UMR 8184

THéorie Économique, Modélisation et Applications

Thema Working Paper n°2008-38
Université de Cergy Pontoise, France

Intra-Firm Human Capital Externalities in Tunisia

Christophe Muller, Christophe J. Nordman

October 2008

UNIVERSITÉ de Cergy-Pontoise

CENTRE NATIONAL DE LA RECHERCHE SCIENTIFIQUE

Intra-Firm Human Capital Externalities in Tunisia†

Christophe Muller*

and

Christophe J. Nordman**

October 2008

Abstract

In this case-study, we use matched worker-firm Tunisian data to elicit the roles of intra-firm human capital and modern firm features in worker remunerations.
We show that the estimated return to education in wage equations is not modified when replacing in the list of regressors the firm dummies, representing observed and unobserved firm heterogeneity, by the first three factors of a Principal Component Analysis of the observed firm characteristics. These factors can be interpreted as: the activity sector, the intra-firm human capital density and the modernity of the firm. These results constitute an interesting argument in favour of the presence of intra-firm human capital externalities.
Moreover, the estimated education coefficient does not change when the three factors are replaced by three surrogate variables, respectively: the textile industry dummy, the intra-firm mean education, and the firm's age.

Keywords: economic development, rate of returns, human capital, wage differentials, intra-firm knowledge externalities, Tunisia.
JEL Classification: J24, J31, O12.

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† This paper under the title 'Which Human Capital Matters for the Rich and Poor's Wages? Evidence from Matched Worker-Firm Data from Tunisia' 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. SEJ2005-02829/ECON, and by the Instituto Valenciano de Investigaciones Economicas. Christophe J. Nordman gratefully acknowledges financial support from the University of Paris I Panthéon-Sorbonne 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.

* Corresponding author. Université de Cergy-Pontoise, THEMA, 33, Bd. du Port, F-95000 Cergy, France.
E-mail: Christophe.muller@u-cergy.fr
** IRD, DIAL, Paris. 4 rue d'Enghien 75010, Paris. Email: nordman@dial.prd.fr. Phone: +33 1 53 24 14 63.
Fax: 33 1 53 24 14 51

1. Introduction

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. This is particularly important for developing countries where the returns to education are expected to be higher.[1] 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.

Furthermore, 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 diffused in the economy. It is also possible that many externalities take place in the firm where the worker operates since that is where technological processes are most frequently exhibited and transmitted. In particular, many tasks require team work, with skills diffused across the workplace.[2] For instance, some workers' training may take place through imitation, i.e. by observing skilled workers performing a given task. Workers' interactions are likely to enhance skills, and knowledge diffusion may be higher in work environment well endowed in

[1] Sahn and Alderman (1988), Behrman (1999). Furthermore, using Indian data, Chanarbagwala (2008) finds that high returns to reduction in wages may increase the likelihood that children attend school. However, Al-Samarrai and Reilly (2008) find that the private rates of return to education in the wage employment sector in Tanzania are low.

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

human capital. Then, a worker of given skill level be more productive and therefore better paid in a firm that is human capital intensive.

Thus, the overall return to human capital explaining worker remuneration may combine personal skill characteristics and firm knowledge characteristics. This may contribute to explaining the typical over-estimation of returns to schooling in Less Developed Countries (LDCs). It is also important to consider these two sources of 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.

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 excludes 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 these interpretations are beyond the possibilities of our data, and we cannot attempt them.

One popular way to account for firm characteristics, including their human capital features, is to base the econometric investigation on matched worker-firm data.[3] 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 which we focus.[4] 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.

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

[4] Matched worker-firm data is collected for example as part of the World Bank's Regional Program for Enterprise Development (RPED) surveys in Africa. Each of these surveys constitutes a sample of about 200

Are there human capital intra-firm externalities influencing Tunisian workers' wages? The Tunisian data we use in this case study provide precise information both on employees and their firms. Therefore, using these data, we first examine the firm's effect on individual earnings, and then refine the firm effect specification by investigating the human capital characteristics of each firm. To this end, we summarize their main characteristics with a preliminary multivariate analysis. To get a better grasp on the intra-firm externalities, we examine returns to: education, firm specific experience, and externalities across different quartiles of the earnings distribution.

