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On-the-job learning and earnings in Benin, Morocco and Senegal

Christophe J. NORDMAN
François-Charles WOLFF

DIAL • 4, rue d'Enghien • 75010 Paris • Téléphone (33) 01 53 24 14 50 • Fax (33) 01 53 24 14 51
E-mail : dial@dial.prd.fr • Site : www.dial.prd.fr

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On-the-job learning and earnings in Benin, Morocco and Senegal [#]

Christophe J. Nordman ^{*}

François-Charles Wolff ^{**}

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Abstract: In this paper, we consider a model of on-the-job learning where workers learn informally by watching and imitating colleagues. We estimate the rate of knowledge diffusion inside the firm using three matched worker-firm data sets from Benin, Morocco and Senegal. We rely on non-linear least squares to estimate the structural parameters of the informal learning model and account for unobserved firm heterogeneity using firm factors derived from a principal component analysis. We find that the rate of knowledge diffusion is around 7 percent in Morocco and Senegal and much higher in Benin, but part of the learning-by-watching returns stems from firm heterogeneity. Informal training significantly affects the shape of returns to tenure in African countries. Finally, we estimate an extended model with both learning-by-watching and learning-by-doing and find significant benefits from imitating colleagues in Morocco.

Keywords: Earnings functions, informal training, learning-by-watching, learning-by-doing, returns to tenure, African countries

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^{*} Corresponding author. IRD, DIAL, 4 rue d'Enghien, 75010 Paris, France. E-mail: nordman@dial.prd.fr

^{**} LEN, Université de Nantes, BP 52231 Chemin de la Censive du Tertre, 44322 Nantes Cedex 3, France; CNAV and INED, Paris, France.

E-mail: wolff@sc-eco.univ-nantes.fr Homepage: <http://www.sc-eco.univ-nantes.fr/~fcwolff>

1. Introduction

Within the academic literature in sociology, there has been a growing interest in workplaces as learning environments and the importance of on-the-job learning in skill formation processes (Garrick, 1998, Boud and Garrick, 1999). In particular, many workplace learning processes are variously described as ‘informal’ or ‘nonformal’ (Billett, 2001, Colley et alii, 2003, Hayward and James, 2004). The perceived importance of informal processes in workplace learning is captured by Coffield’s image of the learning iceberg (2000, p. 1): “If all learning were to be represented by an iceberg, then the section above the surface of the water would be sufficient to cover formal learning, but the submerged two thirds of the structure would be needed to convey the much greater importance of informal learning”.

It is important to appreciate that interest in workplace learning, through both formal and informal processes, is still a relatively recent phenomenon and that the evidence base about effective practices that lead to important labour market outcomes is still relatively scarce (Battu et alii, 2003). Economic research on workplace learning in economics is still in late infancy at best, albeit Mincer (1989) was claiming years ago that informal training may constitute the essential part of training provided by firms. If workplace learning, and in particular informal training, is as important in developing vocational knowledge and skill as research is beginning to suggest, then it is also important to understand the ways in which (and of course the extent to which) skill formation resulting from situated learning affects workers’ productivity and wages.

While the benefits of investments in human capital are clearly established in the economic profession, the accurate calculation of rates of return to informal training remains complex. One reason is that the usual on-the-job training variables are often affected by measurement errors. Some authors have shown that these errors are likely to bias the estimates of the rates of return to training (Barron et alii, 1997, Loewenstein and Spletzer, 1999, Frazis and Loewenstein, 2005). Moreover, for reasons that are inherent in the very nature of informal training, the few direct measures of informal training available today in data sets are even more imperfect (see the discussion in Barron et alii, 1997, Loewenstein and Spletzer, 1999).

Interestingly, formal training is rather simple to measure as it is clearly identifiable. It is generally provided for a determined duration by a recognised trainer in a precise place. Unfortunately, this is not the case for informal training that appears inextricably part of the

employee's productive activity (Brown, 1990). Furthermore, the modeling of a process of informal learning susceptible to be submitted to an empirical test requires the availability of micro data containing information both on workers and on their firm.

In this contribution, we rely on three matched worker-firm data sets for Morocco, Benin and Senegal to assess the relevance on informal training in Africa. The first one is the Firm Analysis and Competitiveness Survey (FACS) conducted in 2000 by the World Bank and the Moroccan Ministry of Trade and Industry, which includes representative data from 859 manufacturing plants. The worker survey collected data from 8375 workers. The two other matched data sets, made available very recently, stem from the Investment Climate Assessment (ICA) surveys conducted by the World Bank between 2001 and 2004 in the framework of the Africa RPED programme. The ICA surveys provide information on about 200 firms and more than 1500 employees.

With a method similar to that of Mincer (1974), our approach consists of estimating the returns to informal training using the individual earnings profiles. For that purpose, a structural model of on-the-job learning is developed to conform to the structure of our data. The first presentation of the model appears in the original work of Lévy-Garboua (1994), and it has been extended and successively estimated by Chennouf et alii (1997), Nordman (2000), Destré and Nordman (2002), Destré (2003) and Destré et alii (2007). However, the previous estimates suffer from limits that this paper intends to overcome.

The model accounts for on-the-job learning. Workers learn informally on the job by watching others performing their tasks¹. They may also learn by themselves, i.e. by a sort of learning-by-doing process. In a setting where gross earnings reflect human capital, it is straightforward to show that one can solve a wage recurrence equation after postulating that the knowledge diffusion process within the firm is time-invariant. The human capital of any given worker is expected to increase with tenure, both by learning-by-watching and learning-by-oneself. One part of the returns to tenure is hence firm dependent. By taking the logarithms of the earnings equation, we find that the log of gross earnings is the sum of a linear-in-tenure Mincerian earnings functions and a correction function. We estimate the structural parameters of the model using non-linear least squares.

