A discusión

# WHICH HUMAN CAPITAL MATTERS FOR RICH AND POOR'S WAGES? EVIDENCE FROM MATCHED WORKER-FIRM DATA FROM TUNISIA*

**Christophe Muller and Christophe Nordman****

WP-AD 2005-30

Corresponding author: Christophe Muller, Departamento de Fundamentos del Análisis Económico, Universidad de Alicante, Campus San Vicente del Raspeig, Apdo. Correos 99, 03080 Alicante, Spain. E-mail: cmuller@merlin.fae.ua.es.

Editor: Instituto Valenciano de Investigaciones Económicas, S.A.
Primera Edición Noviembre 2005
Depósito Legal: V-4680-2005



---

* This paper has been supported by the ESRC under the grant no. R000230326. Christophe Muller is also grateful for the financial support by Spanish Ministry of Sciences and Technology, Project No. BEC2002-0309, and by the Instituto Valenciano de Investigaciones Economicas. Christophe Nordman gratefully acknowledges financial support from TEAM-Développement (University of Paris I Panthéon-Sorbonne and CNRS) to carry out the survey in Tunisia. We have benefited from valuable comments from participants in a seminar at DIAL in Paris, in the Third Spring University of Mediterranean Economies in Ifrane, in the CLS Conference on "Labour Market Models and Matched Employer-Employee Data" in Sonderbörg, particularly from F. Kramarz, in the VII Jornadas de Economia Laboral in Alicante and in the Applied Econometrics Association (AEA) Conference on "Econometrics of Labour Demand" in Mons. Usual disclaimers apply.

** C. Muller: Universidad de Alicante; C. Nordman: DIAL (Paris), e-mail: nordman@dial.prd.fr.

**WHICH HUMAN CAPITAL MATTERS FOR RICH AND POOR'S WAGES?
EVIDENCE FROM MATCHED WORKER-FIRM DATA FROM TUNISIA**

**Christophe Muller and Christophe Nordman**


## ABSTRACT

In this paper, we study the return to human capital variables for wages of workers observed in Tunisian matched worker-firm data in 1999. This reveals us how returns to human capital in a Less Developed Country like Tunisia may differ from the industrial countries usually studied with matched data. We develop a new method based on multivariate analysis of firm characteristics, which allows us most of the benefits obtained by introducing firm dummies in wage equations for studying the effect of education. It also provides a human capital interpretation of the effect of these dummy variables. Moreover, in the studied data, using three firm characteristics easily collectable yields results close to those obtained by using the matched structure of the data.

The workers with low wages or low conditional wages experience greater returns to human capital than workers belonging to the middle of the wage distribution, while their return to schooling is significantly lower than that of high wage workers.

The estimates support the hypothesis that human capital is associated with positive intra-firm externality on wages. Therefore, a given worker would be more productive and better paid in an environment strongly endowed in human capital. However, the low wage workers do not take advantage of the human capital in the firm. Conversely, the low wage workers benefit from working in the textile sector in terms of wages unlike the middle and high wage workers. Finally, the low wage workers and high wage workers benefit from an innovative environment, while the middle wage workers do not.


**Keywords:** Wage, returns to human capital, matched worker-firm data, quantile regressions, factor analysis, Tunisia.

**JEL Classification:** J24, J31, O12.

# 1. Introduction

## *1.1. Worker or firm knowledge?*

Returns to human capital and skills have always been considered dominant explanations for labour compensation. Accordingly, they have been incorporated in individual wage equations by using regressors describing schooling and the worker's experience[1]. This is particularly important for developing countries where the returns to education are expected to be higher[2]. A variety of human capital indicators have been used for this purpose, although it is fair to say that years of schooling and years of work experience are the most popular regressors in such wage equations, often accompanied by their squared values.

On the other hand, it has been recognized that some skills or human capital attributed to workers are also specific to the firm in which they work. The experience accumulated within the firm may be different from experience previously obtained outside the firm. Thus, part of the return to human capital for the worker remuneration can be viewed as if it originated from the firm.

Moreover, the endogenous growth literature emphasizes the presence of technological or social externalities that generate higher returns to traditional factors, notably labour. It is likely that some of these externalities occur in the form of general knowledge that may be diffused in the economy. It is also probable that many externalities take place in the firm where the worker operates since that is where technological processes are most frequently exhibited and transmitted. These externalities may be firm specific or not. They lead to consider that a worker of a given qualification may be more productive and thus better paid in a firm strongly endowed in human capital. In particular, many tasks require team work, with skills diffused across the workplace[3]. For instance, workers' training may take place through imitation, i.e. when less experienced workers observe more skilled ones executing a given task. Then, workers' interactions are likely to enhance skills. The intensity of knowledge diffusion may be higher in professional environment well endowed in human capital.

---

[1] Mincer (1993), Card (1999).

[2] Sahn and Alderman (1988), Behrman (1999).

[3] Battu, Belfield and Sloane (2003).

Thus, the overall return to human capital explaining the remuneration of a given worker may involve personal skill characteristics and firm knowledge characteristics. It seems important to consider these two sources of returns to human capital simultaneously because education policies and policies promoting vocational training may affect the worker's and the firm's human capital environment differently. In particular, not accounting for knowledge externalities within firms may lead to under-estimate the benefits of such policies. Finally, introducing intra-firm human capital externalities may contribute to explaining the typical over-estimation of returns to schooling in LDCs.

In this paper, we want to look at how return to human capital, and notably intra-firm human capital externalities, may arise in Tunisia. The case of Tunisia is interesting as a success story resulting from its fast economic catching up with more developed countries. In this situation, firm and worker knowledge may correspond to different rewards that depend on the human capital investments in long run government strategies. These issues are crucial in the light of the future creation of a free trade zone with the European Union. Henceforth, the improvement of human capital – notably by on-the-job training – constitutes a priority in any productivity progress and in raising the quality of exported products.

We consider as a working hypothesis that when the human capital density in the firm is correlated with worker wages, holding workers' characteristics constant, this mostly reflects intra-firm human capital externalities. This approach does not exclude other interpretations: selectivity or matching effects, economic rents correlated with human capital and other firm characteristics, as in Teal (1996), or unemployment shocks specific to the different human capital categories affecting specifically some industries, as in Hoddinott (1996). The tests of such interpretations are unfortunately beyond the possibilities of our data, and we cannot attempt them.

### *1.2. Crucial data*

One popular way to account for firm characteristics, including for their human capital features, is to base the econometric investigation on matched worker-firm data[4]. Mostly, dummy variables for individual firms are added as independent variables in usual wage equations. We shall avail ourselves of such data, for the first time in the Tunisian case on

---

[4] Abowd, Kramarz and Margolis (1999), Goux and Maurin (1999), Abowd, Kramarz, Margolis and Troske (2001). See Abowd and Kramarz (1999) for a survey.

which we focus[5]. Then, this study will tell us how returns to human capital in a LDC like Tunisia differ from the industrial countries usually studied with matched data.

This data is crucial to understand inter-firm wage differentials. The persistence of wage differentials for individuals with identical productive characteristics is an important stylized fact. Indeed, wage differentials that are not compensated by observed individual characteristics were found on numerous occasions in empirical studies, depending on their industry or firm[6]. Many models attempted to give a theoretical interpretation of these inter-industry or inter-firm wage differentials: some of them stress non-competitive wage determination[7]. Other models, within the competitive framework, emphasize the existence of compensating wages due, for instance, to differences in jobs across industries (Murphy and Topel, 1987).

Nevertheless, data used to study inter-firm wage differentials are scarce. The Tunisian data we use provide precise information both on employees and their firms. Therefore, using these data, we examine the firm's effect on individual earnings, but also refine the fixed effect by investigating the human capital characteristics of each firm.

### *1.3. Policy issues*

Poverty is a major subject of concern in Tunisia. The Tunisian Governments have been successful in reducing the extent of poverty since the independence[8]. Accordingly, poverty has slightly increased from 1990 to 1995. So the global picture is that of a stabilization of poverty, although the poor are increasingly concentrated in peri-urban areas, particularly in Tunis. This is where our survey took place.

Several reforms of the labour market have been recently undertaken by the Tunisian government. First, the Labour Code was revised in 1994 and again in 1996 to clarify the conditions under which workers can be laid off and to establish guidelines for financial compensation. Second, Tunisian producers will face stronger competition in their export markets after the elimination of the Multi-Fibre Arrangements (MFA) scheduled to be completed by 2005. Third, the competition will be fiercer in the local market with full

---

[5] Matched worker-firm data is collected for example as part of the World Bank's RPED surveys in Africa (for Cameroon, Ghana, Kenya, Zimbabwe for instance). Each of these surveys constitutes a short panel of near 200 firms with about 10 interviewed workers in each firm. With such survey, Frazer (2003) studies the returns to education in Ghanaian manufacturing firms. However, such data is not available for Tunisia yet.

[6] Krueger and Summers (1988), Abowd et al. (1999) and Goux and Maurin (1999).

[7] See Katz (1986) for a review of efficiency wage theories and Lindbeck and Snower (1989) for a review of the insider-outsider models.

[8] The World Bank (2000), UNDP Tunis (1994).

implementation in 2007 of the Association Agreement signed with the EU in 1995, which allows free trade provisions. It is expected that better jobs for higher skilled workers will be generated and less skilled workers will encounter greater difficulties in finding and retaining jobs[9]. Indeed, the opening of international markets, notably in the textile sector, implies that Tunisian industries will be confronted not only to European firms, but also and mostly to the competition from countries with very low labour costs, such as China and India. Then, the situation of low-wage workers is worrying in a context of increasing liberalization, economic opening and privatization. A response to policy and structural shocks may be found in the improvement of sector productivity, connected to average skill levels in Tunisia[10]. The Tunisian economy ability to restructure may thus be raised: by shedding labour and changing the skill mixes of its labour forces; by encouraging firms to invest in on-the-job training; and by consolidating Tunisia's positive record in labour relations and working conditions.

As a response to these economic transformations, Tunisia started a large modernization programme of the productive sector in 1996. This programme assists industrial and service firms in adjusting to a free market. Physical and non-physical firm investment is stimulated. Human capital investment will be crucial in this modernization process.

Education reform is instrumental in improving the education system responsiveness to emerging labour market demands. The Tunisian authorities are placing an increasing emphasis on vocational training, which fulfils the double objective of educating and preparing workers for a modern job market. Recently, the government has implemented a programme to rehabilitate vocational training and employment (MANFORME, *Mise à Niveau de la Formation Professionnelle et de l'Emploi*). In the near future, the authorities should consider how to involve private employers in vocational training to match skills demand and supply.

What are the human capital characteristics influencing Tunisian workers' wages at different wage levels? The aim of this paper is to explore this question by using, first, matched worker-firm data and, second, summarizing the main characteristics of firms with a preliminary multivariate analysis. We have therefore a double focus: (1) firm specific experience, and externalities and (2) returns to education across different quartiles of the earnings distribution. This is a deliberate methodological choice since this is the investigation of what happens for different quantiles that allows us to get a better grasp on the intra-firm externalities. We show that, in our data, the lack of linked worker-firm data

[9] Measurement of unemployment in Tunisia is a difficult and contentious issue (Rama, 1998). However, unemployment is a growing concern of the population and government.

[10] Belhareth and Hergli (2000).

could be compensated by some limited information on firms that is easily collected from workers. In Section 2, we present the data. We discuss estimation results for wage equations at different wage levels in Section 3. In this section, we also push the analysis one step further by incorporating firm characteristics and interpreting firm dummy effects using a factor analysis. Finally, Section 4 concludes.

## 2. The Tunisian matched worker-firm data

The matched worker-firm data we use were directly collected in the workplace[11]. Eight firms were selected based on criteria of size (not less than 50 employees), activity, vocation to export and capital ownership[12]. They all belong to the formal sector. After interviewing the employers, the occupational structure within each firm was used to constitute representative sub-samples of their workers. Workers were randomly chosen within each occupation strata and not less than 10 percent of the manpower was interviewed.

