998. Control group sample contains 503 individuals who dropped out the educational system but did not participate in any vocational training program in spite of their eligibility. In order to avoid contamination bias, investigators checked that none of these groups has participated in another training program or benefited from employment assistance.

The questionnaire was designed to collect detailed information on individual and family characteristics, as well as the professional situation of the individual, especially in terms of employment and wage.

Table I shows the main characteristics of the sample of graduates compared to those of non-participants. We see in this table that 58% of individuals who receive training found a job versus 42% for those who don't receive it, the difference between these two groups is statistically significant. Participants have also a higher average wage than non-participants. Regarding age, participants are 3 years younger than non-participants. As for the educational level, there is no big differences between the two groups: Individuals with high school level of education are the majority in the two groups (respectively 49% and 43% for treatment and control groups), followed by those with primary school level (21% versus 22%). As for the year of leaving school, 56% of participants left the general education system between 1990 and 1995 and only 4% before 1990, which is different for non-participants (respectively 38% and 35%). We also see that participants come from larger family than non-participants. Regarding the fathers's occupation, the table does not show any significant difference between the characteristics of control and treatment groups (Individuals whose father is inactive or dead are the majority in the two groups). As for the residence area, it seems that the proportion of individuals leaving in big cities is slightly higher in the control group.

[4]Special fields of Vocational Training available in the Tunisian device are: Building and Civil Engineering Works, Textile industry and Clothing, Leather Craft and Shoes, Mechanical Engineering and Structural Steelwork, Electricity and Electronics, Tertiary Sector, Driving and Maintenance of Vehicles, Hotel Business and Jobs of Reception Facilities, Agriculture.

Table I. Descriptive Statistics

	Treatment Gr.	Control Gr.	Difference
Employed	0.584	0.423	0.160^{***}
Wage	281.663	250.090	31.572^{**}
Man	0.623	0.557	0.065^{**}
Age	25.119	28.200	-3.081^{***}
Educational Level			
None	0.010	0.009	0.001
Primary School	0.216	0.224	-0.008
Middle-High School	0.036	0.071	-0.034^{**}
Two years of High School	0.138	0.153	-0.014
Four years of High School	0.495	0.430	0.065^{*}
College or More	0.101	0.110	-0.008
Year of Leaving School			
Before 1990	0.045	0.358	-0.313^{***}
Between 1990 and 1995	0.560	0.380	0.180^{***}
After 1995	0.393	0.260	0.133^{***}
Family Size			
Under than 6	0.374	0.511	-0.137^{***}
Between 6 and 8	0.512	0.421	0.091^{***}
More than 8	0.112	0.066	0.045^{**}
Head's Occupation			
Inactive, Other (dead)	0.538	0.502	0.036
Unemployed	0.051	0.081	-0.029^{*}
Blue Collar	0.173	0.172	0.0009
White Collar	0.110	0.136	-0.025
Middle Manager, Technician	0.056	0.038	0.017
Executive, Lawyer, Doctor, Engineer	0.069	0.069	-0.0001
Residence			
Big City	0.452	0.645	-0.193^{***}
Small or Medium City	0.452	0.315	0.136^{***}
Rural Area	0.095	0.038	0.056^{***}

(***), (**) and (*) are respectively 1%, 5% and 10% significance levels.

3. Preliminary Estimation

3.1. Training Equation

We begin our empirical analysis by a simple linear probability (OLS) model and a probit regression for training participation. We include in the right hand side year of leaving school, age, gender, place of residence, educational level and father's occupation. Table II gives OLS coefficients and marginal effects for the probit model using the same specification. The two models give in general similar estimates in terms of signs of the coefficients.