We extend the previous results on the learning model in the following way. First, we structurally take into account a flexible form of the returns to schooling. Indeed, the previous

¹ Employees who are getting informal training may not always be conscious that they are doing so.

estimated model did not consider the possibility of convex returns to education (Destré et alii, 2007). Yet, constant rates of return to education are more and more challenged in developed and developing countries (Card, 1999), especially in Africa². Second, we introduce controls for the firm's heterogeneity component thanks to the use of a preliminary factor analysis of the firms' characteristics and show the impact of these firm factors on the structural parameters of the model. Finally, it matters to point out the innovative nature of our estimates for developing countries. To the best of our knowledge, accurate and comparative assessment of the impact and extent to informal on-the-job training in private firms has never been carried out with matched worker-firm data on Africa.

Our empirical results show that informal learning is of importance in African firms. We find that the rate of knowledge diffusion is around 7% in Morocco and Senegal, while it is much higher in Benin. This means that in the former countries, the workers' tenure which is requested to assimilate half of the firm knowledge is about 10 years. However, part of the learning-by-watching returns stems from firm heterogeneity. Informal training significantly affects the shape of returns to tenure in African countries. Intuitively, workers will assimilate faster a given proportion of the knowledge of the firm when there is a lot to learn by watching others. We evidence that the learning potential from the most qualified teacher is much lower in Morocco than in Benin and Senegal. Finally, we estimate the extended model with both learning-by-watching and learning-by-oneself and still evidence significant benefits from imitating colleagues in Morocco.

The remainder of this paper proceeds as follows. In section 2, we present the on-the-job learning model. Section 3 describes the three matched worker-firm surveys together with the information collected from workers and firms respectively for Morocco, Benin and Senegal. In Section 4, we present the econometric strategy to recover the structural parameters of the model. Our results are discussed in Section 5. Section 6 concludes.

2. A model of learning-by-watching

While economists mainly focus on formal training, workers may also improve their skills by learning informally, simply while being in their firm and watching other workers performing their tasks. Unlike formal training, this knowledge acquisition process seems not really costly as a firm does not have to provide specific resources for it.

² See Bigsten et alii (2000), Schultz (2004), Söderbom et alii (2006) and Kuepie et alii (2006).

More productive workers may not necessarily devote time to explain other workers how to improve their own productivity. All the training effort remains informal, in the sense that less productive workers are simply expected to watch those who have more knowledge and experience, and then to replicate what they have observed. This imitation process acts as a positive externality whose benefits extend over time. Workers receiving at a given time some informal training from others will be later in a supply position, showing in turn informally to new incumbents how they can enhance their own productivity.

For the presentation, we draw on the model of learning-by-watching first described in Lévy-Garboua (1994) and extended in Destré et alii (2007). Consider a competitive industry where wage rates are equal to the true marginal product of labour, so that earnings reflect pure human capital. Using a discrete-time framework, we denote by h_t the amount of human capital for a worker at date t . Assume that the worker enters the firm at date 0, so that t corresponds to tenure. Then, h_0 is the value of the worker's human capital when starting his activity in the firm. Each individual has presumably accumulated some experience while working in previous firms. Let x be the number of working years spent outside the current firm, so that individual total experience is $x+t$.

In the firm, each worker is supposed to learn from colleagues who have more human capital than him/her. Let H_t be the highest level of human capital embodied in colleagues. Importantly, we assume that the firm's knowledge is invariant, meaning that $H_t = H$. Owing to the imitation process, a worker's human capital is expected to increase over time by learning from others. The following equation describes the dynamics of human capital formation for a worker (see Lévy-Garboua, 1994):

$$h_t - h_{t-1} = \frac{n}{1+n}(H - h_{t-1}) \quad (1)$$

where n is the rate of knowledge diffusion inside the firm. We assume that the rate of learning-by-watching is the same for each worker and is time-invariant for the sake of simplicity. For a given value of n , human capital will increase faster when the worker has a lot to learn from the most qualified worker. Hence, at the period t , the level of human capital is a weighted sum of human capital in $t-1$ and of human capital of the most capable worker:

$$h_t = \frac{n}{1+n}H + \frac{1}{1+n}h_{t-1} \quad (2)$$

From the recurrence equation (2), we get the following solution for h_t :

$$h_t = \left[1 - \frac{1}{(1+n)^t} \right] H + \frac{1}{(1+n)^t} h_0 \quad (3)$$

which we can also express as:

$$h_t = h_0 \left[1 + \left(1 - \frac{1}{(1+n)^t} \right) \left(\frac{H}{h_0} - 1 \right) \right] \quad (4)$$

As shown in (4), the human capital of a worker is an increasing function of the number of periods spent within the firm ($\partial h_t / \partial t > 0$). Also, we have $\lim_{t \rightarrow \infty} h_t = H$. As time goes by, the individual level of human capital converges towards the firm's job-specific knowledge. In this model, the central interest lies in the estimation of the parameter n .

In the above formulation, all the job-specific information is learnt from colleagues and the highest level of human capital remains constant. A more realistic framework, considered in Destré et alii (2005) and estimated in Destré and Nordman (2002), is to assume that workers learn both by themselves through their own experience and by watching others³. In such setting, the human capital of a worker is both increasing with tenure and it converges towards the firm's job-specific knowledge. However, the latter component is no longer fixed within the firm. Since all workers are expected to learn by themselves, the level of human capital of the most qualified worker is continuously growing.

Let g be a measure of the impact of self-learning. The dynamics of human capital formation may now be expressed as:

$$h_t - h_{t-1} = g h_{t-1} + \frac{n}{1+n} (H_{t-1} - h_{t-1}) \quad (5)$$

By definition, there is no learning-by-watching for the most capable worker, meaning that the highest level of human capital will increase inside the firm only owing to self-learning. This implies that $H_t = (1+g)H_{t-1}$. Using (5) and after some calculations, we finally deduce the following value for h_t ⁴:

³ By repeating tasks within the firm, a worker is expected to improve his/her own productivity and hence human capital.

⁴ For a more detailed analysis, see the presentation in Destré et alii (2007).

$$h_t = (1 + g)^t \left\{ \left(\frac{1 + g(1 + n)}{(1 + g)(1 + n)} \right)^t h_0 + \left[1 - \left(\frac{1 + g(1 + n)}{(1 + g)(1 + n)} \right)^t \right] H_0 \right\} \quad (6)$$

Clearly, we note that when $g = 0$, equation (6) is equivalent to (3), which is the pure learning-by-watching case. To end up with this formal presentation, two comments are in order.