The questionnaire provides precise information about each worker: individual characteristics (matrimonial status, number of dependent children, geographic origin, father's education), wages, educational investments (number of years spent in primary, secondary, higher and vocational education), post-school training (apprenticeships, preliminary internships, formal training within the current firm), total experience in the labour market and occupation in the current firm. Moreover, the data include characteristics of the firms in which workers evolve: organisational features, communication and training policies, innovation and competitive situations.

### *2.1. The workers*

The 231 workers in the final sample were interviewed in February 1999. Table 1 provides some descriptive statistics about these workers, which are matched with a sample of eight firms (four firms in the textile-clothing sector and four in the Mechanics, Metallurgical, Electrical and Electronics Industries, IMMEE). 54.1 percent of the employees work in the textile sector and 45.9 percent in IMMEE. The proportion of women in the overall sample amounts to almost half, 49.8 percent.

---

[11] The methodology of the Tunisian survey appears in Nordman (2002) and Destré and Nordman (2003). The definitions and the descriptive statistics of the variables are in Tables 1 and 2 of the Appendix.

[12] The observed firms were selected among firms exporting their production and not with entirely foreign capital.

The average educational year is 9.6 over the sample when calculated from the workers' questionnaires, using the available information on the highest level of education reached by the workers. Educational years are slightly higher for men (10.6 years) than for women (8.7 years). For men, it corresponds to the first year of high school. In contrast, calculating it from the age at the end of school (from which we deduct 6 years), the average number of schooling years is close to 13. Thus, accounting for unsuccessful years of education[13], we choose to use an education variable net from repeated classes. Consequently, the years of schooling include an important qualitative aspect. 0.8 percent of the observed workers have never gone to school, 9.9 percent have only completed a primary level of education (1 to 5 years), 71.8 percent have obtained an educational level of 6 to 12 years (secondary school) and 17.3 percent have completed studies in higher education (university level). The proportion of employees having received a vocational diploma related to their current job amounts to 31.6 percent.

The average tenure in the current firm is 5.9 years. It amounts to 5 years for women, while it is higher for men (6.75 years). The total professional experience is an average of 9.1 years. On average, men cumulate more than 10 years of experience against less than 8 years for women. Besides, the previous experience apart from the current job is on average of 3.3 years. Women average 2.8 years, compared to 3.6 years for men.

The ratio of tenure to the overall work experience is 64 percent. This suggests an important percentage of young, first-time workers. Indeed, the average age in the sample is small, amounting to 29.5 years and 28 and 31 years for women and men respectively.

Some wage characteristics are worth noting. The average monthly wage declared by employees is 213 US dollars[14], while an average monthly wage for male workers is 1.7 times the female wage. Beyond differences in human capital endowments between sexes, the female proportion of the sample employed in the textiles, where wages are generally low, contributes to this wage differential: 94 percent of the observed women belong to the clothing sector, while male workers of this sector represent only 14 percent of all male workers. Indeed, the average monthly wage in the IMMEE sector is 1.6 times higher than in the textile sector. Educational differences should partially explain this: On average, the

[13] For comparison, Angrist and Lavy (1997) estimate the number of repeated classes at 2 to 3 years in Morocco. Besides, UNDP (1994) shows that Tunisia in the 1980's had a higher rate of repeated classes at the primary school than Morocco.

[14] The average monthly wage corresponds to 1.8 times the monthly SMIG of 1997 for a regime of 48 hours per week (177.8 Tunisian Dinars, that is 125 US dollars in 2001). The declared monthly wages are those of January and February 1999.

IMMEE workers have 10.6 years of education compared to 8.9 years for those working in textiles.

Statistics specific to each wage quartile show that workers' characteristics differ according to wage level. Lower wage workers are less educated, trained and experienced. They are on average younger, mainly females and have suffered longer unemployment spells. These results suggest separate modelling of the wage rates at different wage levels. Naturally, these notions of living standard level are restricted in this paper to wage workers in the formal sector and are not fully representative of all the low wage workers in Tunisia[15]. We now turn to the firm characteristics.

## 2.2. *The firms*

The four firms of each sector are located in the Tunis area. This firm sample is interesting because these firms are typically in the range of shocks and policies we mentioned above. The average size of the establishments visited is 130 employees.

Information about the firm's characteristics have been collected directly from the employers: composition of the workforce, work organization, training and communication policies, organizational or technical innovations and competitive situation of the firm. Table 2 in the Appendix shows descriptive statistics. Figure 1 in the Appendix shows the histogram of observed wages. The two minimum wages are separately indicated by vertical lines for 40 hours a week and 48 hours a week.

Contemporary wages are concentrated around values slightly above the minimum wage, while heavy right tails account for a small number of very skilled workers. Indeed, individuals who earn more than 500 dinars per month (in the upper tail of the wage distribution) only represent 12.5 percent of the overall sample. Also, 80 percent of these workers received degrees in higher education against only 7.4 percent of the workers with monthly wages below 500 dinars. We are now ready to discuss the estimation results.

---

[15] Low (high) skilled workers may not systematically correspond to low (high) pay workers. For instance, only 60 percent of the 25 percent "richest" workers have degrees in higher education. However, the link between wages and skills is rather strong in this data. Another approach could have been to oppose skill categories rather than wage levels. In this paper, we focus on wage categories to capture differential social consequences of training and education policies.

# 3. Estimation results

## *3.1. The model and the estimation method*

The matched worker-firm data enables us to estimate the returns to human capital using both workers' and their firms' information. For this purpose, the average returns to human capital are given by the coefficients of years of schooling and labour market experience in a Mincer-type wage equation[16]. However, returns to human capital can vary across wage categories. For instance, high wage workers should not benefit from the same return to experience than low wage workers since the latter may have fewer incentives to make further on-the-job investment in human capital because they only deal with basic tasks. Alternatively, more educated individuals – generally with higher wages – may have greater incentive to invest in training because they learn more quickly. As a result, the shape of the relationship between the workers' wage level and their returns to education and work experience (former experience plus tenure in the incumbent firm) is not clear. To capture differentiated returns of education and experience between low wages and high wages, we construct four individual dummies indicating the workers' relative position in the sample in terms of hourly wage (quartile 1 to quartile 4). These dummies (QUARTILE*i*, *i*: 1…4) are allowed to interact with the main human capital variables in the wage equation.

As alluded in the introduction, the lack of suitable matched firm-employee data for the wage analysis has been deplored by a number of authors, such as Willis (1986), as such data allows the structure of wages to be modelled while controlling firm-specific effects. With our matched data, we can deal with the firm heterogeneity by introducing firm dummy variables. However, since we have cross-sectional data, we cannot model unobserved individual heterogeneity in the way of Abowd et al. (1999). To temper the effects of unobserved individual heterogeneity which might bias the estimated coefficients, we add control variables to our OLS regressions and perform instrumented regressions (2SLS).

Naturally, using firm dummies is a rough way of accounting for intra-firm human capital externalities. Meanwhile, it is possible that part of what could be interpreted as human capital externalities in the estimates is in fact a consequence of the worker selection by firms and vice versa. For example, very productive firms and workers may choose each other. In this paper, because of data limitations, we do not deal with this difficulty, and we are constrained to assume that selectivity and sub-sampling effects can be neglected. Although

---

[16] Quadratic and more flexible polynomial specifications have been tried but cannot be accurately estimated with these data.

this is not a completely satisfactory hypothesis, that is all that can be done at the moment if one wants to investigate the issues of this paper in the Tunisian case. This does not imply that we shall *always* interpret the effects of firm dummies or characteristics as human capital externalities. As a matter of fact, the factor analysis will incorporate other aspects related to the 'job differences' across firms. In any case, alternative interpretations or results could be based on matching processes. If high skilled workers are relatively more productive at the most productive firms, then there may be sorting of the more productive workers into the more productive firms. In that case, one cannot separately identify the contributions of workers and job characteristics from a simple wage equation with job and firm characteristics. Although, such or other selectivity effects may take place, it is presently impossible to control for this in Tunisia. However, the rigid and inefficient features of the Tunisian formal labour market (with heavy administrative procedures, and little public information on jobs and workers) make plausible that selection effects are less intensive than in industrialised countries.

In the wage equations, we incorporate formal training received in the current firm (ongoing training and past training). In our sample, more educated workers generally receive more formal training: on average 12.2 years of schooling for workers having received formal training compared to 9.1 for the others. Two other dummy variables are retained[17]: One dummy variable controls for the worker's hierarchical position in the firm (executive or supervisor), while the other describes trade union membership. Workers who are executive or supervisor are expected to have higher earnings. The effect of union membership on wages remains unclear in the empirical literature.

The estimated model is:

$$\mathrm{Ln}(w_i) = X'_i\,\beta + T'_i\,\gamma + F_{ij}\,\delta_j + u_i$$

where $w_i$ is the wage rate of worker $i$, $X_i$ describes the set of usual wage determinants listed above, $T_i$ describes the set of training variables, $F_{ij}$ is the dummy variable of firm $j$ worker $i$ belongs to, $u_i$ is an error term. In some versions, the explanatory variables in the $X_i$ and the $T_i$ are crossed with the quartile dummies so as to capture some differential effects across the earnings distribution.

We do not limit our analysis to the OLS or 2SLS results. Introducing dummies for quartiles as regressors creates endogeneity problems that may be imperfectly corrected with instrumental variable methods. A way to avoid this difficulty is by using quantile

[17] All the other socio-economic variables such as sex, matrimonial status and geographic origin are dropped from the regressions for lack of significance and to preserve degrees of freedom.

regressions. Quantile regression estimators have recently become popular estimation methods (Koenker and Bassett, 1978), which have been employed for wage analyses (Buchinsky, 1998a, 1998b, 2001). The popularity of these methods relies on two sets of properties. First, they provide robust estimates, particularly for misspecification errors related to non-normality and heteroscedasticity, but also for the presence of outliers, often due to data contamination. Second, they allow the researcher to concentrate her attention on specific parts of the distribution of interest, which is the conditional distribution of the dependent variable.

As in Buchinski's papers, we do not attempt to correct for possible endogeneity of human capital variables for these estimation methods because of the too small sample to obtain significant results.

Consequently, focusing on the quantiles of error terms in wage equations, introduces an alternative approach that can be contrasted with the quantiles of the wage distribution. Thus, one can compare the low observed level of wages in OLS and 2SLS estimates with the low conditional wage level in the quantile regression estimates. We find that the residuals' quantiles from the quantile regressions are correlated to those obtained when different quartiles are used to define the quantile regression. In contrast, they are not as strongly correlated to the quantiles of the wages themselves. Thus, low quantiles corresponding to the two approaches capture distinct dimensions of wage distribution features. Finally, bootstrap confidence intervals are used for quantile regressions in order to avoid the consequences of the slow convergence of classical confidence intervals of estimates (Hahn, 1995). Let us examine the estimates.

### *3.2. The wage equation estimates*

Our first estimates of the equations of the logarithm of individual hourly wage are reported in Table 3 of the Appendix. The first two columns correspond to OLS estimates without wage quartiles incorporated in regressors. The following two columns show the results obtained when the returns to human capital can vary across wage quartiles through the inclusion of dummy variables for wage quartiles[18].

[18] We also test interactions of these dummies with the quadratic terms of experience variable to take into account possible differentiated decreasing returns to experience across wage quartiles. However, since the results were little significant, we choose to exclude these interactions to preserve on degrees of freedom.