Table II. Training Model

Dependent variable: Training	OLS	Probit
Year of Leaving School (Ref : After 1995)		
Before 1990	-0.279*** (0.062)	-0.351*** (0.066)
Between 1990 and 1995	0.022 (0.035)	0.042 (0.043)
Age	-0.038*** (0.005)	-0.055*** (0.008)
Man	0.042 (0.031)	0.054 (0.038)
Residence (Ref : Rural Area)		
Big City	-0.222*** (0.061)	-0.288*** (0.078)
Small or Medium City	-0.088 (0.062)	-0.129 (0.083)
Educational Level (Ref : None)		
Primary School	0.038 (0.153)	0.055 (0.223)
Middle-High School	-0.096 (0.162)	-0.155 (0.219)
Two Years of High School	-0.018 (0.153)	-0.032 (0.223)
Four Years of High School	0.071 (0.148)	0.097 (0.217)
College or More	0.121 (0.155)	0.192 (0.207)
Head's occupation (Ref : Inactive, Dead)		
Unemployed	0.003 (0.060)	-0.014 (0.076)
Blue Collar	0.020 (0.071)	-0.013 (0.088)
White Collar	-0.111** (0.047)	-0.168*** (0.057)
Middle Manager, Technician	-0.073* (0.042)	-0.114** (0.053)
Executive, Lawyer, Doctor, Engineer	-0.107* (0.061)	-0.151* (0.078)
Constant	1.686*** (0.207)	
R-Squared (Or Pseudo R-Squarred)	0.255	0.221

(***), (**) and (*) are respectively 1%, 5% and 10% significance levels. Standard Errors are in Parenthesis. Probit Model gives Marginal Effects.

The main results show that individuals who left school before 1990 are less likely to be enrolled in a vocational program. The marginal effect of this dummy is around 0.35, which is a large value. In fact, as mentioned above, the vocational training offer in the Tunisian system was very limited before the 90's and vocational tracks were not known to the public. This fact, strictly related to institutional aspects and independent of individual characteristics, will be used earlier as instrument to identify the treatment effect of training. We see also that the probability of participation decreases with age and that it is higher for individuals coming from rural areas and with inactive fathers. We do not see however any gender gap in terms of participation in training.

3.2. Employment Equation

We turn now to the employment equation estimation. We regress the employment dummy on training, and all explanatory variables to obtain a preliminary idea about the main features of our data. This specification is estimated using OLS, Probit, Linear Instrumental Variable (Linear IV) and Probit Instrumental Variable (Probit IV). The results are given in table III. The two first methods, that ignore the endogeneity aspect of training, give a positive and significant estimation of the training effect. The marginal effect in the probit regression says that the treatment increases the likelihood to find a job by 19 probability points. In the two last columns, we give the results obtained when we try to correct for the endogeneity problem using the instrumental variable which is, as we have explained above, the year of leaving school. With these two methods we loose the significance of the training parameter. Its estimates remains positive but not significant.

Table III. Employment Model

Dependent variable: Employment	OLS	Probit	Linear IV	Probit IV
Training	0.187*** (0.037)	0.191*** (0.038)	0.291 (0.198)	0.294 (0.183)
Age	0.005 (0.005)	0.005 (0.005)	0.011 (0.012)	0.011 (0.012)
Man	0.024 (0.034)	0.024 (0.035)	0.018 (0.036)	0.018 (0.037)
Residence (Ref : Rural Area)				
Big City	0.037 (0.069)	0.039 (0.072)	0.060 (0.082)	0.063 (0.083)
Small or Medium City	-0.016 (0.069)	-0.017 (0.072)	-0.007 (0.072)	-0.008 (0.074)
Educational Level (Ref : None)				
Primary School	0.081 (0.168)	0.081 (0.174)	0.093 (0.171)	0.092 (0.174)
Middle-High School	0.375** (0.181)	0.344** (0.124)	0.396** (0.185)	0.356*** (0.120)
Two Years of High School	0.104 (0.171)	0.103 (0.174)	0.114 (0.172)	0.113 (0.173)
Four Years of High School	0.151 (0.167)	0.152 (0.171)	0.145 (0.168)	0.144 (0.171)
College or More	0.193 (0.174)	0.190 (0.165)	0.175 (0.178)	0.171 (0.172)
Head's occupation (Ref : Inactive, Dead)				
Unemployed	-0.005 (0.068)	-0.005 (0.070)	-0.006 (0.068)	-0.006 (0.070)
Blue Collar	-0.044 (0.080)	-0.048 (0.084)	-0.045 (0.081)	-0.049 (0.083)
White Collar	-0.090* (0.053)	-0.093* (0.055)	-0.077 (0.058)	-0.079 (0.061)
Middle Manager, Technician	-0.028 (0.047)	-0.030 (0.048)	-0.021 (0.049)	-0.021 (0.051)
Executive, Lawyer, Doctor, Engineer	-0.104 (0.069)	-0.109 (0.071)	-0.090 (0.074)	-0.095 (0.076)
Constant	0.121 (0.224)		-0.103 (0.479)	
R-Squared (Or Pseudo R-Squarred)	0.057		0.049	

(***), (**) and (*) are respectively 1%, 5% and 10% significance levels. Standard Errors are in Parenthesis. Probit Model gives Marginal Effects.