First, it is unclear whether the firm's job specific knowledge H_t may really be seen as a moving target, increasing at steady state. Imagine a manufacturing firm, with a young worker and a very experienced, older worker. In a context where the technology remains fixed, the latter has certainly nothing more to learn even by him/herself⁵. As a consequence, we estimate first the learning-by-watching model in our empirical analysis and then examine the consequences of self-learning. Second, as clearly shown by (4) and (6), the expression of h_t is a non-linear function of both g and n . When turning to the data, we rely on non-linear models to recover the structural parameters of informal training.

3. Data and descriptive statistics

3.1. The matched worker-firm data

We estimate the previous theoretical model in a comparative context with matched employer-employee data collected in three different African countries, i.e. Benin, Morocco and Senegal. The data for Benin and Senegal stem from the Investment Climate Assessment (ICA) surveys conducted by the World Bank between 2001 and 2004 in the framework of the Africa RPED programme⁶. The data for Morocco come from the Firm Analysis and Competitiveness Survey (FACS) conducted in 2000 by the World Bank and the Moroccan Ministry of Trade and Industry.

These three surveys are based on the notion that the workplace is the microdata unit where labour supply and demand is resolved. In that spirit, the ICA surveys respectively conducted in 2004-2005 for Benin and in 2003-2004 for Senegal and FACS collected data both on the firm characteristics and on a sample of employees in each workplace. The survey instrument was then a written questionnaire addressed to both employers and employees. The

⁵ In fact, the worker may even become less productive as time goes by, and could thus be concerned by a decrease in earnings. We rule out this possibility by assuming that there exists some downward wage rigidity.

⁶ The Africa Regional Program on Enterprise Development (RPED) is an ongoing research project with the overall purpose of generating business knowledge and policy advice useful to private sector manufacturing development in Sub-Saharan Africa.

questionnaires are specifically tailored for each country, but they enable cross-country comparisons as they are made of very similar questions.

In Benin and Senegal, the firms have been randomly selected among the population of formal establishments and belong to the following ten sectors of production: agro-industry, chemicals and paints, construction materials, food, furniture, metal, paper and publishing, plastics, textile and leather and wood industry. There is no constraint on the size of the firms which were selected in the samples. Conversely, in Morocco, the focus is restricted to formal companies which have at least ten employees. The selected firms are in seven industries: electronics, textiles, garments, food, pharmaceuticals, leather and shoes products, and plastics. Clearly, there is less heterogeneity in the firm sample of Morocco.

Let us now describe more precisely the different samples⁷. In Senegal, a sample of 262 manufacturing firms has been surveyed based on a sampling plan made of 1645 formal companies. These firms have been randomly selected using a stratification based on sector, size and localisation and represented 59.6% of the formal manufacturing firms in 2003 and 68.9% of its formal permanent jobs. In Benin, a sample of 197 manufacturing firms has been randomly selected by stratification as well. It represented 78% of the formal manufacturing firms listed in 2002 and gathered 42% of the estimated formal jobs in Benin. For Morocco, the Moroccan Census of Manufactures was used as the establishment sampling frame, with 1933 formal firms of more than ten employees in the seven sectors mentioned above⁸. The sample includes data from 859 manufacturing plants which are representative of the sampling plan in terms of employment, production and exportation.

The structure of the data allows building up matched worker-firm data sets. Indeed, in each surveyed country, up to ten employees have been randomly sampled in each firm following the idea advocated by Mairesse and Greenan (1999). Note that all the employees of small firms have been interviewed, while the sampling rate decreases with the size of the firms. The number of workers interviewed in Benin, Senegal and Morocco are respectively equal to 1781, 1645 and 8561.

⁷ Further details of the surveys and their methodology can be found in World Bank (2005a, 2005b) for Senegal and Benin, and in World Bank (2002) for Morocco.

⁸ A random sample of 1000 establishments and a replacement sample of 500 were drawn by industry, the choice of regions being dictated by the geographical concentration of firms in the selected industries.

3.2. Descriptive statistics of the workers

To estimate the structural parameters of the on-the-job learning model, we need several observations of workers in each firm. Recall that we do as if the more capable worker in a given firm takes up the teaching role, and then estimate the distance to this teacher. We then make the following selections to the initial samples (similar for each country).

First, we restrict the samples to the firms which have information on at least four workers. Second, as our modelling framework is in discrete time, we decide to exclude all the workers having less than one year of tenure in the current firm. In so doing, it may be that we underestimate the rate of knowledge diffusion within the firm, if we assume that the learning-by-watching process is very efficient once entering the firm (and there is less to learn from colleagues a couple of months after). However, we also argue that the level of earnings is unlikely to increase just after being hired and before reaching one year of tenure, even if there is a rise in the worker's productivity due to learning from others. Finally, we drop from the sample all the observations with missing values or outliers.

The final samples are described in Table 1. This leaves us with samples comprising 7622 workers and 822 firms in Morocco, 1566 workers and 188 firms in Benin, and 1284 workers and 180 firms in Senegal. Owing to the large size of its sample, the FACS Moroccan data are expected to be much more informative. More than 75% of workers are employed in firms with 10 completed individual questionnaires. The same proportions are respectively equal to 48.5% in Benin and to 31.9% in Senegal. At the same time, the proportion of workers belonging to firms with information on less than 7 respondents is much higher in Senegal than in Benin (respectively 43.9% instead of 18%)⁹.

Insert Table 1 here

The questionnaires of the different surveys allow us to construct identical human capital indicators for the workers in Benin, Morocco, and Senegal. We compute for each respondent the number of years of completed schooling, the number of years of experience off the current firm and the number of years of tenure in the incumbent firm. All these variables provide good controls for the potential advantage on the labour markets. We further construct a dummy variable which is equal to one when the worker has received formal on-the-job training in the past. Nevertheless, owing to data constraints, this training is off the current job in the case of Morocco, but in the current firm for Benin and Senegal. Finally, we

⁹ The distribution of firms by number of employees is characterized by a U-shaped profile in Senegal.

add two demographic variables, i.e. a dummy for gender and a dummy for whether the individual is married or not¹⁰.