The wage equation which incorporates firm's fixed effect is characterized by a better goodness-of-fit than the standard Mincerian wage function[19]. The return to schooling decreases after controlling for firms' heterogeneity with fixed effects. In OLS regressions, the marginal return to education in Tunisia is 6.9 percent with the firm's fixed effects instead of 8.6 percent without the firm dummies. The drop for Tunisia is in the scope of usual results (Abowd and Kramarz, 1999). Thus, introducing firm dummies brings to the fore a partial answer to the issue of typical over-estimation of education returns in LDCs. To our knowledge, no comparable estimates exist on Tunisia[20].

Columns (3) and (4) elicit returns to human capital that are significantly different across wage quartiles, without and with adding the firm's fixed effect, respectively. Table 4 summarizes the main results of all these estimators by computing the coefficients of education, job tenure and previous experience for each wage quartile. Looking at OLS estimates shows that the low wage workers (first quartile) have significantly higher returns to human capital than the workers belonging to the middle of the wage distribution: The returns to education amount to 4 percent, 0.3 percent and 0.2 percent for the workers belonging to the first, second and third quartiles, respectively. However, the return to schooling of the low wage workers is significantly lower than that of the high wage workers (8.7 percent for the fourth quartile). More generally, except for tenure, the results emphasize a U curve that describes the returns to education and experience as a function of the wage levels (first to fourth quartile). This is consistent with results found from quantile regression estimates in industrialised countries, where returns to schooling are higher for the more skilled individuals (Martins and Pereira, 2004). As for tenure, its return is always significantly higher for the low wage employees than for the other categories, while the U curve corresponding to the estimates of coefficients is generally not significant[21].

Note that there is no mistake with the average education return dropping from 6.9 to 3.3 percent. This result is confirmed by running separate regressions for each quartile and suggests that unconstrained education returns may be strongly biased. Moreover, the returns to experience at the average point of the sample also vary a lot (4.26 percent without quartile

---

[19] The Fisher test of the constrained model (without the firm's fixed effect) against the unconstrained model (fixed effects) shows that we cannot reject the unconstrained model at the 1 percent level.

[20] See Psacharopoulos and Patrinos (2002) for surveys reporting the returns to education in numerous countries. Some of the education effect may be caused by selection. Firm dummies may help control for the selection effects, but other individual and household characteristics are missing which does not allow us to be fully protected against a selectivity bias.

[21] One could raise an objection based on the shape of the histogram of wages: there may be only few observations between mode and extreme observations. Then, the U curve may result from too little information in the data for the second and third quartiles. Drawing the quartile lines of this histogram has shown us that this is not the case and that low density levels only occur from the last quartile.

dummies against 2.56 percent with quartile dummies) and for tenure (respectively 4.51 percent and 2.31 percent).

We control for the possible endogeneity of the education variable by using two-stage least square regression (2SLS) whose estimates are shown in column (5). Moreover, the introduction of the dummies for wage quartiles creates an additional source of endogeneity that must be dealt with. The set of instrument for both education and the wage quartiles is reported at the bottom of Table 3[22]. The instrumentation is mostly based on demographic characteristics entered or insignificant and omitted in the wage equation, on father's characteristics and on past vocational training variables of the worker that were not significant. An important instrument for the worker's education variable is the schooling level of the worker's father[23]. Some of these variables could be deemed endogenous if, for instance, the father has contributed to job access for his child, or if vocational training is freely chosen simultaneously to wage level by the workers. Using the 2SLS estimates relies on the assumption that such situation does not arise and that these variables can be considered as valid instruments. Thus, in this paper, 2SLS are merely another attempt to provide various perspectives on human capital returns in Tunisian firms. This is interesting because the different estimation methods will lead to common features in the results that we shall be able to consider as relatively robust. Thus, even if endogeneity issues, say for quartile dummies, or for untreated on-the-job training, are not perfectly corrected, the convergence of results from OLS, 2SLS, quantile regressions of equations with and without firm effects should help convincing us of their relative solidity.

The presence of fixed effects specific to the firms should strengthen the quality of the used instruments since these effects could for example capture the effect of parental education on the chances of insertion in the labour market. Note also that if one objects to the presence of endogenous quartiles in the OLS regressions, one can turn to quantile regressions which are also based on quartiles but do not include them as dummy regressors.

With 2SLS, the main results remain unchanged (Table 4). However, the returns to human capital are refined[24]: the average return to education decreases from 3.3 percent (OLS) to 2.4 percent (2SLS). This is at odds with the effects of instrumental variables in some empirical works. For example, Card (1999) finds for U.S. data that 2SLS estimates on

---

[22] The values of the F-statistics and $R^2$ in instrumental equations ensure that we are not in the weak instrument case (Abadie et al., 2002). We attempted to instrument the experience variable as well, although this did not yield any good result since we lack additional instrumental variables to perform it in good conditions.

[23] This instrument, popular when using developing country data, may capture various genetic and environment influences (Sahn and Alderman, 1988).

[24] The statistic of the Durbin-Wu-Hausman test indicates that the null hypothesis of exogeneity of the instrumented regressors (education and dummy for quartiles) is strongly rejected (P-value: 0.42).

returns to education are often 15 percent higher than OLS estimates. However, under the assumption that unobserved ability biases the results, the reduction would have to be expected, while increases in the returns are often attributed to a correction of the attenuation bias. The return to education falls for the low wage workers and rises for the high wage workers. The returns to tenure and experience are also enhanced for the poorest workers.

We also investigate whether returns to human capital differ across the wage distribution by using quantile regressions for quantiles 0.25, 0.50 and 0.75. These estimates are shown in columns (6), (7) and (8) of Table 3. The results confirm the gaps across the quartiles in the returns to education, tenure and previous experience (Table 4). Both returns to tenure and experience remain higher for workers belonging to the first quartile than the second and third quartiles. This is in contrast to findings from Portugal in Machado and Mata (2001), where all aspects of human capital are more valued specifically for high paying jobs. However, for Tunisia the last quartile corresponds to the highest returns to education. Meanwhile, the differences across the wage quartiles obtained with quantile regressions are smaller than those for the OLS and 2SLS.

Let us now look at the other estimated coefficients. Completed formal training plays an important role in explaining wage differentials (its coefficient is always significant at a 5 percent level and positive). This is consistent with theories that argue that wage differentials should reflect differences in training investment. On the other hand, the negative coefficient of the ongoing formal training variable, although not always significant, is an additional evidence this time from Tunisian data, consistent with Becker's standard prediction that the costs of general training are shared between employers and employees (also found from US data in Lynch, 1992; Barron et al., 1998; Parent, 1999, but often ambiguous). If this formal training is of general content, then the workers should partly compensate for it by accepting a lower wage during the training period (Leighton and Mincer, 1981; Hashimoto, 1982). As shown by the estimates, workers ultimately benefit from this training through a positive wage premium when training is completed (from 10 percent to 30 percent increase depending on the regression).

Finally, the estimates of the firm dummies' coefficients are large and significant at the 1 percent level. This is in accordance with the usual wage differentials across individuals with identical productive characteristics in empirical studies[25]. Such wage differentials have been found in Tunisia in non-matched data (Abdennadher et al., 1994). Here, workers with comparable measured characteristics earn different wages partly because they belong to different firms. In this study, wage differentials across firms will receive further

[25] See Krueger and Summers (1988), Abowd et al. (1999) and Goux and Maurin (1999).

consideration in the next sub-section where the firm fixed effect is interpreted in terms of each company's features.

### *3.3. Principal component analysis of the firm's characteristics*

We use a principal component analysis (PCA) to summarize the information about the surveyed firms[26]. There are three possible uses of factor analysis in this context. First, and foremost, factor analyses are generally used to elicit hidden characteristics correlated with observable characteristics. Accordingly, we look for hidden characteristics which could replace the firm dummies. Second, we use the PCA results as a guide to replace these hidden firm characteristics with observable characteristics correlated with the main factors. Third, we use the PCA as a substitute for regressions of firm dummies. Indeed, with only eight firms there is no hope for explaining firm effects with regression analysis (as in Cardoso, 1998). In contrast, the PCA allows us to investigate the determinants of the firm effects in our data.

Table 5 shows the results of the principal component analysis, with the definition of the main three inertia axes (the factors), which are linear components of the firm's characteristics used for the analysis. The other factors represent a negligible amount of statistical information and are dropped from the analysis[27]. In our basic specification without quartile dummies, OLS estimates without the firms' dummies nor factors explain 67 percent of the log-wage variance. Adding our three factors raises this proportion by 8 percent, and the firms' dummies instead by 9 percent. The correlation coefficients of these characteristics with the first three factors are indicated for the interpretation. Clearly, the first factor corresponds to the activity sector (textile against IMMEE), grouping the firms most oriented towards exports[28]. The second factor describes the 'density in the firm' of the human capital characteristics. The third factor is closely associated with the firm's modern features, reflecting the firm's age and its capacity to promote innovations and new technology.

[26] This method is based on the calculation of the inertia axes for a cloud of points that represents the data in table format. In principal component analysis, a set of variables is transformed into orthogonal components, which are linear combinations of the variables and have maximum variance subject to being uncorrelated with one another. Typically, the first few components account for a large proportion of the total variance of the original variables, and hence can be used to summarize the original data. We tried many other techniques of factor analysis. They lead to similar conclusions. We omit them in the presentation to save space.

[27] The percentage of inertia incorporated into the three first components amounts to 72.9 percent, showing that most of the useful statistical information about firms is incorporated in the factors.

[28] The export orientation of the firm could be more relevant than the sector to characterise the first factor. However, the impact of the sector on wages seems to make more sense given the strong sector segmentation of the market in Tunisia. Indeed, every three years collective wage bargaining at sector level are conducted for 45 sectors.

Naturally, as it is always the case in factor analysis, these interpretations are somehow subjective. The reader may substitutes her own if wished.

Table 6 indicates the Pearson's correlation coefficients of the first three factors with the firm dummies on one hand, and a few education and gender characteristics of workers in the firm on the other hand. They confirm common wisdom about how the firm is characterized by each factor. Firms in the textile sector have a higher proportion of female workers and less educated or trained workers. Firms with high human capital density exhibit higher average education levels. Modern firms invest more in formal training.

### *3.4. Wage equations with firm factors*

The three principal components (factors) summarize the main information on the firms' characteristics[29]. By contrast with the firms' fixed effects introduced in the wage regressions in Table 3, the factors suggest qualitative characteristics of the firms. In Table 7, we present the estimates of the wage equations in which the firm fixed effects are replaced by the three factors.

The first column reports the OLS estimates. The coefficient of the first factor is statistically significant at 5 percent level and has a negative sign. This is consistent with the fact that in Tunisia the textile sector is the manufacturing industry with the lowest wage.

The second factor has a significant positive impact on wage differentials. Then, the firm's human capital may generate positive wage externality. A worker with given skills would be more productive and better paid in an environment highly endowed in human capital. The third factor has no significant effect in this specification.

In the following two regressions (columns 2 and 3), wage quartile dummies are incorporated and allowed to interact with the three factors in order to explain if differentiated effects of factors and variables exist across wage groups. The factors' effects are summarized in Table 4.

First, from the OLS regression, it appears that low wage workers (first quartile) benefit from working in the textile sector unlike medium and high-wage workers. Second, low wage workers do not seem to take advantage of the firm's human capital since they

[29] Various studies tried to separate the external effects of the group or the sector in which the workers evolve from the purely individual effects on their earnings differentials. Mean variables were added in earnings functions, after a control for the individual characteristics, by Dickens and Katz (1987), Krueger and Summers (1988), Blanchflower and Oswald (1994), Chennouf et al. (1997), Kölling et al. (2002), Battu et al. (2003) and Alcalá and Hernandez (2005). Using factors is a further step in this direction.

experience a negative impact on their wages from Factor 2. This result may reflect differences in bargaining power within firms across wage groups, or be associated with differences in the role of human capital in typical tasks across wage levels. Also, the transmission of knowledge might be reserved for high wage or high skilled workers. Finally, the correlation coefficient of Factor 2 with the importance of supervision is 0.98, while it is 0.96 with the managerial/staff proportion. Then, the negative effect of Factor 2 on the first quartile wage may result from excessive supervision preventing development of human capital externalities because it restricts individual responsibility and improvement possibilities. High wage workers are the ones who benefit the most from the firm's human capital density. As for Factor 3 (firm modernity), its impacts on wages follow a U curve across wage groups. Low wage and high wage workers benefit from an innovating environment, while workers in the middle of the wage distribution do not.