3.3. Log-Earning Equation

We turn now to the estimation of the wage determinants. The earning regression suffers from two problems. The first problem concerns the endogenous selection of the sample because we do not observe a wage for unemployed individuals in our sample. The second one concerns the endogeneity of the treatment variable of training.

Table IV. Log-Earning Model

Dependent variable: Log Earning	OLS	Linear IV	Heckman
Training	0.160*** (0.045)	0.068 (0.314)	0.159*** (0.045)
Age	0.062*** (0.299)	0.284*** (0.081)	0.321*** (0.064)
Age Squarred	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
Man	0.233*** (0.041)	0.231*** (0.042)	0.243*** (0.042)
Residence (Ref : Rural Area)			
Big City	0.053 (0.082)	0.037 (0.099)	0.054 (0.082)
Small or Medium City	0.116 (0.083)	0.107 (0.088)	0.110 (0.083)
Educational Level (Ref : None)			
Primary School	0.095 (0.246)	0.103 (0.249)	0.104 (0.246)
Middle-High School	0.098 (0.251)	0.103 (0.253)	0.174 (0.257)
Two Years of High School	0.012 (0.248)	0.027 (0.254)	0.024 (0.247)
Four Years of High School	0.095 (0.243)	0.128 (0.269)	0.123 (0.243)
College or More	0.393 (0.249)	0.432 (0.282)	0.439* (0.251)
Head's occupation (Ref : Inactive, Dead)			
Unemployed	0.136* (0.076)	0.133* (0.077)	0.135* (0.077)
Blue Collar	0.277*** (0.093)	0.291*** (0.106)	0.268*** (0.094)
White Collar	0.074 (0.066)	0.072 (0.066)	0.046 (0.069)
Middle Manager, Technician	-0.057 (0.056)	-0.065 (0.061)	-0.066 (0.056)
Executive, Lawyer, Doctor, Engineer	-0.051 (0.093)	-0.056 (0.095)	-0.084 (0.096)
Constant	0.641 (0.920)	0.973 (1.454)	0.210 (0.971)
R-Squared (Or Pseudo R-Squarred)	0.275	0.268	

(***), (**) and (*) are respectively 1%, 5% and 10% significance levels. Standard Errors are in Parenthesis.

Table IV gives three estimation results of the earning equation: *(i)* Naive OLS regression ignoring these two problems, *(ii)* Linear IV Regression, where an instrument is used to identify the causal effect of training, and *(iii)* Heckman Selection Model taking into account the selection of the sample. The two first models are estimated on the sub-sample of employed individuals and the third one is estimated on the whole sample. Main Result says that training increases the expected wage by 16% when estimated by OLS or Selection Model and the effect is not significant with IV strategy. Wage manifests also the classical concave function of age and the traditional gender gap.

4. THE COMPLETE MODEL

After presenting the results of preliminary estimation where the effect of training programs is estimated separately on employment and wage, we present now the complete model we use in our empirical analysis. As we said in the introduction, we estimate a parametric selection model in which we simultaneously estimate the equations of treatment (training) and observed outcomes (employment and wage here).

So, for each individual i in the sample, we observe simultaneously three variables. Denote by D_i a dummy variable equal 1 if the individual i has participated in the training program and 0 otherwise; E_i a dummy variable equal 1 if the individual i has found a job and 0 otherwise; and Y_i the variable representing the wage offered to the individual i for the found job.

The econometric model is then a double selection model (Lee 1978, Maddala 1983) which corresponds to a system of three equations specified as follows:

$$D_i = \begin{cases} 1, & \text{if } D_i^* = X_{1i}\beta_1 + \varepsilon_{1i} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$E_i = \begin{cases} 1, & \text{if } E_i^* = X_{2i}\beta_2 + \varepsilon_{2i} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$\ln Y_i = X_{3i}\beta_3 + \alpha_Y D_i + \nu_i \tag{3}$$

where X_{1i} represents the set of exogenous variables that may explain the participation in training; X_{2i} is the set of exogenous factors that may explain the employment and X_{3i} are exogenous variables that determine the wage. Note that X_{2i} includes the treatment variable D.