In Table 2, we present some descriptive statistics related to the different covariates introduced into the earnings equations. A first result is that the Moroccan workers are on average the least educated. While the Moroccan employees show on average 8.7 years of education, their Beninese and Senegalese counterparts exhibit 9.4 and 10.3 years of schooling respectively. This is surprising because Sub-Saharan African countries are often believed to be less endowed in human capital as compared to North African ones. An explanation is that an overwhelming proportion of poorly educated individuals actually work in the informal sectors of Benin and Senegal (see DIAL, 2007). The latter are thus not in the sample design of the ICA surveys, as the data we use stem from formal manufacturing firms and their workers. The formal private sector in Senegal and Benin, highly selective, might be in fact reserved to the most educated workers. This is probably less true for Morocco where uneducated workers are also found in significant proportion in garment firms for instance.

Insert Table 2 here

Another explanation may certainly be found in the proportion of females in the three surveys. It is well known that girls face lower educational achievement than boys, especially in developing countries. Interestingly, the proportion of women amounts to 40% in the case of Morocco, while these proportions are around 15% in the Beninese and Senegalese cases (respectively 13.9% and 16%). Nevertheless, we would like to stress that the specific gender composition of the Moroccan subsample is not so influential when explaining the lower education observed in that country. Indeed, while the mean number of years of schooling is equal to 8.8 among men, it is only slightly lower among women, equal to 8.5 years. Another finding on demographic characteristics is that the proportion of married workers is nearly the same in Benin and Senegal. It is lower in Morocco, but with a different definition.

In terms of work experience, the workers of the three samples have nearly the same amount of potential experience off the current firm, which stands at more than 12 years. Tenure in the current firm is on average higher for the Senegalese workers (8.9 years), while the Beninese are the least tenured workers (6.0 years). Finally, we note that in Senegal workers received in higher proportion formal job training in the incumbent firm as compared

¹⁰ In order to ensure perfect comparability of the variables used in the model, this variable is approximated in the case of Morocco where the marital status was not collected from the workers. Instead, we use the fact of having declared children. In Morocco, it is reasonable to assume that all individuals who have declared children are (or have been) married because of the social norms in force.

to their Beninese counterparts (35% versus 20%). The figure is much lower in Morocco, but it relates to a formal job training episode off the current firm.

To summarize, we evidence quite similar profiles for the workers in the three countries, the two main differences stemming from education and female composition (respectively lower and higher in Morocco than in Benin and Senegal). As returns to on-the-job learning are expected to depend on both workers' and firms' characteristics, we now further investigate the differences in the composition of the firms.

3.3. Firm heterogeneity

For the sake of comparability, it matters to know whether there are any differences in the characteristics of the firms¹¹. In Table 3, we summarize the descriptive statistics of the final samples of selected firms for each country.

Insert Table 3 here

For Morocco, 40.9% of the 822 firms are small and medium-sized plants with less than 50 permanent employees. Firms with more than 150 permanent employees represent 23% of the firm sample. Most of these firms are found in the textile and garment sectors (60.3%). More than half of these firms are exporting companies, therefore submitted to strong market competition, especially in the garment sector. However, less than 5 percent of the sample of firms can be described as 'multinationals', i.e. with more than 75% foreign capital. Note that 62 percent of the firms have positive profits (hereafter 'profitable' firms).

For Benin, the 188 firms are mostly located in the region of Cotonou (69%), the economic capital, a share close to the geographical distribution of the formal firms of Benin (World Bank, 2005b). More than 84% of them are small firms with less than 50 employees. Large-sized firms represent only 8% of the firm sample. Another difference with the Moroccan sample lies in the sectoral distribution, which is less concentrated with 20.6% of plants being in the agro-industry sector, 18.8% in the sector of furniture and 21.5% in the paper industry. Foreign companies are also very few (8%) but profitable firms are on the contrary predominant (92%).

¹¹ It also matters for the estimation strategy. If there are very similar firms in the three countries, then one could consider the possibility of pooling all the observations and estimate a single regression. However, this is clearly not the case with the available data sets.

The Senegalese sample represents well the actual distribution of jobs and firms in the manufacturing sector of Senegal (World Bank, 2005a). The firm size is quite similar to that of the Moroccan sample, with 52% of the 180 plants being small and medium-sized companies. Large-sized firms are also found in relatively fair proportion (21%). Firms in agro-industry are predominant (34%), the second most important sector being the industry of paper, closely followed by the textile and leather firms (10%). There are slightly more foreign owned companies in the Senegalese sample (15%), while profitable firms are also well represented (84%).

To conclude, while the samples of workers look alike in many ways across the three countries, the firm samples are made of very different types of firms, with distinct sizes, belonging to quite different sectors of activity. This justifies taking care of this firm heterogeneity with cautious in the empirical strategy. Besides, in terms of the few principal firm characteristics mentioned above (notably size and sectoral distribution), the Senegalese and Moroccan firm samples exhibit more similarities, while the Beninese sample mainly differs due to the size of its firms, which are essentially small companies.

4. Econometric specification

We turn to a structural econometric analysis to recover the values of the different parameters of interest. We first consider equation (4) and then show how to add the impact of self-learning into the estimation strategy. By taking the logarithm of h_t , we get:

$$\ln h_t = \ln h_0 + \ln \left[1 + \left(1 - \frac{1}{(1+n)^t} \right) \left(\frac{H}{h_0} - 1 \right) \right] \quad (7)$$

In a setting with only learning-by-watching, we get a human capital earnings function which depends on the human capital of both the worker's initial stock and the most qualified worker. It is also non-linear in both the rate of knowledge diffusion and tenure, so that the appropriate econometric approach is to rely on non-linear least squares.

Suppose that the initial earning (when entering the firm) is not observed. We can then approximate the level h_0 using a Mincerian earnings function. We introduce into the earnings function both years of education and years of experience outside the firm in a quadratic way. Several studies have indeed shown that returns to education are convex in African countries¹².