The results with 2SLS and quantile regressions show similar features for the positive effect of the second factor. However, as expected, because of the accuracy lost in the instrumentation, the coefficient of the various equations incorporating factor dummies are often non-significant with the 2SLS, particularly when factor dummies are interacted with quartile dummies. Finally, the quantile regression estimates of factor effects differ in that they are not based on interacted effects of factors and quartiles. In this case, the first factor corresponds to a significant negative effect, the second factor to a significant positive effect, while the third factor has no significant impact. These results illustrate the differences in the two notions of wage positions, respectively based on wage quantiles or wage conditional quantiles.

Finally, we conduct a simple regression by replacing the three factors with three of the firm's characteristics ('surrogate variables') that seem better reflect each of them: a dummy for the textile sector (Factor 1), the average education level in the firm (Factor 2) and the firm's age (Factor 3)[30]. Using a questionnaire addressed to workers (e.g. through a labour force survey), it would be easy to collect information on these three characteristics (sector, proxy of average education in this firm, age of this firm) and use them as regressors in the wage equation. We call this regression the "pseudo factor" model (PFM, column 4 of Table 7). The coefficients of the three selected variables are statistically significant at 1 percent and have the expected sign. The returns to human capital obtained from the PFM are closer to those of the firm fixed effects model (FFEM, column 2 in Table 3) than to the corresponding returns drawn from the Mincerian Model (MM, column 1 in Table 3). More specifically, the

[30] Eliminating the wage observation of the considered individual in this mean does not qualitatively change the results.

PFM yields a return to education similar to that obtained by the FFEM (6.8 percent compared to 6.9 percent with the FFEM, while it amounts to 8.6 percent with the MM).

Let us mention a few points about estimates with specific quartile effects of the surrogate variables that we do not show to save space. There is no significant differentiated effect of the sector variable across wage quartiles. In contrast, OLS estimates show that the external effect of mean education on wages is lower for workers belonging to the third quartile than that of the low wage and high wage workers. Finally, the establishment's age has a negative impact on the wages of the low wage and high wage workers (-1.8 percent), and a positive impact for workers in the second (3.9 percent) and third quartile (3.7 percent).

Comparing the estimation results based on firms' fixed effects with the estimation results based on factors is instructive. Indeed, the fixed effects may partly result from unobserved human capital characteristics of firms. In our data, three of the firm's observable characteristics suffice to account for most of the impact of the firm's effects on wages.

When all quarters are considered together, returns to education when omitting all firm's characteristics or effects are substantially different from the returns to education when the firms' fixed effects are incorporated. As in Chennouf et al. (1997) for Algeria, the returns to education diminish when the firms' effects are introduced. Meanwhile, the returns to education obtained with the firms' fixed effects are almost indistinguishable from the returns in equations with factors, and from the returns in equations with instead the mean education of the firms. This suggests that the missing firm's effects can be accounted for by introducing mean education variables *if the main interest is to estimate returns to education.*

Finally, the factors may be used to better interpret the firm dummies in equations with the firms' fixed effects. For example, the characteristics of firm number 1 (respectively firm number 6, respectively firm number 7) are very close to that of Factor 1, 'textile type industry with high export orientation' (respectively Factor 2, 'high qualification', respectively Factor 3, 'modern firm').

One pending question is whether our results on the role of factors with eight firms can be extended to other firm samples and questionnaires. Would the same factors, and such a small number of factors, compensate for unobserved firm effects with other data sets? This is doubtful. However, what is plausible is that the approach of using factors to replace firm dummies is fruitful, notably when the interest is exclusively to estimate the coefficient of education in wage equations. What would be needed, for a given context, is an investigation of the robustness of finding with other data sets, at the moment unavailable for Tunisia.

## 4. Conclusion

In this paper, we study the return to human capital variables for wages of workers observed in Tunisian matched worker-firm data in 1999. Our results illustrate how returns to human capital in a developing country such as Tunisia may differ from industrial countries usually studied with matched data. We develop a new method based on multivariate analysis of firm characteristics. This method allows us many of the benefits obtained by introducing firm dummies in wage equations for studying the effect of worker's education. It also provides a human capital interpretation of the effect of these dummy variables. Moreover, in the studied data, using three firm characteristics easily collectable (average education level of workers, sector, age of the firm) yields results close to those obtained by using the matched structure of the data.

Some results are similar to what has been found in industrial countries. Wage equations incorporating the firms' fixed effects have a better fit than the standard Mincerian wage functions. All the wage equations show large effects from the firm dummies. The impact of formal job training on earnings is consistent with general predictions of human capital theory: individuals invest in training during an initial period and receive a lower wage than what they could receive elsewhere without training. Workers may collect returns from their investment at a later period through higher marginal products and higher wages.

Other results differ from typical findings with industrialised country data. With or without controlling for firm characteristics and for possible endogeneity of the education variable, the low wage workers (whether defined in terms of wages or conditional wages) experience greater returns to human capital variables than workers belonging to the middle of the wage distribution. However, the return to schooling of the low wage workers is significantly lower than that of the high wage workers.

Using a factor analysis to summarize the information on the surveyed firm, we show that the activity sector of the firm, its human capital characteristics and modern features concentrate most of the statistical information from the employer survey. Wage regressions, including the computed factors, confirm that the firm's stock of human capital is correlated with positive intra-firm externality on wages, although the low wage workers do not benefit from it. Conversely, the low wage workers benefit from working in the textile sector unlike the medium and highly paid workers. Finally, the low wage and high wage workers, as opposed to workers in the middle of the wage distribution, benefit from an innovating firm environment.

An alternative interpretation of such results is that the estimated intra-firm externality on wages partially captures the role of unobserved physical capital. Indeed, it may be that high human capital and training are correlated with high capitalistic intensity across firms. If that is the case, the impacts of human firm capital and physical firm capital on wages should be analysed jointly. This calls for accurate measurement of these two variables, notoriously hard to observe. Also, the intra-firm human capital effects may originate from selectivity or matching effects. For example, because of specific technologies requiring high skills, some firms hire workers with high human capital and pay well this specific human capital.

What are the policy implications? In the Tunisian context, emerging tensions in the labour market – resulting from uncertainty about job tenure and deterioration in relative wages for lower-skilled workers – will need to be closely followed through comprehensive monitoring of unemployment, skill composition and location. The role of education and vocational training is central in dealing efficiently with these tensions. One of the outcomes of the estimations is that human capital investment should partly proceed through the work organisation and training policy of the firm and not only stem from public education policies.

Moreover, poverty in Tunisia has been found to be more concentrated in the textile sector among manufacturing sectors. This is consistent in our data with lower wages observed in the textile sector. However, since the return to human capital is particularly high for the low wage workers in this industry, the textile sector could play a role of skill promoter for low-skilled manpower. Once workers have raised their productivity by working in this industry, they may be able to switch to another activity sector in search of better remunerations, although we cannot test this hypothesis with our data.

Finally, what can we expect from education policies against poverty and inequality? The U-curve of the returns to the different human capital variables in wage equations implies that human capital accumulation is likely to help alleviate poverty but may have ambiguous effects on inequality. A possible surge of inequality may be especially worrying if the findings of Mesnard and Ravallion (2001) are confirmed: raising inequality in Tunisia depletes the aggregate number of business starts-up, and therefore may reduce future economic growth. In these conditions, welfare public programmes based on reinforcement of workers' skills and knowledge should be accompanied by monitoring the benefits that every social group would receive from education and training, including in the workplace itself.