In Section 2, we present the data. We discuss estimation results for wage equations in Section 3. In this section, we also push the analysis one step further by incorporating firm characteristics and interpreting firm dummy effects using the factor analysis. Finally, Section 4 concludes.

2. The Tunisian matched worker-firm data

2.1. The labour market context

Several changes in the labour market framework have recently taken place in Tunisia. First, the Labour Code was revised in 1994 and 1996 to clarify the conditions under which workers can be laid off and to establish guidelines for financial compensation. Second, Tunisian producers face stronger competition in their export markets after the disappearance of the Multi-Fibre Arrangements (MFA) in 2005. Third, the competition will be fiercer in the local market with full 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

firms with about 10 interviewed workers in each firm. With such surveys, Frazer (2006) studies apprenticeship in Ghanaian manufacturing firms while Nordman and Wolff (2008) analyse firm effects on the extent of the finding and retaining jobs.[5] 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 to firms 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 improving sector productivity, connected to average skill levels in Tunisia.[6] The ability of the Tunisian economy to restructure may thus be raised, in particular by encouraging firms to invest in on-the-job training (OJT).

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 freer market. Human capital investment will be crucial in this modernization process.

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. In 1995, the government implemented a programme to rehabilitate vocational training and employment (MANFORME, *Mise à Niveau de la Formation Professionnelle et de l'Emploi*). MANFORME's main objective was to reinforce the quality, effectiveness and capacity of the public and private vocational training systems and consequently, to contribute to improving Tunisian firms' competitiveness. In such context, it is interesting to assess the existence of intra-firm human capital externalities in Tunisian firms in order to appraise the potential spillovers that such vocational education policies may foster.

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gender wage gap in Madagascar and Mauritius. However, such data is not available for Tunisia yet.

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

[6] Belhareth and Hergli (2000).

2.2. The survey

The matched worker-firm data we use were directly collected in the workplace in 1999.[7] Eight firms were selected based on criteria of size (not less than 50 employees), activity, vocation to export and capital ownership.[8] 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. Because these data cannot be claimed as representative of complete sectors, we treat them as an interesting case study. Accordingly, we only show estimates with standard errors uncorrected for clustering and stratification. However, we checked that accounting for these features of the sampling scheme does not change the significance of the commented results.[9]

The questionnaire provides accurate information about each worker: individual characteristics, wages, educational investments, post-school training, total experience in the labour market and occupation in the current firm. Moreover, the data include characteristics of the firms in which workers evolve.

2.3. 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

[7] The methodology of the Tunisian survey appears in Nordman (2002) and Destré and Nordman (2003). The definitions and descriptive statistics of the variables are in Tables 1 and 2 of the Appendix and Muller and Nordman (2005).

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

amounts to almost half, 49.8 percent; however female workers predominate in textile firms, while men workers do in IMMEE firms.

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,[10] we choose to use an education variable net from repeated classes. 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 with a vocational diploma related to their current job reaches 31.6 percent.

The average tenure in the current firm is 5.9 years (5 years for women, 6.75 years for men). The total professional experience is an average of 9.1 years (10 years for men; 8 years for women). Besides, the previous experience apart from the current job is on average of 3.3 years.

The ratio of tenure to the overall work experience is 64 percent because of an important percentage of young, first-time workers. Indeed, the average age in the sample is small, amounting to 29.5 years.

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[9] Tables with corrected standard errors are available from the authors.

[10] 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.

Some wage characteristics are worth noting. The average monthly wage declared by employees is 213 US dollars,[11] 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 also partially explain this: On average, the 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. Muller and Nordman (2005) find in estimated wage equations that on-the-job training substantially affects wages across all quantiles. Lower wage workers are less educated, trained and experienced. They are on average younger, mainly females and have suffered longer unemployment spells. 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.[12] We now turn to the firm characteristics.