¹² The assumption of convex returns to human capital seems important. Taking into account a linear form for the returns to education when the "true" profile is convex is likely to lead to an overestimated value of the rate of

We denote by s , e and t respectively years of education, years of experience off the firm and tenure. We express h_0 as:

$$h_0 = \exp(\alpha_0 + \alpha_1 s + \alpha_2 s^2 + \alpha_3 e + \alpha_4 e^2) \quad (8)$$

since $t=0$ by definition when entering the firm. Assume now that we can perfectly observe the most qualified worker to whom each individual is exposed to. Following the same approach, we can rely on a Mincerian earnings function to approximate the level H . With S , E and T respectively years of education, years of experience outside the firm and tenure for the most qualified worker and using quadratic profiles for these three covariates, it follows:

$$H = \exp(\alpha_0 + \alpha_1 S + \alpha_2 S^2 + \alpha_3 E + \alpha_4 E^2 + \alpha_5 T + \alpha_6 T^2) \quad (9)$$

A difficulty with the data is that we have no information on the most productive worker who may be imitated by each individual. Such observation would require a description of student-teacher interactions within establishments. To overcome this shortcoming, we follow the method of Destré and Nordman (2002) and Destré et alii (2007). There are then two important assumptions. First, as we have matched employer-employee data and observe a random sample of employees from the same firm, we consider the whole set of employees for each firm and suppose that the most qualified worker within the firm is the one with the highest characteristics recorded in the survey¹³. Second, as we are not sure that an individual is really subject to the influence of the most qualified worker (as measured with the data), we account for a distance indicator between the maximum position and the individual situation.

Formally, this means that for an exogenous covariate denoted by \bar{X} for the most productive worker and by x for the selected individual, we suppose that the characteristic of the teacher is such that:

$$X = \delta_x \bar{X} + (1 - \delta_x) x \quad (10)$$

with δ_x a parameter to be estimated ($0 \leq \delta_x \leq 1$). It measures the relative distance between the individual and the most capable worker within the firm. δ_x takes the value 0 if the individual has no possibility of learning from others and the value 1 if his/her most qualified teacher corresponds effectively to the worker having the biggest \bar{X} of the firm's sub-sample. This implies that there are three parameters of relative distance to estimate, i.e. δ_s , δ_e and δ_t .

knowledge diffusion, since workers will benefit less from the rewards of their own personal characteristics when estimating the model.

¹³ In that sense, this means that we tend to underestimate the rate of learning-by-watching. Indeed, there may be even more productive workers within the firms, who have not been interviewed during the survey process.

After some calculations, we finally deduce the following non-linear form for the earnings equation under learning-by-watching:

$$\ln h_t = \ln \left[1 + \left(1 - \frac{1}{(1+n)^t} \right) \exp \left(\begin{array}{l} \alpha_1 \delta_s (\bar{S} - s) + \alpha_2 \delta_s^2 (\bar{S} - s)^2 + 2\alpha_2 \delta_s (\bar{S} - s)s + \\ \alpha_3 \delta_e (\bar{E} - e) + \alpha_4 \delta_e^2 (\bar{E} - e)^2 + 2\alpha_4 \delta_e (\bar{E} - e)e + \\ \alpha_5 \delta_t \bar{T} + \alpha_6 \delta_t^2 \bar{T}^2 \end{array} \right) \right] \quad (11)$$

$$+ \alpha_0 + \alpha_1 s + \alpha_2 s^2 + \alpha_3 e + \alpha_4 e^2 + \beta Z + \varepsilon$$

where Z is a set of control variables, β is the corresponding vector of estimates, and ε is a random perturbation. We estimate equation (11) using non-linear least squares (NLSQ) to get the coefficients of both the parameters and the explanatory variables. Let us briefly discuss identification issues. Clearly, the parameters α_0 , α_1 , α_2 , α_3 , α_4 , δ_s and δ_e are identified according to the data. However, since we have only two estimates for $\alpha_5 \delta_t$ and $\alpha_6 \delta_t^2$, this implies that we cannot recover the individual values of the three coefficients α_5 , α_6 and δ_t .

A very similar strategy is used to estimate the model with both self-learning and learning-by-watching. There is now an additional parameter to estimate, i.e. g . From (6), we can express $\ln h_t$ as a function of $\ln h_0$, $\ln(1+g)^t$ and a third term, more complex, which depends on the ratio H_0/h_0 , n and g . The term H_0 is defined as in (9). Then, using (8) and (10), we obtain a non-linear form which is very similar to (11), except that the log earnings equation is now a function of an additional term $\ln(1+g)^t$ and that both n and g affect the exponential expression corresponding to H_0/h_0 .

While the estimation of both non-linear models is quite straightforward using NLSQ, a difficulty stems from the fact that we cannot model unobserved individual heterogeneity as the three data sets are cross-sectional. However, owing to the importance of the work environment in which workers are placed, which is more or less favourable to learning by watching other colleagues, it seems important to control for firm heterogeneity. In theory, firm heterogeneity could be handled in our setting. As we have information on several workers per firm, we can control for such heterogeneity in Mincerian earnings linear regressions through the use of fixed effects models.

The problem is much more complex when estimating (11). As the extended earnings equations are intrinsically highly non linear, we cannot control for firm heterogeneity using firm fixed effects. A possibility would be simply to add dummy variables for each firm, but the large number of firms in our data clearly rules out the possibility of using this method.

Another strategy to temper the effects of firm heterogeneity consists in adding a large number of control variables to our regressions. In this paper, we rely on an alternative strategy to control for unobserved firm heterogeneity which is likely to bias the estimated coefficients and rely on a factor analysis following Muller and Nordman (2004) and Jellal et alii (2007). We proceed in the following way.

Our approach consists of summarising the main statistical information on the firms' characteristics using first a multivariate analysis and then introducing the computed principal components (factors) into the earnings functions deriving from this analysis. Using factors may be seen as a further step with respect to those studies which have added mean firm variables into earnings functions, individual characteristics being controlled for. With respect to firm fixed effects, the factors are expected to pick up the impact of more qualitative characteristics of the firms. Specifically, we use a principal component analysis (PCA) to summarise the information about the surveyed companies¹⁴. This method is based on the calculation of the inertia axes for a cloud of points that represents the data in table format. As long as the computed factors account for most of the firm heterogeneity bias, this approach allows us to obtain consistent estimates close to those of the fixed effect estimator. The complete list, definitions and descriptive statistics of the firms' characteristics introduced in the PCA appear in Table 2.