To estimate this model, we suppose that the vector of disturbances $(\varepsilon_{1i}, \varepsilon_{2i}, \nu_i)$ follows a trivariate normal disturbances with mean zero and covariance matrix Ω such as:

$$\begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \nu_i \end{pmatrix} \rightsquigarrow N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_1\sigma \\ \rho_{12} & 1 & \rho_2\sigma \\ \rho_1\sigma & \rho_2\sigma & \sigma^2 \end{pmatrix}\right] \tag{4}$$

where ρ_{12} is the correlation coefficient between ε_1 and ε_2; ρ_1 is the correlation coefficient between ε_1 and ν; ρ_2 is the correlation coefficient between ε_2 and ν; and σ^2 is the variance of ν.

The estimation method we use is that of maximum likelihood. The likelihood function is based on the joint density of the perturbations $(\varepsilon_{1i}, \varepsilon_{2i})$ conditional on the error term ν_i. We use the theorem of marginal and conditional normal distributions (Greene (2005)) to prove that[5]:

$$(\varepsilon_{1i}, \varepsilon_{2i}) \mid \nu_i \rightsquigarrow N\left[\begin{pmatrix} \dfrac{\nu_i\rho_1}{\sigma} \\ \dfrac{\nu_i\rho_2}{\sigma} \end{pmatrix}, \begin{pmatrix} 1-\rho_1^2 & \rho_{12}-\rho_1\rho_2 \\ \rho_{12}-\rho_1\rho_2 & 1-\rho_2^2 \end{pmatrix}\right] \tag{5}$$

[5] See the proof in Appendix.

Let $\mu_1^* = \frac{\rho_1}{\sigma}\nu_i$ be the the conditional expectation of $\varepsilon_{1i} \mid \nu_i$; $\mu_2^* = \frac{\rho_2}{\sigma}\nu_i$ the conditional expectation of $\varepsilon_{2i} \mid \nu_i$; $\sigma_1^* = \sqrt{1-\rho_1^2}$ the conditional standard deviation of $\varepsilon_{1i} \mid \nu_i$; $\sigma_2^* = \sqrt{1-\rho_2^2}$ the conditional standard deviation of $\varepsilon_{2i} \mid \nu_i$; and $\rho_{12}^* = \frac{\rho_{12}-\rho_1\rho_2}{\sqrt{(1-\rho_1^2)(1-\rho_2^2)}}$ the correlation coefficient of ε_{1i} and ε_{2i} conditionally on ν_i.

Using these parameters, we explicit the likelihood of the model. Four situations can occur depending on the values taken by the three endogenous variables (D_i, E_i and Y_i).

- $D_i = 0$; $E_i = 0$; Y_i *not observed*
  $$\begin{aligned}\mathcal{L}_i &= \text{Prob}(D_i = 0,\ E_i = 0)\\ &= \Phi_2(-X_{1i}\beta_1,\ -X_{2i}\beta_2,\ \rho_{12})\end{aligned}$$
  We set: $A_i = -X_{1i}\beta_1$; $B_i = -X_{2i}\beta_2$; So that $\Rightarrow \mathcal{L}_i = \Phi_2(A_i,\ B_i,\ \rho_{12})$; where Φ_2 is the distribution function of bivariate normal distribution.
- $D_i = 1$; $E_i = 0$; Y_i *not observed*
  $$\begin{aligned}\mathcal{L}_i &= \text{Prob}(D_i = 1,\ E_i = 0)\\ &= \Phi_2(-A_i,\ B_i,\ -\rho_{12})\end{aligned}$$
- $D_i = 0$; $E_i = 1$; Y_i *observed*
  $$\begin{aligned}\mathcal{L}_i &= \text{Prob}(D_i = 0,\ E_i = 1,\ Y_i = y_i)\\ &= \text{Prob}(D_i = 0,\ E_i = 1/Y_i = y_i) \times \text{Prob}(Y_i = y_i)\\ &= \frac{1}{\sigma}\phi(\frac{C_i}{\sigma}) \times \Phi_2(F_i,\ -G_i,\ -\rho_{12}^*);\end{aligned}$$
  where
  $$C_i = \ln Y_i - X_{3i}\beta_3 - \alpha_y D_i = \nu_i;$$
  $$F_i = \frac{(-X_{1i}\beta_1 - \mu_1^*)}{\sigma_1^*} = \frac{(-X_{1i}\beta_1 - \rho_1 C_i/\sigma)}{\sqrt{1-\rho_1^2}};$$
  $$G_i = \frac{(-X_{2i}\beta_2 - \mu_2^*)}{\sigma_2^*} = \frac{(-X_{2i}\beta_2 - \rho_2 C_i/\sigma)}{\sqrt{1-\rho_2^2}};$$
  and ϕ is the density function of the standard normal distribution.
- $D_i = 1$; $E_i = 1$; Y_i *observed*
  $$\begin{aligned}\mathcal{L}_i &= \text{Prob}(D_i = 1,\ E_i = 1,\ Y_i = y_i)\\ &= \text{Prob}(D_i = 1,\ E_i = 1/Y_i = y_i) \times \text{Prob}(Y_i = y_i)\\ &= \frac{1}{\sigma}\phi(\frac{C_i}{\sigma}) \times \Phi_2(-F_i,\ -G_i,\ \rho_{12}^*).\end{aligned}$$