2.4. The firms

The four firms of each sector are located in the Tunis area. These firms are interesting because they are typically in the range of labour market events we mentioned above. The average size of the visited establishments is 130 employees.

[11] 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.

[12] 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

Information about the firm's characteristics has 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 provides descriptive statistics.

Figure 1 in the Appendix shows the histogram of observed wages. The two minimum wages are separately indicated by vertical lines. They respectively correspond to two standard labour durations: 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.

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.[13] However, returns to human capital can vary across unobserved ability categories. For instance, high ability workers should not benefit from the same return to experience than low ability workers since the latter may have fewer incentives to make further on-the-job investment in human capital because they only deal with

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than wage levels. In this paper, we focus on conditional wage categories to capture differential social consequences of training and education policies.

basic tasks. Alternatively, higher ability individuals – generally with higher wages conditionally to observable characteristics – may have greater incentive to invest in training because they learn faster. To capture differentiated returns to education and experience between low and high abilities, we estimate quantile regressions characterising different levels of wages conditionally on observable characteristics.

Since we are interested in intra-firm human capital externalities, we also distinguish off-firm experience and tenure. Dividing the tenure variable by the firm's age to account for the large heterogeneity in firm ages does not change the obtained qualitative results.

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 attempt 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.

Alternative interpretations or results could be based on matching processes. Assume 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 with these data. However, the rigid and inefficient features of the Tunisian formal labour market (with sluggish

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

administrative procedures, and little public information on jobs and workers) make plausible that selection effects are less intensive than in industrialised countries.

Then, we are constrained to assume that selectivity and sub-sampling effects can be neglected. Although 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 the wage equations, we incorporate formal training received in the current firm. 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.[14] One dummy variable controls for the worker's hierarchical position in the firm (executive or supervisor), while the other describes trade union membership.

The estimated model is:

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

where w_i is the hourly 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.

We do not limit our analysis to the OLS or 2SLS results, but we also use quantile 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

[14] 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.

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.[15]

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. 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

The first estimates of the equations of the logarithm of individual hourly wage are reported in Table 3 in Appendix. The first two columns correspond to OLS estimates while columns (3) to (7) report the 2SLS and quantile regression results. Table 4 summarizes the main results of all these estimators by computing the coefficients of education, job tenure and previous experience.

The wage equation which incorporates firm dummies is characterised by a better goodness-of-fit than without them (columns 1 and 2).[16] The return to schooling decreases after controlling for firms' heterogeneity with firm dummies. In OLS regressions, the marginal return to education is 6.9 percent with the firm effects instead of 8.6 percent without them. This drop is in the scope of usual results (Abowd and Kramarz, 1999). To our knowledge, no comparable estimates exist on Tunisia.[17]

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[15] Quantile regressions can also be used to estimate counterfactuals as in Melly (2005). However, this may be of little interest for a case study.

[16] Fisher test results of the constrained model (without the firm's dummies) against the unconstrained one show that we fail to reject the unconstrained model at the 1 percent level. The null hypothesis is that of no effects of firm dummies.

[17] Psacharopoulos and Patrinos (2004) report the returns to education in many countries. Some of the education effect may be caused by selection. Firm dummies may help control for some selection effects, but other individual and household characteristics are missing which does not allow us to fully avoid a possible selectivity bias.

We attempt to control for the possible endogeneity of the education variable by using two-stage least square regression (2SLS) whose estimates are shown in columns (3) and (4). The set of instrument for both education and experience variables is reported at the bottom of Table 3.[18] The instrumentation is mostly based on demographic characteristics entered or insignificant and omitted in the wage equation, on father's characteristics and on former 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.[19] The presence of firm dummies in the wage equations should strengthen the quality of the used instruments since these dummies could capture the role of parental education for labour market insertion.

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, the 2SLS are useful 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 on-the-job training, are not perfectly corrected, the convergence of results from OLS, 2SLS, quantile regressions of equations with and without firm dummies should help convincing us of their relative solidity.