In the case of Morocco, the first ten inertia axes, defined as the estimated factors which are linear components of all the firm's characteristics, concentrate a large proportion of the total variance of the original variables (63%). This reflects therefore a fair amount of the relevant information about the firm's characteristics¹⁵. For the two other countries, Benin and Senegal, firm heterogeneity seems to be greater according to very basic descriptive statistics. We thus choose to rely on twelve factors which concentrate respectively 58% and 55% of the total variance of the firm variables.

The correlation coefficients of the firms' characteristics with the factors are used for the interpretation of the computed factors. The ten first factors are closely associated with the firms' sectoral belonging and size (factors 2, 5, 6, 7 and 9 for Morocco, factors 1, 4, 6, 7 and 10 for Benin, factors 5, 7 and 10 for Senegal), the firms' performances such as their sales, production and profitability (factors 1 and 10 for Morocco, factors 1, 3 and 8 for Benin and 1,

¹⁴ In a 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.

¹⁵ The detailed results of the three factor analyses (one for each country) are not reported here to save space and are available from the authors upon request.

2 and 8 for Senegal), their labour intensity and workforce composition such as whether production, skilled, or executives workers are dominant (factors 3, 6 and 8 for Morocco, 6, 7 and 9 for Benin and Senegal)¹⁶. Hence, the ten factors reflect a wide range of firm characteristics that can mainly be summarised by the sector affiliation, size, performances, and workforce composition.

5. Econometric results

5.1. Basic earnings regressions

For the sake of comparability, we begin by estimating earnings equations with a set of individual demographic and labour characteristics as control variables. We wonder then whether controlling for firm heterogeneity has an impact or not on our findings. Under the assumption that both $n = 0$ and $g = 0$, we estimate the earnings functions using simple OLS regressions. The dependent variable is defined as the log of the hourly earnings, which is computed as the ratio of monthly earnings divided by the number of worked hours per month. The corresponding results are in Table 4.

Insert Table 4 here

In panel A, we describe the estimates obtained without control for firm heterogeneity. Models (1A), (2A) and (3A), respectively for Morocco, Benin and Senegal, include as regressors education and off the firm work experience along with their squared values, and three dummy variables for being female, married and the receipt of formal job training. The different regressions also include dummy variables related to occupations¹⁷. For all three countries, the results exhibit a convex profile in years of education and a concave profile in off the firm experience, except in Senegal where the latter is insignificant. These increasing marginal returns to education are expected results for Africa.

Interestingly, this finding contradicts much of the comparative studies on the rates of return to education across countries which often use a linear in education specification of the earnings function (see Trostel et alii, 2002). However, constant or decreasing rates are more and more challenged in both developed and developing countries and non-linearities (mostly

¹⁶ Other important firm characteristics are their risk of lost in the business due to workforce reliability (factors 3, 4 and 8 for Morocco, 2 and 5 for Benin, 3 and 4 for Senegal) and the firms' general features such as their vocation to export and status of ownership (factors 1 and 4 for Morocco, 1 and 4 for Benin and 5 for Senegal).

¹⁷ As they are not immediately comparable, we do not report the coefficients associated to occupations in Table 4. There are 9 occupational dummies in Morocco, and 6 occupational dummies in Benin and Senegal.

convexity) in the returns to education have been recently put forward by some studies on Africa (Bigsten et alii, 2000, Schultz, 2004, Söderbom et alii, 2006, Kuepie et alii, 2006). This result goes against the traditional model of human capital accumulation whereby the marginal return to education is assumed to be constant or even decreasing. When estimating the learning model, we structurally take into account this non-linear profile in education and assess its role on the returns to informal training on earnings.

Concerning the other covariates, we find curiously that the gender dummy is only significant in Morocco. In that country, Nordman and Wolff (2007) have evidenced using quantile regressions the presence of a glass ceiling effect, such that the gender earnings gap is higher at the top of the earnings distribution than at the bottom. The fact that there is no gender difference in Benin and Senegal is somewhat surprising, but this result may be due to the low number of female workers in the corresponding samples. Being married has a positive effect in the three countries, and the receipt of formal training (which is treated as exogenous) only matters in Morocco. Finally, we note that the values of the R^2 in the regressions are reasonably high (around 0.4), but there are less significant explanatory variables in Senegal.

In columns (1B), (2B) and (3B), we add in the list of covariates the years of tenure in the firm and rely on a cubic form¹⁸. Several comments are in order. First, this additional covariate does not really affect the previous estimates, except the marital status whose effect is now much lower. Second, the squared and cubic tenure terms are only significant in Morocco, while they turn to be insignificant both in Benin and Senegal¹⁹. Third, we evidence a U-shaped profile for the returns to years of tenure in the current firm without control for firm heterogeneity in Morocco and Benin, while the shape is continuously decreasing in Senegal. This result is of interest as it stands in contrast with the standard Mincerian earnings function, which relies on a quadratic profile for years in tenure, so that the returns to tenure are necessarily linearly decreasing.

Fourth, we find lower returns to years of tenure in Morocco than in Benin and Senegal. The returns to tenure remain rather flat in the former country, equal to 2% after either 5, 10 or 20 years of tenure. These returns amount to 4%, 3% and 3% in Benin and 4%, 3% and 2% in Senegal respectively after 5, 10 and 20 years of tenure²⁰. Fifth, we find that it

¹⁸ Murphy and Welch (1990) show for the US that more flexible forms of tenure in the earnings function, such as third or fourth order polynomials, better fit to the data.

¹⁹ We have experimented alternative profiles for the effect of years of experience, in particular quadratic and quartic, but these alternative profiles provide a worse fit of the data.