## APPENDIX

**FIGURE 1. Distribution of workers' observed monthly wages**

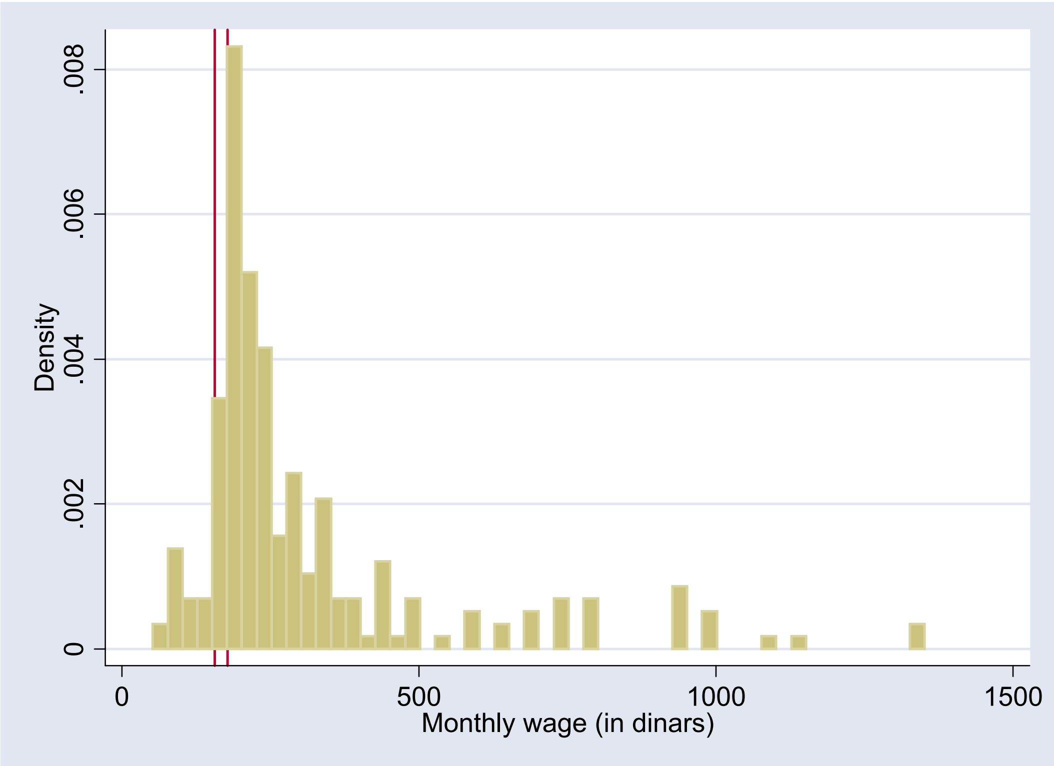

**TABLE 1. Descriptive statistics of the workers' characteristics**

| Variables | Mean | Standard deviation | min | max |
|---|---|---|---|---|
| Age of individuals (AGE) | 29.532 | 7.774 | 15 | 52 |
| Sex (FEMALE, 1: woman; 0 man; conversely for MALE) | 0.498 | 0.501 | 0 | 1 |
| Geographical origin (PROVE, 1: rural area; 0 otherwise) | 0.147 | 0.355 | 0 | 1 |
| Matrimonial situation (MARI, 1: if married; 0 if divorced, widowed or single) | 0.368 | 0.483 | 0 | 1 |
| Single male (CELIBAH, 1: yes; 0 otherwise) | 0.303 | 0.460 | 0 | 1 |
| Number of dependent children (ENFT) | 0.580 | 1.060 | 0 | 5 |
| Father has a level of Primary school (PPRIM, 1: yes; 0 otherwise) | 0.173 | 0.379 | 0 | 1 |
| Father has a level of Secondary school (PSECON, 1: yes; 0 otherwise) | 0.164 | 0.371 | 0 | 1 |
| Father has a level of Higher education (PSUP, 1: yes; 0 otherwise) | 0.125 | 0.332 | 0 | 1 |
| Father is illiterate (PANAL, 1: yes; 0 otherwise) | 0.194 | 0.396 | 0 | 1 |
| Years of schooling (EDUCATION) | 9.676 | 3.880 | 0 | 18 |
| Previous apprenticeship in a firm (APPRENTI, 1: yes; 0 otherwise) | 0.363 | 0.482 | 0 | 1 |
| Periods of internship related to the current job (STAGA, in years) | 1.468 | 3.617 | 0.00 | 24.0 |
| Periods of internship not related to the current job (STAGAN, in years) | 0.121 | 0.759 | 0.00 | 6.00 |
| Periods of unemployment (CHOMA, in years) | 1.385 | 2.825 | 0.00 | 18.0 |
| Previous relevant experience (EMSIM, 1: yes; 0 otherwise) | 0.554 | 0.498 | 0 | 1 |
| Previous professional experience (EXPERIENCE*, in years) | 3.261 | 4.689 | 0 | 22 |
| Start date in the current firm (ENTREE) | 1992.1 | 5.901 | 1968 | 1997 |
| Tenure in the current firm (TENURE, in years) | 5.898 | 5.902 | 0.17 | 30.08 |
| Formal training received in the current firm (FORMAD, 1: yes; 0 otherwise) | 0.182 | 0.387 | 0 | 1 |
| Formal training period in the current firm in years (FORMAA) | 0.091 | 0.323 | 0 | 3 |
| Ongoing formal training in the current firm (FORSTIL, 1: yes; 0 otherwise) | 0.017 | 0.130 | 0 | 1 |
| Member of an union (SYNDIC, 1: yes; 0 otherwise) | 0.203 | 0.403 | 0 | 1 |
| Work in team (EQUIPE, 1: yes; 0 otherwise) | 0.367 | 0.483 | 0 | 1 |
| Work in chain (CHAINE, 1: yes; 0 otherwise) | 0.320 | 0.467 | 0 | 1 |
| Executive or supervisor (ENCADR, 1: yes; 0 otherwise) | 0.190 | 0.394 | 0 | 1 |
| Hourly wage (salh, in dinars) | 1.893 | 1.347 | 0.29 | 7.57 |
| Log of hourly wage (lnsalh) | 0.197 | 0.251 | -0.54 | 0.88 |
| Monthly wage (sal, in dinars) | 315.131 | 231.382 | 52 | 1350 |
| Firms' fixed effects** | | | | |
| Firm 1 (IMMEE sector) | 0.134 | 0.342 | 0 | 1 |
| Firm 2 (IMMEE sector) | 0.160 | 0.368 | 0 | 1 |
| Firm 3 (Textile sector) | 0.143 | 0.351 | 0 | 1 |
| Firm 4 (Textile sector) | 0.130 | 0.337 | 0 | 1 |
| Firm 5 (Textile sector) | 0.130 | 0.337 | 0 | 1 |
| Firm 6 (IMMEE sector) | 0.087 | 0.282 | 0 | 1 |
| Firm 7 (IMMEE sector) | 0.078 | 0.269 | 0 | 1 |
| Firm 8 (Textile sector) | 0.139 | 0.346 | 0 | 1 |

*: This experience variable is an actual measure, as opposed to a potential one. It excludes experience in the current job (TENURE) and possible unemployment and inactivity periods.

**: The means of the firms' fixed effects (dummies for each firm) indicate the sample distribution of the workers across firms and sectors.

**TABLE 2. Firms' descriptive statistics**

| Variables | Mean | Standard deviation | min | max |
|---|---|---|---|---|
| Average education in the firm | 10.07 | 2.546 | 7.7 | 15.4 |
| Average tenure in the firm | 5.818 | 3.631 | 1.43 | 13.60 |
| Average total experience in the firm* | 9.002 | 3.869 | 3.61 | 16.9 |
| Average age of employees in the firm | 29.717 | 2.880 | 26.19 | 34.55 |
| Work independence stimulated (1: yes; 0: no) | 0.250 | 0.463 | 0 | 1 |
| Level of stimulated internal communication (1 to 3) | 0.900 | 1.039 | 0 | 3 |
| Level of competition (1 to 5) | 3.125 | 1.642 | 1 | 5 |
| Regular work control (1: yes; 0: no) | 0.500 | 0.535 | 0 | 1 |
| Age of the firm | 10.438 | 5.766 | 3.5 | 20 |
| Number of intermediary levels of management | 5.000 | 0.535 | 4 | 7 |
| Size (number of employees) | 131.250 | 100.954 | 70 | 371 |
| Existing system of formal training (1: yes; 0: no) | 0.250 | 0.463 | 0 | 1 |
| Task definition (1: globally defined; 0: precisely defined) | 0.250 | 0.463 | 0 | 1 |
| Organizational innovation the last four years (1: yes; 0: no) | 0.5 | 0.534 | 0 | 1 |
| Technological innovation the last four years (1: yes; 0: no) | 0.625 | 0.517 | 0 | 1 |
| Percentage of exported production | 0.603 | 0.462 | 0 | 1 |
| Firm is export oriented (1: yes; 0: no) | 0.75 | 0.462 | 0 | 1 |
| System of versatility (job rotation) implemented (1: yes; 0: no) | 0.625 | 0.518 | 0 | 1 |
| Percentage of employees working in chain | 0.358 | 0.409 | 0.00 | 0.91 |
| Sector (1: textiles; 0: IMMEE) | 0.500 | 0.535 | 0 | 1 |
| Rate of supervision | 0.103 | 0.069 | 0.05 | 0.25 |
| Rate of management | 0.146 | 0.278 | 0.02 | 0.83 |

*: This variable is calculated from the total actual experience of the workers in each firm. It therefore includes experience and tenure.

**TABLE 3. Wage equations**

Dependent variable: Log hourly wage (lnsalh)

| | *OLS* | | *OLS* | | *OLS* | | *OLS* | | *IV (2SLS)* | | ***Quantile regressions*** **(bootstrap standard error: 20 iterations) Firm fixed effects models** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Explanatory variables** | (1) | | Firm fixed effects model (FFEM) (2) | | (3) | | Firm fixed effects model (4) | | Firm fixed effects model (5) | | *0.25 Quantile* (6) | | *0.50 Quantile* (7) | | *0.75 Quantile* (8) | |
| Constant | -0.7324***<br>(0.0864) | *0.00* | 0.0090<br>(0.1275) | *0.94* | -0.1616<br>(0.2186) | *0.46* | -0.0459<br>(0.2093) | *0.82* | -0.1034<br>(0.4177) | *0.81* | 0.2098<br>(0.3110) | *0.50* | 0.5531**<br>(0.2798) | *0.04* | 0.2570<br>(0.2652) | *0.33* |
| Education | 0.0861***<br>(0.0071) | *0.00* | 0.0691***<br>(0.0068) | *0.00* | 0.0857***<br>(0.0103) | *0.00* | 0.0870***<br>(0.0124) | *0.00* | 0.0915***<br>(0.0248) | *0.00* | 0.0498***<br>(0.0114) | *0.00* | 0.0448***<br>(0.0156) | *0.00* | 0.0686***<br>(0.0157) | *0.00* |
| QUARTILE1 | – | | – | | -0.5933**<br>(0.2369) | *0.01* | -0.3702<br>(0.2271) | *0.10* | -0.4284<br>(0.4424) | *0.33* | – | | – | | – | |
| QUARTILE2 | – | | – | | 0.2733<br>(0.2365) | *0.25* | 0.5047**<br>(0.2268) | *0.02* | 1.0567*<br>(0.5536) | *0.06* | – | | – | | – | |
| QUARTILE3 | – | | – | | 0.6223***<br>(0.2353) | *0.01* | 0.7992***<br>(0.2253) | *0.00* | 0.7524<br>(0.4845) | *0.12* | – | | – | | – | |
| Education*QUARTILE1 | – | | – | | -0.0433***<br>(0.0159) | *0.01* | -0.0464***<br>(0.0152) | *0.00* | -0.0596*<br>(0.0335) | *0.08* | – | | – | | – | |
| Education*QUARTILE2 | – | | – | | -0.0809***<br>(0.0154) | *0.00* | -0.0839***<br>(0.0146) | *0.00* | -0.1286***<br>(0.0363) | *0.00* | – | | – | | – | |
| Education*QUARTILE3 | – | | – | | -0.0814***<br>(0.0147) | *0.00* | -0.0848***<br>(0.0139) | *0.00* | -0.0806***<br>(0.0293) | *0.01* | – | | – | | – | |
| Tenure | 0.0255**<br>(0.0107) | *0.02* | 0.0452***<br>(0.0099) | *0.00* | -0.0071<br>(0.0085) | *0.41* | 0.0099<br>(0.0087) | *0.25* | 0.0107<br>(0.0160) | *0.50* | 0.0448**<br>(0.0233) | *0.05* | 0.0271**<br>(0.0141) | *0.05* | 0.0362***<br>(0.0122) | *0.00* |
| Tenure$^2$ | -0.0004<br>(0.0005) | *0.43* | -0.0012***<br>(0.0004) | *0.01* | 0.0006**<br>(0.0003) | *0.05* | 0.0002<br>(0.0003) | *0.54* | 0.0002<br>(0.0005) | *0.76* | -0.0009<br>(0.0009) | *0.33* | -0.0006<br>(0.0006) | *0.34* | -0.0008*<br>(0.0005) | *0.10* |
| Tenure*QUARTILE1 | – | | – | | 0.0699***<br>(0.0128) | *0.00* | 0.0621***<br>(0.0130) | *0.00* | 0.0755**<br>(0.0339) | *0.03* | – | | – | | – | |
| Tenure*QUARTILE2 | – | | – | | 0.0022<br>(0.0091) | *0.81* | -0.0094<br>(0.0090) | *0.29* | -0.0362<br>(0.0276) | *0.19* | – | | – | | – | |
| Tenure*QUARTILE3 | – | | – | | -0.0015<br>(0.0062) | *0.81* | -0.0091<br>(0.0062) | *0.14* | -0.0085<br>(0.0135) | *0.53* | – | | – | | – | |

**TABLE 3. Wage equations**

Dependent variable: Log hourly wage (lnsalh)