With 2SLS, the main qualitative results remain unchanged although the levels of specific coefficients can vary.[20] However, the returns to human capital are refined: the average return to education in the firm dummies models (FDM) increases from 6.9 percent (OLS) to

[18] 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).

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

[20] The statistic of the Durbin-Wu-Hausman test indicates that the null hypothesis of exogeneity of the instrumented regressors is strongly rejected.

9.0 percent (2SLS). This confirms the effects of using instrumental variables found in many empirical works. For example, Card (1999) finds for U.S. data that 2SLS estimates on returns to education are often 15 percent higher than OLS estimates. However, under the assumption that unobserved ability biases the results, a reduction would have been expected, while increases in the returns are often attributed to a correction of the attenuation bias., What we are estimating here is slightly different from the typical literature since we are measuring the *within-firm* returns to human capital. 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 quantiles 0.25, 0.50 and 0.75. These quantile regression estimates are reported in columns (5), (6) and (7) of Table 3. The low conditional wage workers (first quartile) have significantly higher returns to human capital than the workers belonging to the middle of the conditional wage distribution: The returns to education amount to 5 percent, 4.5 percent and 6.9 percent for the workers belonging to the first, second and third conditional quartiles, respectively. Then, the return to schooling of the low ability workers is significantly lower than that of the high ability workers.

More generally, except for tenure, the summary results reported in Table 4 emphasize a U curve that describes the returns to education and experience as a function of the conditional wage levels. This is consistent with some 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 conditional wage employees than for the other categories, while the U curve corresponding to the estimates of coefficients is generally not significant.[21] These findings for

[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

the experience variables are then in contrast to those on 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, and we deal with intra-firm human capital returns rather than average returns as Machado and Mata.

Let us now look at the other estimated coefficients. Completed OJT plays an important role in explaining wage differentials (its positive coefficient is significant at 5 percent level).[22] We find that workers benefit from this training through a positive wage premium when training is completed (from 20 percent to about 40 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 usually found wage differentials across individuals with identical productive characteristics while working in different sectors.[23] 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 the next sub-section the firm effects are interpreted in terms of each company's features.

3.3 Principal component analysis

We use a principal component analysis (PCA) to summarize the observed information about the surveyed firms.[24] There are three possible uses of factor analysis in this context.

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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.

[22] A dummy for the four observations corresponding to ongoing OJT has been introduced as a control. Not only it is rarely significant, but omitting it changes very little the other estimated coefficients.

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

[24] 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.

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. We particularly look for hidden characteristics related to intra-firm human capital. 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). By contrast, the PCA allows us to investigate the determinants of the firm effects in our data.

Table 5 reports 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.[25] The factors are identified by the set of firm characteristics presented in Table 5. These characteristics represent the information collected in the survey questionnaire. In our basic specification, 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 the observed firm characteristics with the first three factors are indicated in Table 5 for the interpretation. Clearly, the first factor corresponds to the activity sector (textile against IMMEE), grouping the firms most oriented towards exports.[26] The second factor describes the intra-firm density 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. Naturally, as it is always the case in

[25] 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 first three factors.

[26] 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, collective wage bargaining at sector level are conducted every three years for 45 sectors.

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 characterised 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 OJT.

3.4 Wage equations with firm factors

The three principal components (factors) summarize the main observed firm characteristics.[27] 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 dummies 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 the textile sector is the manufacturing industry with the lowest wage in Tunisia.

The second factor has a significant positive impact on wage differentials. This suggests that 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. This result will be refined below. The third factor has no significant effect in this specification. The factors' effects are summarized in Table 4.

[27] 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

The results with 2SLS (column 2) and quantile regressions (columns 3, 4, 5) show similar features for the positive effect of the second factor. Some accuracy is lost in the instrumentation, while not too much. For the three chosen quantiles in the quantile regressions, the first three factors have respectively effects that are: significant negative, significant positive, and insignificant. Whatever the specifications tried, the positive impact on conditional wages of the density of human capital in the firm emerges as a robust result.