²⁰ It is interesting to compare our results with those found in Anglophone African countries with similar data sets. For instance, Bigsten et alii (2000) obtain lower rates of return to tenure, though it is difficult to compare

matters to control for unobserved heterogeneity. In the three countries, we evidence that the returns to tenure are lower when being calculated with either firm fixed effects or firm factors models (see Figure 1). However, there are some differences between these two approaches. In Morocco and to a lesser extent in Senegal, the shape of the returns curve is not really affected by the use of either fixed effects or firm factors²¹. Conversely, in Benin, the results are rather sensitive to the underlying method of control. The returns measured with firm factors are sometimes much lower than those measured with fixed effects, especially for intermediate numbers of years of tenure.

Insert Figure 1

We conclude from this estimation of earnings regressions that it matters to control for firm heterogeneity. While the firm factor strategy appears to perform well both in Morocco and in Senegal, the poor results evidenced in Benin may be the sign that there is more heterogeneity in this sample of firms, which may be due to the presence of very small production units in the sample.

5.2. Estimation of the learning-by-watching model

We now turn to the estimation of the structural model of learning-by-watching. For each country, the model is estimated twice using NLSQ, once with only individual covariates and once with inclusion of firm factors in order to pick up the impact of firm unobserved heterogeneity. The corresponding estimates are in Table 5. A first remark is that introducing the possibility of learning-by-watching colleagues does not really affect the coefficients obtained through Mincerian equations for education, experience off the firm, gender or marital status. For instance, being a woman reduces the hourly earnings in Morocco by 7.8% with the Mincerian specification (without firm controls), and by 7.3% with the possibility of informal on-the-job training. Interestingly, we still find a convex profile for years of schooling in the three countries, at least when firm heterogeneity is controlled for²². Conversely, years of experience off the firm exhibit a concave profile.

their estimates with ours with accuracy as their specifications differ somewhat from ours in that they use a quadratic term in tenure only. From their sample statistics and estimates, however, we can evaluate their rates at 1.8% for Ghana at the sample mean (after 4 years of tenure), 0.2% for Kenya (after 7 years), 3.4% for Zambia (after 6 years) and 0.9% for Zimbabwe (after 9 years).

²¹ In Senegal, the two profiles are different for a number of years of tenure less than 5 or above 25.

²² Without firm factors, the squared term for education is not significant in Senegal and is negative, but only significant at the 10 percent level in Benin.

Let us focus on the values of the structural parameters of the model. When firm heterogeneity is not controlled for, we find a significant value for n in Morocco, Benin and Senegal. The parameter n is always significant at the 1 percent level, meaning that the learning-by-watching mechanism described in the theoretical section is indeed operative in the selected countries. These results are in accordance with the previous findings reported in Chennouf et alii (1997) for Algeria and Canada, Nordman (2000) for Morocco and Mauritius, Destré and Nordman (2002) for Morocco, Tunisia and France and Destré (2003) for France.

However, we note some very important difference in the rate of knowledge diffusion within firm respectively in Morocco and Senegal and in Benin. While the parameter n is comprised between 6% and 8% in the former group of countries, its value is much higher in Benin, equal to 58.5%. Two comments are in order. First, our rate of knowledge diffusion in Morocco is slightly lower than the estimated values found in Nordman (2000) and Destré and Nordman (2002), who have evidenced a rate of diffusion around 15%²³. Second, it remains unclear why n is so large in Benin. An explanation could lie in a more flexible mode of wage fixation in this country, albeit there is no clear support for this assumption.

In Figure 2, we show how the diffusion of the firm specific knowledge is sensitive to the parameter n . Specifically, we calculate the number of years of tenure which is requested to assimilate a given proportion of the knowledge of the firm. Denoting by ϑ the share of the firm knowledge, it can easily be shown that the number of years t to assimilate ϑ is given by $t = -\ln(1 - \vartheta) / \ln(1 + n)$. Hence, as clearly shown in Figure 2, a worker will get faster a given proportion of the firm knowledge when n is important. For the sake of illustration, suppose that we seek the number of years in tenure to assimilate half of the firm knowledge. We find that t is equal to 11.3 years in Morocco, 9.5 years in Senegal, but only 1.5 years in Benin. The requested years in tenure are respectively equal to 26.3, 18.9 and 3 when $\vartheta = 0.8$.

It is of interest to investigate the pattern of δ_s and δ_e . These parameters measure the relative distance which separates the average worker from the most qualified teacher inside the firm, respectively in terms of years of education and in terms of experience off the firm. We find that the educational distance is much lower in Morocco, as it is equal to 0.069. This explains in turn the low value which is found for n . As the average worker is rather close to

²³ Note that the sample used for Morocco in Nordman (2000) and Destré and Nordman (2002) is a non-representative sample of workers in only two manufacturing sectors. Interestingly, results reported in Destré (2003) for a representative sample of French workers in the private sector, with n standing at about 5%, are closer to our estimates for Morocco and Senegal.

his/her most qualified teacher, the potential of learning-by-watching is less important. At the same time, the relative distance in terms of experience off the firm is not significant, as is the case in Benin. Conversely, the distance to the most educated teacher is much more important in Benin, with a coefficient of 0.548 and to a lower extent in Senegal (0.430). However, this potential of learning translates into rapid rise in earnings only in Benin.

Another point of interest relates to the role of firm unobserved heterogeneity. By neglecting the influential role of firm characteristics, it may be that we overestimate the rate of job-specific knowledge diffusion. This would be the case if there are some differences in wage policies among firms related to sectors of activity or to the size of the firm for instance. In model (1B), (2B) and (3B) of Table 5, we add in the country-specific regressions a set of firm factors obtained by the PCAs.

Insert Table 5 here

The main conclusion is that controlling for firm characteristics does significantly reduce the value of the rate of knowledge diffusion. The magnitude of this coefficient is now twice lower both in Morocco and Senegal. It amounts to 3.6% for the former country and to 3.5% for the latter, but the parameter is only significant in Morocco at the 10 percent level. In Benin, the rate of knowledge diffusion is also lower, 49.2% versus 58.5%. Nevertheless, a potential shortcoming with that country is that the firm factors approach appears less efficient to control for firm heterogeneity (see the above discussion).