5. RESULTS

We estimate the model presented above using the whole sample. The exogenous variables introduced in the equations are age, gender, level of education, place of residence and head of the household's occupation. In addition to these exogenous variables, we introduce in the equation of participation an instrumental variable to identify the impact of training programs on employment and wage. This variable is supposed to determine the participation of the individual in the training without having any direct effect on his employment or his wage, every thing being equal. We introduce the same instrument used in preliminary estimation, which is the year of leaving school. As we show in section 3 this variable is an important determinant of participation in training programs. Those who left school before 1990 were less likely to participate in vocational program because of a limited supply. On an other hand and from an economically intuitive point of view, we do not believe that the year of leaving school can have any direct relation with productivity. Employment and wage are the consequences of observed traits such as education and training and unobserved ones such as ability and motivation, rather than by demographic aspects such as age or year of birth.

In addition to this instrument in the treatment equation, we introduce in the employment equation an exclusion variable to facilitate the identification of the selection mechanism. Note that theoretically, in the case of a selection model with normal disturbances, it is possible to identify the model parameters without strictly having to use an exclusion restriction. However, in practice the introduction of such relationship is often preferable. It ensures that identification of the policy parameter does not depend only on the distributional assumption made, making hence the estimator more robust. For our model, we introduce the variable family size as an exclusion restriction. We think that when the family is large, individuals have more chance to find a job owing to connections that may have the family members. Wage obtained in the labor market remains always a consequence of the individual productivity and training.

Table V gives the results of the simultaneous estimation of the three equations and the correlation matrix. The β_1 column of the table gives the estimates of the treatment equation parameters. The coefficients of our instrumental variable are significant with the expected signs. Individuals who left school before 1990 have less chance to be enrolled in a training program. Younger people have more chance to participate, without any significant gender gap. Other results show that individuals whose parents are white collar or higher are less likely to enter training and that, comparatively to rural area, living in a big city decreases the probability of participating in training programs.

Results of the employment equation are given in β_2 column. We can see that the coefficient of training dummy is significant and positive which means that individuals who participate in training programs are more likely to find a job than those who don't. Concerning the exclusion variable parameter, we see that people belonging to large families have more chance to integrate the labor market. Other results show that the probability of employment is higher for individuals with middle-high school level of education, every thing being equal.

The last column of table V gives the parameter estimates of the wage equation. As we can see, the salary has the classical concave function of age, and the usual gender gap in favor of men. The most important result of our study concerns the impact of training on wage. This sign of α_y is positive and significant. Thus, the individuals who participated in training have on average higher wages than those who did not participate, controlling for socio-demographic characteristics and taking into account the selection bias. The magnitude of the parameter says that training increases wage by 56%. This value can be seen at first glace as very high. But given the duration of training and the skills and teachings it provides it can be justified. In fact, to be more concrete the minimum wage in Tunisia is around 320 Tunisian National Dinars (TND). This wage, which is comparable to the average wage level in the control group, corresponds to the expected wage of an individual employed in tertiary or industrial sector entering without any qualification[6]. Saying that the vocational training increases wage by 56% is equivalent to setting the counterfactual wage

[6]The entry wage of a High School Professor is around 900 TND, and of an Engineer or Doctor in general medicine is around 1300 TND.