Finally, we conduct a simple regression by replacing the three factors with the firm's characteristics (which we call: '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).[28] Collecting information on these three characteristics (sector, proxy of average education in this firm, age of this firm) would be easy by using a questionnaire addressed to workers. Then, these variables could be used as regressors in a typical wage equation. We call such regression the "pseudo factor" model (PFM, column 3 of Table 7). The coefficients of the three variables are statistically significant at 1 percent level with the expected sign corresponding to the factors they replace. The returns to human capital obtained from the PFM are closer to those of the firm dummies model (FDM, column 2 in Table 3) than to the corresponding returns drawn from the (extended by introducing tenure) Mincerian Model (MM, column 1 in Table 3). More specifically, the PFM yields a return to education similar to that obtained by the FDM (6.8 percent compared to 6.9 percent with the FDM, while it amounts to 8.6 percent with the MM).

Comparing the estimation results based on firm dummies with the estimation results based on factors is instructive. Indeed, the effects described by the firm dummies may partly result from unobserved human capital characteristics of firms. In our data, three of the firm's

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(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.

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

observable characteristics suffice to account for most of the impact of the firm dummies on wages.

The returns to education obtained with the firm dummies are almost indistinguishable from the returns in equations with factors, and from the returns in equations with the mean education of the firms instead. Thus, the firm dummies effects can be accounted for by introducing intra-firm mean education *if the main interest is to estimate returns to education.* Such results suggest that human capital externalities are at work.

Finally, let us direct our attention beyond the education returns. The factors may be used to interpret the firm dummies in equations with the firm effects by looking at the correlations of some firm dummies with the factors. 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’). Thus, the role of at least some of the firm dummies can be rationalized in terms of the factor interpretations. So, even if different factors may be elicited in different data sets, our approach of using factors to replace firm dummies appears useful for a variety of reasons.

4. Conclusion

In this case study, we use matched worker-firm 1999 Tunisian data to elicit the substantial roles of intra-firm human capital and modern firm features in worker remunerations. We show that the estimated return to education in wage equations is not modified when replacing in the list of regressors the firm dummies, representing observed and unobserved firm heterogeneity, by the first three factors of a principal components analysis of the observed firm characteristics. These factors can be interpreted as the activity sector, the intra-firm human capital density and the modernity of the firm. These results constitute an interesting argument in favour of the presence of intra-firm human capital externalities.

Moreover, the estimated education coefficient does not change when the three factors are replaced by three surrogate variables, respectively the textile industry dummy, the intra-firm mean education, and the firm's age.

With or without controlling for firm characteristics and for possible endogeneity of the human capital variables, the low conditional wage workers - perhaps corresponding to low unobserved ability workers - experience greater returns to human capital variables than workers belonging to the middle of the conditional wage distribution. However, the return to schooling of low conditional wages is significantly lower than that of high conditional wages.

An alternative interpretation of the results could be 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 will need to be closely monitored through 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.