| | *OLS* | | *OLS* | | *OLS* | | *OLS* | | *IV (2SLS)* | | ***Quantile regressions* (bootstrap standard error: 20 iterations) Firm fixed effects models** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Explanatory variables** | (1) | | Firm fixed effects model (FFEM) (2) | | (3) | | Firm fixed effects model (4) | | Firm fixed effects model (5) | | *0.25 Quantile* (6) | | *0.50 Quantile* (7) | | *0.75 Quantile* (8) | |
| Experience | 0.0325***<br>(0.0127) | *0.01* | 0.0426***<br>(0.0117) | *0.00* | 0.0373***<br>(0.0103) | *0.00* | 0.0495***<br>(0.0102) | *0.00* | 0.0426***<br>(0.0171) | *0.01* | 0.0467**<br>(0.0233) | *0.04* | 0.0306**<br>(0.0148) | *0.04* | 0.0322**<br>(0.0166) | *0.05* |
| Experience² | -0.0004<br>(0.0007) | *0.57* | -0.0011*<br>(0.0006) | 0.10 | -0.0006<br>(0.0004) | *0.20* | -0.0009**<br>(0.0004) | *0.03* | -0.0005<br>(0.0006) | *0.40* | -0.0015<br>(0.0016) | *0.33* | -0.0010<br>(0.0008) | *0.24* | -0.0002<br>(0.0012) | *0.87* |
| Experience*QUARTILE1 | – | | – | | 0.0057<br>(0.0130) | *0.66* | -0.0022<br>(0.0127) | *0.86* | 0.0274<br>(0.0344) | *0.43* | – | | – | | – | |
| Experience*QUARTILE2 | – | | – | | -0.0290***<br>(0.0083) | *0.00* | -0.0345***<br>(0.0079) | *0.00* | -0.0512***<br>(0.0168) | *0.00* | – | | – | | – | |
| Experience*QUARTILE3 | – | | – | | -0.0270***<br>(0.0082) | *0.00* | -0.0347***<br>(0.0079) | *0.00* | -0.0324**<br>(0.0150) | *0.03* | – | | – | | – | |
| Ongoing formal training | -0.4972***<br>(0.1798) | *0.00* | -0.4159***<br>(0.1577) | *0.01* | -0.1542<br>(0.1001) | *0.13* | -0.1288<br>(0.0948) | *0.17* | -0.0821<br>(0.1211) | *0.50* | -0.3502<br>(0.2522) | *0.16* | -0.4649**<br>(0.2236) | *0.04* | -0.3384<br>(0.2501) | *0.17* |
| Completed formal training | 0.4885***<br>(0.0660) | *0.00* | 0.2710***<br>(0.0735) | *0.00* | 0.2103***<br>(0.0384) | *0.00* | 0.1313***<br>(0.0445) | *0.00* | 0.1107**<br>(0.0547) | *0.04* | 0.3275**<br>(0.1433) | *0.02* | 0.2270**<br>(0.0961) | *0.02* | 0.1853*<br>(0.1007) | *0.06* |
| Union | -0.0835<br>(0.0649) | *0.19* | 0.0012<br>(0.0619) | *0.99* | -0.0715*<br>(0.0403) | *0.08* | -0.0573<br>(0.0401) | *0.15* | -0.0434<br>(0.0559) | *0.44* | -0.0030<br>(0.1023) | *0.97* | 0.0884<br>(0.0696) | *0.20* | 0.0373<br>(0.1113) | *0.73* |
| Executive or supervisor | 0.2124***<br>(0.0698) | *0.00* | 0.2655***<br>(0.0618) | *0.00* | 0.0940**<br>(0.0395) | *0.02* | 0.1272***<br>(0.0384) | *0.00* | 0.1264***<br>(0.0480) | *0.01* | 0.1941**<br>(0.0824) | *0.02* | 0.3436***<br>(0.0764) | *0.00* | 0.2889***<br>(0.0861) | *0.00* |
| Firm1 | – | | -0.5318***<br>(0.1041) | *0.00* | – | | -0.2797***<br>(0.0679) | *0.00* | -0.2460***<br>(0.0890) | *0.01* | -0.7944***<br>(0.2545) | *0.00* | -0.8185***<br>(0.1240) | *0.00* | -0.6331***<br>(0.2587) | *0.01* |
| Firm2 | – | | -0.4824***<br>(0.1019) | *0.00* | – | | -0.3066***<br>(0.0651) | *0.00* | -0.2877***<br>(0.0865) | *0.00* | -0.6706***<br>(0.2293) | *0.00* | -0.7262***<br>(0.1503) | *0.00* | -0.5229***<br>(0.1752) | *0.00* |
| Firm3 | – | | -0.7895***<br>(0.1033) | *0.00* | – | | -0.3567***<br>(0.0680) | *0.00* | -0.3002***<br>(0.0904) | *0.00* | -0.9655***<br>(0.2586) | *0.00* | -1.0392***<br>(0.1550) | *0.00* | -0.8133***<br>(0.1766) | *0.00* |
| Firm4 | – | | -0.7425***<br>(0.1082) | *0.00* | – | | -0.3745***<br>(0.0716) | *0.00* | -0.3208***<br>(0.1012) | *0.00* | -0.9637***<br>(0.2648) | *0.00* | -0.9987***<br>(0.1995) | *0.00* | -0.8391***<br>(0.1962) | *0.00* |

**TABLE 3. Wage equations**

Dependent variable: Log hourly wage (lnsalh)

| | *OLS* | *OLS* | | *OLS* | *OLS* | | *IV (2SLS)* | | ***Quantile regressions* (bootstrap standard error: 20 iterations) Firm fixed effects models** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Explanatory variables** | (1) | Firm fixed effects model (FFEM) (2) | | (3) | Firm fixed effects model (4) | | Firm fixed effects model (5) | | *0.25 Quantile* (6) | | *0.50 Quantile* (7) | | *0.75 Quantile* (8) | |
| Firm5 | – | -0.7227*** (0.1055) | *0.00* | – | -0.4016*** (0.0682) | *0.00* | -0.3643*** (0.0953) | *0.00* | -0.9420*** (0.2426) | *0.00* | -0.9317*** (0.1855) | *0.00* | -0.7328*** (0.1602) | *0.00* |
| Firm7 | – | -0.6098*** (0.1036) | *0.00* | – | -0.3015*** (0.0701) | *0.00* | -0.2852*** (0.0946) | *0.00* | -0.7814*** (0.2368) | *0.00* | -0.6602*** (0.1522) | *0.00* | -0.6072*** (0.1134) | *0.00* |
| Firm8 | – | -0.7736*** (0.1007) | *0.00* | – | -0.3297*** (0.0667) | *0.00* | -0.2473*** (0.0909) | *0.01* | -0.9083*** (0.2455) | *0.00* | -0.9900*** (0.1611) | *0.00* | -0.7999*** (0.1902) | *0.00* |
| $R^2$ | 0.67 | 0.76 | | 0.91 | 0.92 | | 0.905 | | Pseudo $R^2$ 0.43 | | Pseudo $R^2$ 0.54 | | Pseudo $R^2$ 0.61 | |
| Observations | 231 | 231 | | 231 | 231 | | 231 | | 231 | | 231 | | 231 | |

Standard errors are given in parentheses. *P*-values appear in italic. ***, ** and * mean respectively significant at the 1%, 5% and 10% levels.

The instrumented variables in the IV regression (5) are: Education QUARTILE1 QUARTILE2 QUARTILE3 Education*QUARTILE1 Education*QUARTILE2 Education*QUARTILE3 Tenure*QUARTILE1 Tenure*QUARTILE2 Tenure*QUARTILE3 Experience*QUARTILE1 Experience*QUARTILE2 Experience*QUARTILE3

The instruments used in the IV regression include: AGE, $(AGE)^2$, APPRENTI, CELIBAH, CHAINE, CHOMA, $(CHOMA)^2$, CHOMA*FEMALE, EMSIM, ENFT, $(ENFT)^2$, LOG(ENFT), ENFT*AGE, ENTREE, EQUIPE, FORMAA, $(FORMAA)^2$, $(FORMAA)^3$, FORMAA*FEMALE, FORSTIL*FEMALE, MARI*FEMALE, MARI*FEMALE, MARI*MALE, PANAL, PANAL*AGE, PANAL*CHOMA, PANAL*ENFT, PANAL*FORMAA, PPRIM, PPRIM*AGE, PPRIM*CHOMA, PPRIM*ENFT, PPRIM*FORMAA, PROVE, PSECON, PSECON*AGE, PSECON*CHOMA, PSECON*ENFT, PSECON*FORMAA, PSUP, PSUP*AGE, PSUP*CHOMA, PSUP*ENFT, PSUP*FORMAA, STAGA, $(STAGA)^2$, $(STAGA)^3$, STAGAN, $(STAGAN)^2$, $(STAGAN)^3$.

The definitions of the variables and instruments appear in Table 1.

**TABLE 4. Returns to human capital and wage effects of factors on quartiles**

| | *OLS* | | | | | *2SLS* | | | | | *Quantile regressions* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Quartiles | | | | | Quartiles | | | | | | | |
| | 1st | 2nd | 3rd | 4th | *mean*[b] | 1st | 2nd | 3rd | 4th | *mean*[b] | *0.25 Quantile* | *0.50 Quantile* | *0.75 Quantile* |
| *Independent variables* | *Firm fixed effects models* | | | | | | | | | | | | |
| Education | 0.0405 | 0.0031 | 0.0022 | 0.0870 | *0.0330* | 0.0318 | -0.0371 | 0.0108 | 0.0915 | *0.0240* | 0.0498 | 0.0448 | 0.0686 |
| Tenure[a] | 0.0621 | 0.0027[ns] | 0.0031[ns] | 0.0121[ns] | *0.0231* | 0.0755 | -0.0237[ns] | 0.0040[ns] | 0.0125[ns] | *0.0203* | 0.0448 | 0.0271 | 0.0266 |
| Experience[a] | 0.0414 | 0.0091 | 0.0088 | 0.0435 | *0.0256* | 0.0700 | -0.0087 | 0.0102 | 0.0426 | *0.0285* | 0.0467 | 0.0306 | 0.0322 |
| | *Factors effects models* | | | | | | | | | | | | |
| Factor 1 | 0.0205 | -0.0131 [nd] | -0.0128 [nd] | -0.0175 | *-0.0166* | -0.0363 [ns] | 0.0285 [ns] | 0.0001 [ns] | 0.0127 [ns] | *-0.0049* [ns] | -0.0544 | -0.0561 | -0.0360 |
| Factor 2 | -0.0935 | -0.0014 [nd] | 0.0114 | 0.0506 | *0.0392* | 0.3382 [nd] | -0.3171 | 0.0206 [nd] | 0.0318 | *0.0324* | 0.1026 | 0.1020 | 0.0764 |
| Factor 3 | 0.0112 | -0.0190 | -0.0134 | 0.0295 | *-0.0014* [ns] | -0.0296 [nd] | 0.0179 [nd] | -0.0347 | 0.0774 | *0.0050* | -0.0121 [ns] | -0.0099 [ns] | -0.0113 [ns] |

[a] : returns calculated at the average point of the sub-sample. [b] : mean of the effects for the different quartiles. [ns] : no significantly different from zero at 10% level.

[nd] : no significantly different from the coefficient of the 4th quartile at 10% level.

**TABLE 5. Principal component analysis**

| Firm characteristics | Vectors | | | Correlations | | |
|---|---|---|---|---|---|---|
| | Factor 1 | Factor 2 | Factor 3 | Factor 1 | Factor 2 | Factor 3 |
| ***Average human capital of employees in the firm*** | | | | | | |
| Average age | -0.269 | -0.075 | 0.006 | -0.75* | -0.20 | 0.01 |
| Average education | -0.079 | 0.319 | -0.196 | -0.22 | 0.86* | -0.33 |
| Average tenure | -0.226 | -0.205 | 0.049 | -0.63* | -0.55 | 0.08 |
| Average total experience | -0.219 | -0.237 | 0.133 | -0.61 | -0.64* | 0.23 |
| Variance of education | 0.012 | -0.268 | 0.091 | 0.03 | -0.73* | 0.15 |
| Variance of tenure | -0.278 | -0.196 | -0.049 | -0.78* | -0.53 | -0.08 |
| Variance of total experience | -0.316 | -0.140 | -0.110 | -0.88* | -0.38 | -0.19 |
| ***General characteristics of the firm*** | | | | | | |
| Sector (1: textiles; 0: IMMEE) | 0.319 | -0.107 | 0.112 | 0.89* | -0.29 | 0.19 |
| Size (number of employees) | 0.219 | -0.054 | -0.144 | 0.61 | -0.14 | -0.24 |
| Exportation (1: yes; 0: no) | 0.254 | 0.152 | -0.156 | 0.71* | 0.41 | -0.26 |
| Percentage of exported production | 0.331 | 0.041 | 0.082 | 0.93* | 0.11 | 0.14 |
| Level of competition (1 to 5) | 0.302 | -0.141 | -0.128 | 0.85* | -0.38 | -0.22 |
| Firm age | 0.062 | -0.074 | -0.554 | 0.17 | -0.20 | -0.95* |
| Rate of supervision | -0.165 | 0.319 | -0.058 | -0.46 | 0.86* | -0.10 |
| Rate of management | -0.051 | 0.355 | 0.061 | -0.14 | 0.96* | 0.10 |
| Number of intermediary levels of management | -0.025 | -0.303 | -0.086 | -0.07 | -0.82* | -0.15 |
| Existing system of formal training (1: yes; 0: no) | -0.225 | 0.198 | 0.255 | -0.63* | 0.54 | 0.44 |
| Organisational innovation the last four years (1: yes; 0: no) | 0.049 | 0.085 | 0.332 | -0.08 | 0.39 | 0.71* |
| Technological innovation the last four years (1: yes; 0: no) | -0.029 | 0.143 | 0.415 | 0.14 | 0.23 | 0.57 |
| Level of stimulated internal communication (1 to 3) | -0.128 | 0.267 | -0.157 | -0.36 | 0.72* | -0.27 |
| ***Characteristics of employees' tasks*** | | | | | | |
| Work independence stimulated (1: yes; 0: no) | 0.076 | 0.233 | -0.097 | 0.21 | 0.63* | -0.17 |
| Frequent work control (1: yes; 0: no) | 0.039 | 0.177 | -0.194 | 0.11 | 0.48 | -0.33 |
| Versatility system implemented (1: yes; 0: no) | 0.156 | 0.100 | 0.234 | 0.44 | 0.27 | 0.40 |
| Percentage of employees working in chain | 0.293 | -0.097 | 0.205 | 0.82* | -0.26 | 0.35 |
| Task definition (1: globally defined; 0: precisely defined) | -0.088 | 0.195 | -0.010 | -0.25 | 0.53 | -0.02 |

*: significant at the 10% level.