Table V. Results of the Complete Model

Independent variables	β_1	β_2	β_3 & α_y
Training		0.719* (0.427)	0.448** (0.256)
Year of Leaving School (Ref : After 1995)			
Before 1990	-0.948*** (0.207)		
Between 1990 and 1995	0.052 (0.122)		
Family Size (Ref : More than 8)			
Under than 6		0.078 (0.154)	
Between 6 and 8		0.252* (0.152)	
Age	-0.142*** (0.020)	0.029 (0.027)	0.330*** (0.070)
Age Squarred			-0.005*** (0.001)
Man	0.142 (0.098)	0.039 (0.093)	0.228*** (0.044)
Residence (Ref : Rural Area)			
Big City	-0.761*** (0.213)	0.136 (0.204)	0.121 (0.103)
Small or Medium City	-0.342 (0.215)	-0.043 (0.185)	0.088 (0.136)
Educational level (Ref : None)			
Primary School	0.075 (0.579)	0.293 (0.447)	0.142 (0.251)
Middle-High School	-0.474 (0.603)	1.108** (0.485)	0.253 (0.268)
Two years of High School	-0.131 (0.576)	0.324 (0.451)	0.067 (0.254)
Four years of High School	0.188 (0.564)	0.415 (0.441)	0.125 (0.247)
College or More	0.441 (0.584)	0.513 (0.465)	0.411* (0.257)
Head's occupation (Ref : Inactive, Other (dead))			
Unemployed	-0.044 (0.193)	0.017 (0.177)	0.133* (0.079)
Blue Collar	-0.043 (0.223)	-0.133 (0.211)	0.264*** (0.096)
White Collar	-0.455*** (0.155)	-0.230 (0.152)	0.074 (0.073)
Middle Manager, Technician	-0.136** (0.299)	-0.077 (0.127)	-0.045 (0.060)
Executive, Lawyer, Doctor, Engineer	-0.384* (0.205)	-0.254 (0.193)	-0.049 (0.102)
Constant	4.435*** (0.790)	-1.737 (1.095)	-0.351 (1.248)
	ρ_{12}	ρ_1	ρ_2
Other Parameters	-0.145 (0.270)	-0.325 (0.318)	0.469** (0.210)

Log-likelihood= -1281.812; Wald stat. (16)= 184.08; p-value= 0.000. (***), (**) and (*) are respectively 1%, 5% and 10% significance levels. Standard Errors are in Parenthesis.

of this individual to 500 TND if he is graduated from a vocational training program. That's why we believe that this is not an implausible estimates in the Tunisian context. Our result is also consistent with what Salehi-Isfahani et al. (2009) have reported for Turkey. The authors show that the marginal returns to vocational training in Turkey (measured by their effect on hourly wage) is about 61% in 2003 and are higher than those to upper secondary. Vocational returns are much lower in Egypt (about 22% in 2006) and Iran (about 33% in 2006). The authors assign this to the fact that Turkey's economy is more dynamic and open than the two countries. Differences between countries in the returns to vocational training seems also to be due to how individuals are selected into vocational programs. In opposite to Egypt and Iran, the selection into the vocational programs in Turkey is not compulsory and extensive. This is also the case of vocational training programs in Tunisia.

We turn now to the correlation coefficients of residuals. The parameter estimates of ρ_2 is positive and significant saying that unobservable factors increasing employment are positively correlated with those increasing wage, which are mainly motivation and ability. However the other correlation coefficients ρ_{12} and ρ_1 are not significant. This results predicts that the correlation between employment and training as well as selectivity into treatment seem to pass only through observable variables.

6. Conclusion

This paper studies the effect of vocational training programs offered in Tunisia on employment and wage of individuals. Exploiting a sample from the survey of vocational training program graduates conducted in 2001 by the Tunisian Ministry of Vocational Training and Employment, we use different econometric approaches to estimate the impact of these programs. The basic result obtained on our complete model is that vocational training in Tunisia has a positive treatment effect on the probability of employment and on wage. This result on the treatment effect of vocational training is unique in the Tunisian context. It needs to be confirmed and reinforced by other studies on richer data sets to provide a strong recommendation in terms of vocational training public policy.

Appendix

Conditional distribution of disturbances

We define ε_1, ε_2 and ν three random variables such that:

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \nu \end{pmatrix} \rightsquigarrow N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}; \begin{pmatrix} 1 & \rho_{12} & \rho_1\sigma \\ \rho_{12} & 1 & \rho_2\sigma \\ \rho_1\sigma & \rho_2\sigma & \sigma^2 \end{pmatrix}\right] \qquad (A)$$

We define $\varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix}$ the vector of disturbances ε_1 and ε_2.

$$\varepsilon \rightsquigarrow N(\mu_\varepsilon, \Omega_{\varepsilon\varepsilon});$$

where $\mu_\varepsilon = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$ and $\Omega_{\varepsilon\varepsilon} = \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix}$.

from another side:

$$\nu \rightsquigarrow N(\mu_\nu, \Omega_{\nu\nu})$$

where $\mu_\nu = 0$ and $\Omega_{\nu\nu} = \sigma^2$.