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APPENDIX

Figure 1. Distribution of workers' observed monthly wages

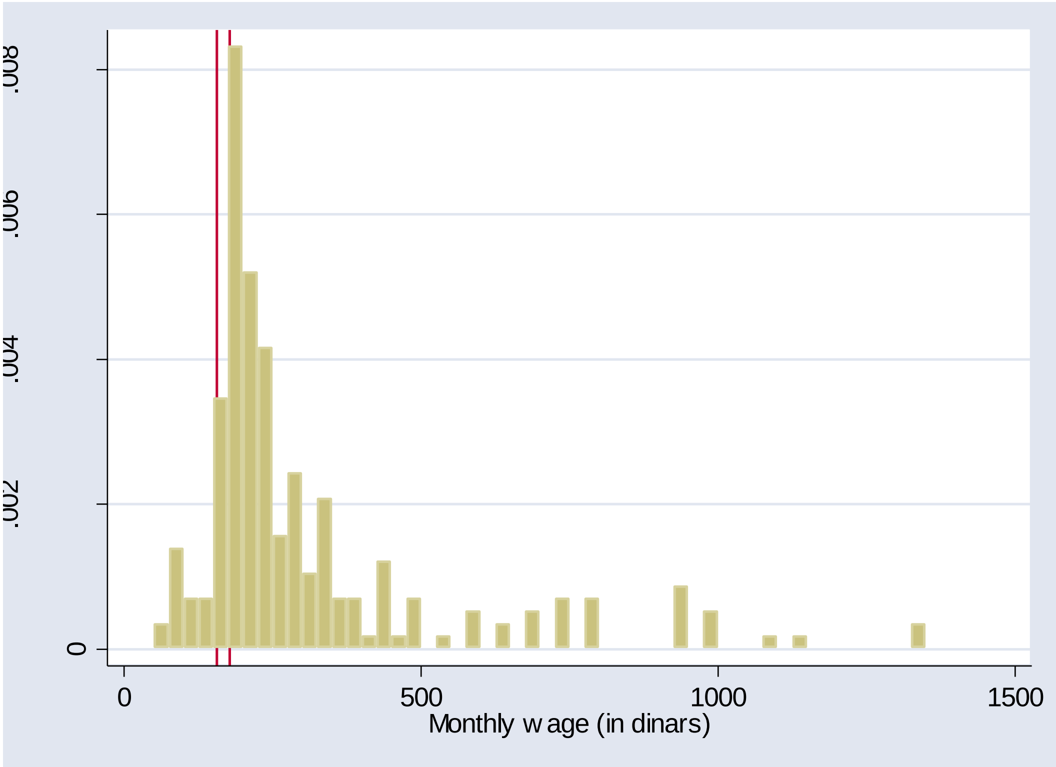

Table 1. Descriptive statistics of the workers' characteristics

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
Previous unemployment years (CHOMA)	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 production line (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
*Firm dummies***				
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 firm dummies 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 production line	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		**IV (2SLS)**		**Quantile regressions Firm dummies model (FDM)** (bootstrap standard errors: 20 iterations)		
	Mincerian Model (MM)	**Firm dummies model (FDM)**	**Mincerian Model (MM)**	**Firm dummies model (FDM)**	**Quantile .25**	**Quantile .50**	**Quantile .75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Education	0.0861***	0.0691***	0.1126***	0.0903***	0.0498***	0.0448***	0.0686***
	(0.0071)	(0.0068)	(0.0094)	(0.0097)	(0.0143)	(0.0107)	(0.0110)
Tenure	0.0255**	0.0452***	0.0081	0.0548***	0.0448**	0.0271***	0.0362***
	(0.0107)	(0.0099)	(0.0184)	(0.0184)	(0.0225)	(0.0079)	(0.0133)
Tenure^2	-0.0004	-0.0012**	0.0008	-0.0014	-0.0009	-0.0006*	-0.0008
	(0.0005)	(0.0004)	(0.0009)	(0.0009)	(0.0009)	(0.0003)	(0.0006)
Experience	0.0325**	0.0426***	0.0557***	0.0588***	0.0467***	0.0306**	0.0322**
	(0.0127)	(0.0117)	(0.0192)	(0.0181)	(0.0157)	(0.0142)	(0.0127)
Experience^2	-0.0004	-0.0011*	-0.0018	-0.0020*	-0.0015	-0.0010	-0.0002
	(0.0007)	(0.0006)	(0.0011)	(0.0010)	(0.0013)	(0.0012)	(0.0011)
Ongoing formal training	-0.4972***	-0.4159***	-0.5220***	-0.3918**	-0.3502	-0.4649***	-0.3384**
	(0.1798)	(0.1577)	(0.1914)	(0.1646)	(0.2578)	(0.1276)	(0.1478)
Completed formal training	0.4885***	0.2710***	0.3875***	0.2492***	0.3275*	0.2270***	0.1853**
	(0.0660)	(0.0735)	(0.0734)	(0.0760)	(0.1696)	(0.0864)	(0.0754)
Union	0.0835	0.0012	0.0599	-0.0008	-0.0030	0.0884	0.0373
	(0.0649)	(0.0619)	(0.0715)	(0.0648)	(0.1057)	(0.0890)	(0.0977)
Executive or supervisor	0.2124***	0.2655***	0.0906	0.1876***	0.1941*	0.3436***	0.2889***
	(0.0698)	(0.0618)	(0.0784)	(0.0712)	(0.1122)	(0.0690)	(0.0937)
Firm dummies (reference : Firm 6)							
Firm 1		-0.5318***		-0.4642***	-0.8463***	-0.8185***	-0.6331***
		(0.1041)		(0.1105)	(0.1757)	(0.1311)	(0.1982)
Firm 2		-0.4824***		-0.3859***	-0.7225***	-0.7262***	-0.5229***
		(0.1019)		(0.1115)	(0.2391)	(0.1056)	(0.1232)
Firm 3		-0.7895***		-0.6975***	-1.0174***	-1.0392***	-0.8133***
		(0.1033)		(0.1148)	(0.2260)	(0.1008)	(0.1272)
Firm 4		-0.7425***		-0.6433***	-1.0155***	-0.9817***	-0.8391***