**TABLE 6. Pearson's correlation coefficients between factors, firm fixed effects and characteristics of education in the firms**

| | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|
| *Firms' fixed effects* | | | |
| Firm 1 | -0.72* | -0.26 | 0.47 |
| Firm 2 | -0.21 | -0.27 | -0.12 |
| Firm 3 | 0.38 | -0.04 | 0.47 |
| Firm 4 | 0.32 | -0.07 | 0.03 |
| Firm 5 | 0.26 | -0.18 | 0.10 |
| Firm 6 | -0.11 | 0.96* | 0.10 |
| Firm 7 | -0.31 | 0.01 | -0.74* |
| Firm 8 | 0.38 | -0.14 | -0.32 |
| *Average education in the firm* | | | |
| Average years of secondary school | -0.12 | 0.87* | -0.21 |
| Proportion of university diploma | -0.24 | 0.94* | -0.09 |
| Average amount of formal training | -0.78* | -0.06 | 0.43 |
| Proportion of females | 0.91* | -0.21 | 0.19 |

*: significant at the 10% level.

**TABLE 7. Wage equations with factors**

Dependent variable: Log hourly wage (lnsalh)

| Explanatory variables | *OLS* | | *OLS* | | *IV (2SLS)* | | *OLS* | | ***Quantile regressions*** **(bootstrap standard errors: 20 iterations) Factor effects models** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Factor effects model (1) | | Factor effects model (2) | | Factor effects model (3) | | Pseudo factor model (PFM) (4) | | *0.25 Quantile* (5) | | *0.50 Quantile* (6) | | *0.75 Quantile* (7) | |
| Constant | -0.2646 (0.2080) | *0.205* | -0.4134** (0.2097) | *0.050* | -0.0103 (0.2097) | *0.976* | -0.8529*** (0.1396) | *0.000* | -0.5536*** (0.2122) | *0.010* | -0.3307*** (0.1112) | *0.003* | -0.3844** (0.1540) | *0.013* |
| Education | 0.0843*** (0.0123) | *0.000* | 0.0906*** (0.0124) | *0.000* | 0.0719*** (0.0208) | *0.001* | 0.0679*** (0.0069) | *0.000* | 0.0552*** (0.0128) | *0.000* | 0.0570*** (0.0116) | *0.000* | 0.0768*** (0.0121) | *0.000* |
| QUARTILE1 | -0.4394** (0.2247) | *0.052* | -0.4562** (0.2384) | *0.057* | -0.2405 (0.3915) | *0.540* | – | | – | | – | | – | |
| QUARTILE2 | 0.4424** (0.2253) | *0.051* | 0.5391** (0.2413) | *0.027* | -0.3072 (0.4451) | *0.491* | – | | – | | – | | – | |
| QUARTILE3 | 0.7727*** (0.2254) | *0.001* | 0.8522*** (0.2303) | *0.000* | 0.4892 (0.3559) | *0.171* | – | | – | | – | | – | |
| Education*QUARTILE1 | -0.0416*** (0.0150) | *0.006* | -0.0487*** (0.0154) | *0.002* | -0.0302 (0.0319) | *0.345* | – | | – | | – | | – | |
| Education*QUARTILE2 | -0.0803*** (0.0145) | *0.000* | -0.0860*** (0.0145) | *0.000* | -0.0811*** (0.0305) | *0.008* | – | | – | | – | | – | |
| Education*QUARTILE3 | -0.0863*** (0.0139) | *0.000* | -0.0886*** (0.0145) | *0.000* | -0.0745*** (0.0264) | *0.005* | – | | – | | – | | – | |
| Tenure | 0.0066 (0.0085) | *0.438* | 0.0133 (0.0087) | *0.127* | 0.0133* (0.0087) | *0.062* | 0.0432*** (0.0098) | *0.00* | 0.0442** (0.0229) | *0.054* | 0.0303** (0.0129) | *0.019* | 0.0213 (0.0154) | *0.168* |
| Tenure² | 0.0003 (0.0003) | *0.388* | 0.0002 (0.0003) | *0.579* | 0.0002 (0.0003) | *0.833* | -0.0012*** (0.0005) | *0.007* | -0.0010 (0.0009) | *0.310* | -0.0007 (0.0006) | *0.243* | -0.0002 (0.0006) | *0.725* |
| Tenure*QUARTILE1 | 0.0599*** (0.0125) | *0.000* | 0.0549*** (0.0133) | *0.000* | – | | – | | – | | – | | – | |
| Tenure*QUARTILE2 | -0.0079 (0.0089) | *0.376* | -0.0144 (0.0092) | *0.120* | – | | – | | – | | – | | – | |
| Tenure*QUARTILE3 | -0.0079 (0.0061) | *0.199* | -0.0120* (0.0065) | *0.067* | – | | – | | – | | – | | – | |
| Experience | 0.0431*** (0.0098) | *0.000* | 0.0427*** (0.0097) | *0.000* | 0.0268** (0.0113) | *0.019* | 0.0375*** (0.0114) | *0.001* | 0.0494*** (0.0146) | *0.001* | 0.0304** (0.0140) | *0.031* | 0.0336** (0.0155) | *0.032* |
| Experience² | -0.0007* (0.0004) | *0.083* | -0.0005 (0.0004) | *0.229* | -0.0007 (0.0006) | *0.220* | -0.0008 (0.0006) | *0.231* | -0.0026** (0.0011) | *0.020* | -0.0003 (0.0011) | *0.769* | 0.0001 (0.0011) | *0.895* |
| Experience*QUARTILE1 | 0.0003 (0.0124) | *0.983* | 0.0014 (0.0127) | *0.911* | – | | – | | – | | – | | – | |
| Experience*QUARTILE2 | -0.0341*** (0.0079) | *0.000* | -0.0340*** (0.0080) | *0.000* | – | | – | | – | | – | | – | |

**TABLE 7. Wage equations with factors**

Dependent variable: Log hourly wage (lnsalh)

| Explanatory variables | *OLS*<br>Factor effects model<br>(1) | | *OLS*<br>Factor effects model<br>(2) | | *IV (2SLS)*<br>Factor effects model<br>(3) | | *OLS*<br>Pseudo factor model (PFM)<br>(4) | | ***Quantile regressions* (bootstrap standard errors: 20 iterations) Factor effects models**<br>*0.25 Quantile*<br>(5) | | *0.50 Quantile*<br>(6) | | *0.75 Quantile*<br>(7) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Experience*QUARTILE3 | -0.0312***<br>(0.0078) | *0.000* | -0.0327***<br>(0.0077) | *0.000* | – | | – | | – | | – | | – | |
| Ongoing formal training | -0.1367<br>(0.0949) | *0.151* | -0.0985<br>(0.1089) | *0.367* | -0.1364<br>(0.1799) | *0.449* | -0.4685***<br>(0.1596) | *0.004* | -0.3530<br>(0.2983) | *0.238* | -0.5131<br>(0.3611) | *0.157* | -0.4418*<br>(0.2643) | *0.096* |
| Completed formal training | 0.1262***<br>(0.0415) | *0.003* | 0.1179***<br>(0.0417) | *0.005* | 0.1594***<br>(0.0575) | *0.006* | 0.2180***<br>(0.0685) | *0.002* | 0.1897**<br>(0.0884) | *0.033* | 0.1413*<br>(0.0753) | *0.062* | 0.1510<br>(0.1146) | *0.189* |
| Union | -0.0541<br>(0.0391) | *0.168* | -0.0420<br>(0.0405) | *0.301* | -0.1793***<br>(0.0405) | *0.003* | -0.0228<br>(0.0621) | *0.714* | 0.0033<br>(0.0707) | *0.963* | 0.0473<br>(0.0777) | *0.543* | 0.0886<br>(0.1268) | *0.485* |
| Executive or supervisor | 0.1367***<br>(0.0381) | *0.000* | 0.1239***<br>(0.0386) | *0.002* | 0.0764<br>(0.0556) | *0.171* | 0.2842***<br>(0.0621) | *0.000* | 0.2013**<br>(0.0902) | *0.027* | 0.3345***<br>(0.0710) | *0.000* | 0.3064***<br>(0.0845) | *0.000* |
| Factor 1 | -0.0166**<br>(0.0069) | *0.017* | -0.0175*<br>(0.0069) | *0.105* | 0.0127<br>(0.0069) | *0.557* | – | | -0.0544***<br>(0.0171) | *0.002* | -0.0561***<br>(0.0144) | *0.000* | -0.0360**<br>(0.0185) | *0.052* |
| Factor 2 | 0.0392***<br>(0.0071) | *0.000* | 0.0506***<br>(0.0082) | *0.000* | 0.0318**<br>(0.0082) | *0.021* | – | | 0.1026***<br>(0.0343) | *0.003* | 0.1020***<br>(0.0165) | *0.000* | 0.0764***<br>(0.0213) | *0.000* |
| Factor 3 | -0.0014<br>(0.0088) | *0.872* | 0.0295*<br>(0.0173) | *0.090* | 0.0774*<br>(0.0173) | *0.083* | – | | -0.0121<br>(0.0141) | *0.395* | -0.0099<br>(0.0214) | *0.645* | -0.0113<br>(0.0227) | *0.620* |
| Sector<br>(textiles: 1; IMMEE: 0) | – | | – | | – | | -0.2470***<br>(0.0522) | *0.000* | – | | – | | – | |
| Average education in the firm | – | | – | | – | | 0.0621***<br>(0.0131) | *0.000* | – | | – | | – | |
| Age of the firm | – | | – | | – | | -0.0162***<br>(0.0045) | *0.000* | – | | – | | – | |
| Factor 1*QUARTILE1 | – | | 0.0380*<br>(0.0223) | *0.090* | -0.0490<br>(0.0543) | *0.367* | – | | – | | – | | – | |
| Factor 1*QUARTILE2 | – | | 0.0045<br>(0.0201) | *0.825* | 0.0158<br>(0.0443) | *0.721* | – | | – | | – | | – | |
| Factor 1*QUARTILE3 | – | | 0.0047<br>(0.0148) | *0.750* | -0.0127<br>(0.0351) | *0.718* | – | | – | | – | | – | |
| Factor 2*QUARTILE1 | – | | -0.1442**<br>(0.0709) | *0.043* | 0.3064<br>(0.1965) | *0.121* | – | | – | | – | | – | |
| Factor 2*QUARTILE2 | – | | -0.0520<br>(0.0612) | *0.397* | -0.3490*<br>(0.1918) | *0.070* | – | | – | | – | | – | |
| Factor 2*QUARTILE3 | – | | -0.0393**<br>(0.0157) | *0.013* | -0.0113<br>(0.0359) | *0.753* | – | | – | | – | | – | |

**TABLE 7. Wage equations with factors**

Dependent variable: Log hourly wage (lnsalh)

| | *OLS* | *OLS* | | *IV (2SLS)* | | *OLS* | ***Quantile regressions*** **(bootstrap standard errors: 20 iterations) Factor effects models** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Explanatory variables** | Factor effects model (1) | Factor effects model (2) | | Factor effects model (3) | | Pseudo factor model (PFM) (4) | *0.25 Quantile* (5) | *0.50 Quantile* (6) | *0.75 Quantile* (7) |
| Factor 3*QUARTILE1 | – | -0.0183 (0.0277) | *0.510* | -0.1070 (0.0806) | *0.185* | – | – | – | – |
| Factor 3*QUARTILE2 | – | -0.0485* (0.0267) | *0.071* | *-0.0595* *(0.0909)* | *0.514* | – | – | – | – |
| Factor 3*QUARTILE3 | – | -0.0429* (0.0231) | *0.065* | *-0.1121*** *(0.0576)* | *0.053* | – | – | – | – |
| $R^2$ | 0.923 | 0.929 | | 0.880 | | 0.754 | Pseudo $R^2$ | | |
| | | | | | | | 0.40 | 0.59 | 0.59 |
| Observations | 231 | 231 | | 231 | | 231 | 231 | 231 | 231 |

Standard errors are given in parenthesis. *P*-values appear in italic. ***, ** and * mean respectively significant at the 1%, 5% and 10% levels.