Furthermore, we define the following matrices:

$$\Omega_{\varepsilon\nu} = \begin{pmatrix} \sigma\rho_1 \\ \sigma\rho_2 \end{pmatrix} \quad \text{et} \quad \Omega_{\nu\varepsilon} = \Omega'_{\varepsilon\nu} = \begin{pmatrix} \sigma\rho_1 & \sigma\rho_2 \end{pmatrix}.$$

The conditional distribution of the vector ε knowing ν is a normal (Greene (2005) p.845) as:

$$\varepsilon \mid \nu \rightsquigarrow N(\mu_{\varepsilon.\nu}, \Omega_{\varepsilon\varepsilon.\nu});$$

where $\mu_{\varepsilon.\nu} = \mu_\varepsilon + \Omega_{\varepsilon\nu}\Omega_{\nu\nu}^{-1}(\nu - \mu_\nu)$;
$\Omega_{\varepsilon\varepsilon.\nu} = \Omega_{\varepsilon\varepsilon} - \Omega_{\varepsilon\nu}\Omega_{\nu\nu}^{-1}\Omega_{\nu\varepsilon}$

- Determination of the conditional expectation $\mu_{\varepsilon.\nu}$:

$$\mu_{\varepsilon.\nu} = \mu_\varepsilon + \Omega_{\varepsilon\nu}\Omega_{\nu\nu}^{-1}(\nu - \mu_\nu).$$

under (A),

$$\begin{aligned} \mu_{\varepsilon.\nu} &= \Omega_{\varepsilon\nu}\Omega_{\nu\nu}^{-1}\nu; \\ &= \frac{1}{\sigma^2}\begin{pmatrix} \sigma\rho_1 \\ \sigma\rho_2 \end{pmatrix}\nu \\ \Rightarrow \mu_{\varepsilon.\nu} &= \begin{pmatrix} \frac{\nu\rho_1}{\sigma} \\ \frac{\nu\rho_2}{\sigma} \end{pmatrix} \end{aligned}$$

- Determination of conditional covariance matrix $\Omega_{\varepsilon\varepsilon.\nu}$:

$$\begin{aligned} \Omega_{\varepsilon\varepsilon.\nu} &= \Omega_{\varepsilon\varepsilon} - \Omega_{\varepsilon\nu}\Omega_{\nu\nu}^{-1}\Omega_{\nu\varepsilon} \\ &= \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix} - \begin{pmatrix} \sigma\rho_1 \\ \sigma\rho_2 \end{pmatrix}\frac{1}{\sigma^2}\begin{pmatrix} \sigma\rho_1 & \sigma\rho_2 \end{pmatrix} \\ &= \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix} - \frac{1}{\sigma^2}\begin{pmatrix} \sigma^2\rho_1^2 & \sigma^2\rho_1\rho_2 \\ \sigma^2\rho_1\rho_2 & \sigma^2\rho_2^2 \end{pmatrix} \\ &= \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix} - \begin{pmatrix} \rho_1^2 & \rho_1\rho_2 \\ \rho_1\rho_2 & \rho_2^2 \end{pmatrix} \\ \Rightarrow \Omega_{\varepsilon\varepsilon.\nu} &= \begin{pmatrix} 1-\rho_1^2 & \rho_{12}-\rho_1\rho_2 \\ \rho_{12}-\rho_1\rho_2 & 1-\rho_2^2 \end{pmatrix} \end{aligned}$$

Finally,

$$(\varepsilon_1, \varepsilon_2) \mid \nu \rightsquigarrow N\left[\begin{pmatrix} \frac{\nu\rho_1}{\sigma} \\ \frac{\nu\rho_2}{\sigma} \end{pmatrix}, \begin{pmatrix} 1-\rho_1^2 & \rho_{12}-\rho_1\rho_2 \\ \rho_{12}-\rho_1\rho_2 & 1-\rho_2^2 \end{pmatrix}\right].$$

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