Table 3 : (Continued)

	OLS		IV (2SLS)		Quantile Firm dummies	regressions model (FDM)	
					Quantile 0.25	Quantile 0.50	Quantile 0.75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		(0.1082)		(0.1274)	(0.2316)	(0.1063)	(0.1278)
Firm 5		-0.7227***		-0.6499***	-0.9939***	-0.9317***	-0.7328***
		(0.1055)		(0.1182)	(0.2237)	(0.1069)	(0.1341)
Firm 7		-0.6098***		-0.6015***	-0.8332***	-0.6708***	-0.6072***
		(0.1036)		(0.1102)	(0.2048)	(0.1183)	(0.0814)
Firm 8		-0.7736***		-0.7052***	-0.9723***	-0.9567***	-0.7999***
		(0.1007)		(0.1120)	(0.2041)	(0.0986)	(0.1234)
Constant	-0.7324***	0.0090	-0.9489***	-0.3077*	0.2617	0.5531***	0.2571
	(0.0864)	(0.1275)	(0.1099)	(0.1587)	(0.3429)	(0.1818)	(0.1885)
R-squared	0.68	0.77					
Pseudo Squared			0.64	0.66	0.43	0.55	0.61
Durbin-Wu-Hausman statistic (p-value)			26.14 (0.00)	17.76 (0.00)			
Observations	231	231	231	231	231	231	231

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

The instrumented variables in the IV regressions (3) and (4) are: education, tenure and off-firm experience.

The instruments used in the IV regressions include: AGE, $(\text{AGE})^2$, APPRENTI, CELIBAH, CHAINE, CHOMA, $(\text{CHOMA})^2$, CHOMA*FEMALE, EMSIM, ENFT, $(\text{ENFT})^2$, LOG(ENFT), ENFT*AGE, ENTREE, EQUIPE, FORMAA, $(\text{FORMAA})^2$, $(\text{FORMAA})^3$, 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, $(\text{STAGA})^2$, $(\text{STAGA})^3$, STAGAN, $(\text{STAGAN})^2$, $(\text{STAGAN})^3$, 8 firm dummies.

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

Table 4. Returns to human capital[#] and wage effects of firm factors

Independent variables	*OLS*	*2SLS*	*0.25 Quantile*	*0.50 Quantile*	*0.75 Quantile*
Education	0.0691	0.0903	0.0498	0.0448	0.0686
Tenure[a]	0.0310	0.0382	0.0448	0.0271	0.0266
Experience[a]	0.0354	0.0457	0.0467	0.0306	0.0322
Factor 1	-0.0557	-0.0530	-0.0544	-0.0561	-0.0360
Factor 2	0.0756	0.0667	0.1026	0.1020	0.0764
Factor 3	-0.0017 [ns]	0.0068 [ns]	-0.0121 [ns]	-0.0099 [ns]	-0.0113 [ns]

[#] The human capital returns stem from the firm dummies models (FDM) reported in Table 3.