The instrumented variables in the IV regression (3) are: Education QUARTILE1 QUARTILE2 QUARTILE3 Education*QUARTILE1 Education*QUARTILE2 Education*QUARTILE3 Factor1*QUARTILE1 Factor1*QUARTILE2 Factor1*QUARTILE3 Factor2*QUARTILE1 Factor2*QUARTILE2 Factor2*QUARTILE3 Factor3*QUARTILE1 Factor3*QUARTILE2 Factor3*QUARTILE3

The instruments used in the IV regression include: AGE, $(AGE)^2$, APPRENTI, CELIBAH, CHAINE, CHOMA, $(CHOMA)^2$, CHOMA*FEMALE, EMSIM, ENFT, $(ENFT)^2$, LOG(ENFT), ENFT*AGE, ENTREE, EQUIPE, FORMAA, $(FORMAA)^2$, $(FORMAA)^3$, FORMAA*FEMALE, FORSTIL*FEMALE, MARI*FEMALE, MARI*FEMALE, MARI*MALE, PANAL, PANAL*AGE, PANAL*CHOMA, PANAL*ENFT, PANAL*FORMAA, PPRIM, PPRIM*AGE, PPRIM*CHOMA, PPRIM*ENFT, PPRIM*FORMAA, PROVE, PSECON, PSECON*AGE, PSECON*CHOMA, PSECON*ENFT, PSECON*FORMAA, PSUP, PSUP*AGE, PSUP*CHOMA, PSUP*ENFT, PSUP*FORMAA, STAGA, $(STAGA)^2$, $(STAGA)^3$, STAGAN, $(STAGAN)^2$, $(STAGAN)^3$.

## REFERENCES


Abadie, A., Angrist J., and Imbens G. (2002), "Instrumental Variables Estimates of the Effect of Subsidized Training on the Quantiles of Trainee Earnings," *Econometrica*, 70(1), pp. 91-117.

Abdennadher, C., Karaa A. and Plassard J.-M. (1994), "Tester la dualité du marché du travail: l'exemple de la Tunisie," *Revue d'Economie du Développement*, 2, pp. 39-63.

Abowd, J.M. and Kramarz F. (1999), "The Analysis of Labor Markets Using Matched Employer-Employee Data," in Ashenfelter O. and Card D. (eds), *Handbook of Labor Economics*, vol. 3B, Elsevier Science Publishers BV, Pays-Bas, pp. 2629-2710.

Abowd, J.M., Kramarz F. and Margolis D.N. (1999), "High-Wage Workers and High-Wage Firms," *Econometrica*, 67(2), pp. 251-333.

Abowd, J.M., Kramarz F., Margolis D.N. and Troske K.R. (2001), "The Relative Importance of Employer and Employee Effects on Compensation: A Comparison of France and the United States," *Journal of the Japanese and International Economies*, 15, pp. 419-436.

Alcalá, F. and P.J. Hernández (2005), "Las Externalidades del Capital Humano en la Empresa Española," mimeo, Universidad de Murcia. *(this is not by the author(s) of this manuscript)*

Angrist, J.D. and Lavy V. (1997), "The Effect of a Change in Language of Instruction on the Returns to Schooling in Morocco," *Journal of Labor Economics,* 15(1), pp. S48-S76.

Barron, J.M., Berger M.C. and Black D.A. (1998), "Do Workers Pay for On-the-Job Training," *The Journal of Human Resources*, 34(2), pp. 235-252.

Battu, H., Belfield C., and Sloane P. (2003), "Human Capital Spillovers within the Workplace: Evidence for Great Britain," *Oxford Bulletin of Economics and Statistics*, 65, pp. 575-594.

Behrman, J.R. (1999), "Labor Markets in Developing Countries," Chapter 43 in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, Elsevier.

Belhareth, M. and Hergli M. (2000), *Flexibilité de l'emploi et redéploiement des ressources humaines : cas de la Tunisie*, Tunis, Arforghe Editions.

Blanchflower, D.G. and Oswald A.J. (1994), *The Wage Curve*, Cambridge, The MIT Press.

Buchinsky, M. (1998a), "Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research," *The Journal of Human Resources*, 33(1), pp. 88-126.

Buchinsky, M. (1998b), “The Dynamics of Changes in the Female Wage Distribution in the USA: A Quantile Regression Approach,” *Journal of Applied Econometrics*, 13, pp. 1-30.

Buchinsky, M. (2001), “Quantile Regression with Sample Selection: Estimating Women's Return to Education in the U.S.,” *Empirical Economics*, 26(1), pp. 87-113.

Card, D. (1999), “The Causal Effect of Education on Earnings,” in Ashenfelter O. and Card D. (eds), *Handbook of Labor Economics*, vol. 3A, Elsevier Science Publishers BV, Netherlands, pp. 1801-1863.

Cardoso, A.R. (1998), “Firms’ Wage Policies and the Rise in Labor Market Inequality: the Case of Portugal,” *Industrial and Labor Relations Review*, 53(1), pp. 87-102.

Chennouf, S., Lévy-Garboua L. and Montmarquette C. (1997), “Les effets de l’appartenance à un groupe de travail sur les salaires individuels,” *L’Actualité Économique*, 73, pp. 207-232.

Destré, G. and Nordman C. (2003), “The Impacts of Informal Training on Earnings: Evidence from French, Moroccan and Tunisian Matched Employer-Employee Data,” *SSRN Electronic Library*, *Human Capital Journal*: http://ssrn.com/abstract=314421. Published in French in *L’Actualité Économique*, 78(2), pp. 179-205, 2002.

Dickens, W.T. and Katz L.F. (1987), “Inter-Industry Wage Differences and Industry Characteristics,” in K. Lang and J. S. Leonard (eds), *Unemployment and the Structure of Labor Markets*, Oxford Blackwell.

Frazer, G. (2003), “Linking Firms and Workers: Heterogeneous Labor and Returns to Education,” mimeo, University of Toronto. *(this is not by the author(s) of this manuscript)*

Goux, D. and Maurin É. (1999), “Persistence of Interindustry Wage Differentials: A Reexamination Using Matched Worker-Firm Panel Data,” *Journal of Labor Economics*, 17(3), pp. 492-533.

Hahn, J. (1995), “Bootstrapping Quantile Regression Estimators,” *Econometric Theory*, 11, pp. 105-121.

Hashimoto, M. (1982), “Minimum Wage Effects on Training on the Job,” *American Economic Review*, 72(5), pp. 1070-1087.

Hoddinott, J. (1996), “Wages and Unemployment in an Urban African Labour Market,” *The Economic Journal*, 106, pp. 1610-1626.

Katz, L.F. (1986), “Efficiency Wage Theories: A Partial Evaluation,” in S. Fisher (ed), *NBER Macroeconomics Annual*, Cambridge, Mass., MIT Press.

Koenker, R. and Bassett G. (1978), “Regression Quantiles,” *Econometrica*, 46, pp. 33-50.

Kölling, A., Schnabel C. and Wagner J. (2002), "Establishment Age and Wages: Evidence from German Linked Employer-Employee Data," IZA Discussion Paper No. 679, December.

Krueger, A.B. and Summers L. H. (1988), "Efficiency Wages and the Inter-Industry Wage Structure," *Econometrica*, 56(2), pp. 259-293.

Leighton, L. and Mincer J. (1981), "The effects of Minimum Wages on Human Capital Formation," in S. Rottemburg (ed), *The Economics of Legal Minimum Wages*, Washington, DC: American Enterprise Institute.

Lindbeck, A. and Snower D. J. (1989), *The Insider-Outsider Theory of Employment and Unemployment*, Cambridge, MIT Press.

Lynch, L.M. (1992), "Private-Sector Training and the Earnings of Young Workers," *American Economic Review*, 82(1), pp. 299-312.

Machado, J. and Mata J. (2001), "Earning Functions in Portugal 1982-1984: Evidence from Quantile Regressions," *Empirical Economics*, 26, pp. 115-134.

Martins, P.S. and Pereira P.T. (2004), "Does Education Reduce Wage Inequality? Quantile Regression Evidence from 16 Countries," *Labour Economics*, 11, pp. 355-371.

Mesnard, A. and Ravallion M. (2001), "Is Inequality Bad for Business? A Nonlinear Microeconomic Model of Wealth Effects on Self-Employment," World Bank Policy Research Working Paper 2527, January.

Mincer, J. (1993), *Schooling, Experience, and Earnings*, New York: Gregg Revivals, 1993.

Murphy, K. M. and Topel R. H. (1987), "Unemployment, Risk, and Earnings: Testing for Equalizing Wage Differences in the Labor Market," in K. Lang and J. S. Leonard (eds), *Unemployment and the Structure of Labor Markets*, London, Basil Blackwell.

Nordman, C. (2002), "Diffusion du capital humain et effets d'entreprise: Approche par frontière de gains sur données appariées marocaines et tunisiennes," *Revue Economique*, 53(3), pp. 647-658.

Parent, D. (1999), "Wages and Mobility: The Impact of Employer-Provided Training," *Journal of Labor Economics*, 12(2), pp. 298-317.

Psacharopoulos, G. and Patrinos H. A. (2002), "Returns to Investment in Education: A Further Update," World Bank Policy Research Working Paper 288, September.

Rama, M. (1998), "How Bad Is Unemployment in Tunisia? Assessing Labor Market Efficiency in a Developing Country," *The World Bank Research Observer*, 13(1), pp. 59-77.

Sahn, D.E. and Alderman H. (1988), "The Effects of Human Capital on Wages and the Determinants of Labor Supply in a Developing Country," *Journal of Development Economics*, 29, pp. 157-183.

Teal, F. (1996), “The Size and Sources of Economic Rents in a Developing Country Manufacturing Labour Market,” *The Economic Journal*, 106, pp. 963-976.

UNDP (1994), *Le PNUD en Tunisie*, Tunis.

World Bank (2000), “Republic of Tunisia: Social and Structural Review 2000. Integrating into the World Economy and Sustaining Economic and Social Progress,” Report No. 20976, June, Washington, D.C.: World Bank.

Willis, R. (1986), “Wage Determinants: a Survey and Reinterpretation of Human Capital Earnings Functions,” in *Handbook of Labor Economics*, vol. 1, chap.10, Ashenfelter O. and Layard R. (eds).