[a] : returns calculated at the average point of the sub-sample.

[ns] : no significantly different from zero at 10% level.

[nd] : no significantly different from the coefficient of the 4^{th} 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 production line	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 dummies and characteristics of education in the firms

	Factor 1	Factor 2	Factor 3
Firm dummies			
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 OJT	-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)

	Factor effects model		Pseudo factor model (PFM)	Quantile regressions (bootstrap standard errors: 20 iterations) Factor effects models		
	OLS	IV (2SLS)	OLS	.25 Quantile	.5 Quantile	.75 Quantile
	(1)	(2)	(3)	(4)	(5)	(6)
Education	0.0674***	0.0854***	0.0679***	0.0552***	0.0570***	0.0768***
	(0.0069)	(0.0091)	(0.0069)	(0.0127)	(0.0114)	(0.0122)
Tenure	0.0369***	0.0450***	0.0432***	0.0442*	0.0303**	0.0213
	(0.0097)	(0.0168)	(0.0098)	(0.0229)	(0.0128)	(0.0161)
Tenure^2	-0.0010**	-0.0013	-0.0012***	-0.0010	-0.0007	-0.0002
	(0.0005)	(0.0009)	(0.0005)	(0.0009)	(0.0006)	(0.0007)
Experience	0.0363***	0.0440***	0.0375***	0.0494***	0.0304**	0.0336**
	(0.0115)	(0.0167)	(0.0114)	(0.0160)	(0.0123)	(0.0156)
Experience^2	-0.0007	-0.0011	-0.0008	-0.0026**	-0.0003	0.0001
	(0.0006)	(0.0010)	(0.0006)	(0.0012)	(0.0011)	(0.0011)
Ongoing formal training	-0.4740***	-0.4567***	-0.4685***	-0.3530	-0.5131	-0.4418
	(0.1614)	(0.1615)	(0.1596)	(0.3196)	(0.3641)	(0.2894)
Completed formal training	0.2101***	0.1804**	0.2180***	0.1897**	0.1413**	0.1510
	(0.0714)	(0.0714)	(0.0685)	(0.0873)	(0.0632)	(0.1281)
Union	0.0220	0.0272	-0.0228	0.0033	0.0473	0.0886
	(0.0618)	(0.0624)	(0.0621)	(0.0686)	(0.0800)	(0.1205)
Executive or supervisor	0.2953***	0.2303***	0.2842***	0.2013**	0.3345***	0.3064***
	(0.0629)	(0.0689)	(0.0621)	(0.0925)	(0.0705)	(0.0793)
Factor 1	-0.0557***	-0.0530***		-0.0544***	-0.0561***	-0.0360*
	(0.0106)	(0.0113)		(0.0162)	(0.0138)	(0.0212)
Factor 2	0.0756***	0.0667***		0.1026***	0.1020***	0.0764***
	(0.0112)	(0.0117)		(0.0338)	(0.0163)	(0.0211)
Factor 3	-0.0017	0.0068		-0.0121	-0.0099	-0.0113
	(0.0142)	(0.0148)		(0.0141)	(0.0202)	(0.0227)
Sector (textiles: 1; IMMEE: 0)			-0.2470***			
			(0.0522)			
Average years of education in the firm			0.0621***			
			(0.0131)			
Age of the firm			-0.0162***			

Table 7: (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
			(0.0045)			
Constant	-0.4969***	-0.6998***	-0.8529***	-0.5536***	-0.3307***	-0.3844**
	(0.0832)	(0.1019)	(0.1396)	(0.2109)	(0.1114)	(0.1673)
Observations	231	231	231	231	231	231
R-squared	0.75		0.75			
Pseudo Squared		0.74		0.40	0.52	0.59
Durbin-Wu-Hausman statistic (p-value)		12.86 (0.02)				

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

The instrumented variables in the IV regression (2) are: Education, tenure and off-firm experience.

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, $(STAGAN)^2$, $(STAGAN)^3$, 8 Firm dummies.