Finally, we have computed the marginal returns to tenure in the learning-by-watching model. Of course, if workers have the opportunity to learn a lot from colleagues, they are expected to improve quickly their earnings and then the returns to tenure should exhibit a more convex profile. Doing as if the time variable t is continuous, we first express equation (11) as $\ln h_t = \ln[1 + (1 - (1 + n)^{-t})A] + B$, A being the exponential term in (11) and B a constant (these two terms are independent of t). The derivative $\partial \ln h_t / \partial t$ is then:

$$\frac{\partial \ln h_t}{\partial t} = \frac{A \ln(1 + n)(1 + n)^{-t}}{1 + (1 - (1 + n)^{-t})A} \quad (12)$$

which is clearly not linear in t as with Mincerian earnings functions. We describe in Figure 3 the profiles of returns to tenure. For each country, we compare the results from earnings regression with a cubic profile in tenure to those of learning-by-watching models, both without and with firm factors.

Insert Figure 3 here

In Benin, we find that the returns to informal training are very high, characterized by an unequal distribution over time. The benefits from learning-by-watching others are essentially reaped by workers just after hiring. The returns to tenure are strongly decreasing till five years of tenure. A quite similar profile, albeit less pronounced, is evidenced in Senegal. Owing to the opportunities of imitating others, the returns are more important just after being hired with the learning-by-watching model. In Morocco, the returns curves of the Mincerian and learning-by-watching model cross at around 20 years in tenure²⁴. Finally, in Senegal, the returns to tenure are more convex with the Mincerian specification, so that there are fewer differences with the learning-by-watching model. The possibility of imitating other colleagues conveys again an economic benefit in the first years of the career (at least with no firm factors).

5.3. Learning from others or learning by oneself?

In the previous estimations, we do as if workers cannot acquire any job knowledge by themselves. We now relax this constraint and estimate the extended model of on-the-job learning given by equation (6), with learning from both others and oneself. Owing to the particular pattern of knowledge diffusion among the Beninese firms, we restrict our attention in what follows to the Moroccan and Senegalese samples. The model is again estimated using non-linear least squares, without or with firm factors, and we present the various estimates in Table 6.

For the sake of comparison, we begin by considering a simple model of human capital formation with no possibility of learning-by-watching, i.e. $n = 0$. The dynamics of human capital is simply $h_{t+1} = (1 + g)h_t$, so that we easily deduce $h_t = (1 + g)^t h_0$. Taking the logarithm of this expression and assuming that $h_0 = \exp(\alpha_0 + \alpha_1 s + \alpha_2 s^2 + \alpha_3 e + \alpha_4 e^2)$ as in (8), we estimate the following regression²⁵:

$$\ln h_t = t \ln(1 + g) + \alpha_0 + \alpha_1 s + \alpha_2 s^2 + \alpha_3 e + \alpha_4 e^2 + \beta Z + \varepsilon \quad (13)$$

²⁴ We also note that in Morocco the returns to tenure are slightly lower with the learning-by-watching model with firm factors. As the rate of knowledge diffusion is lower in that case, there are fewer opportunities for workers to learn quickly from others (and then less economic benefits).

²⁵ Clearly, equation (12) is a restrictive case of (11). It is obtained when the rate of knowledge diffusion is equal to zero, meaning that the characteristics of the most qualified worker are in fact those of the considered worker (there is nothing to learn from others).

It is straightforward to estimate this model with only learning-by-oneself. We find very similar values for the parameter g in both countries²⁶. It is equal to 1.3% per year in Morocco and to 1.1% in Senegal. Results lead to somewhat different findings once accounting for the possibility of imitation within the firm.

In the case of Senegal, we find a more important value for g with the extended learning model (columns 2B and 2C). Indeed, this parameter takes a value of 2.1% without firm factors and 1.8% with firm factors. At the same time, we fail to evidence a significant value for the rate of knowledge diffusion. In models (2B) and (2C), the parameter n is still positive and is equal to 0.041 once controlling for firm heterogeneity. A similar result was found with the pure learning-by-watching specification, with an insignificant parameter of 0.035. A last remark, which suggests that there is still something to learn from colleagues despite the insignificant rate of job-specific knowledge diffusion, is that the relative distance separating the average worker from the most qualified worker remains highly significant. In the meantime, the distance is quite low, around 0.14 in presence of firm factors.

In Morocco, introducing the possibility of learning-by-imitation leads to higher returns to learning-by-oneself, just like in the Senegalese case. The parameter g is indeed equal to 3.2% without firm factors and to 5% with firm factors. At the same time, while n turns out to be insignificant in model (1B), it appears significant at the 1 percent level and equal to 4% in model (1C) which controls for firm heterogeneity. Among Moroccan firms, there is thus a real potential benefit of learning from colleagues and this learning-by-watching process also conveys higher benefits to self-learning. Finally, we note that the rate of diffusion of 4% in the learning-by-oneself and others model (2B) of Table 6 is very close to the value of 3.5% found in the pure learning-by-watching model (1B) of Table 5.

Finally, it is worth comparing our results with those of Destré and Nordman (2002)²⁷. For Morocco, these authors have found that the learning-by-oneself process is the only component of informal training that has a significant impact on earnings. Conversely, they exhibit both a high rate of knowledge diffusion and a significant impact of learning-by-oneself (1.9%) for Tunisian workers. Hence, their respective findings for Morocco and Tunisia look like ours in the case of Senegal and Morocco. In Destré and Nordman (2002), the argument advocated to explain this difference is that the distance with the most educated,

²⁶ We have also estimated the parameter g in Benin. We get a value of 1.3%, significant at the 1 percent level, which is then very similar to the estimates found in Morocco and Senegal.

²⁷ Recall that they use small non-representative samples of manufacturing firms in Morocco and Tunisia.

i.e. $\bar{S} - s$, in the Tunisian firms is on average higher than in the Moroccan ones, while the number of years of schooling is equivalent in both of the cases studied. These statistics may justify the possibilities that learning by imitation are much more important for the Tunisian employees.

In our case, however, these statistics do not seem to be relevant explanations for the divergence of learning effects in the Moroccan and Senegalese cases. While $\bar{S} - s$ amounts on average to 5.5 years for the Moroccan workers, it is 6.7 years in Senegal. Besides, the average education is slightly higher for the Senegalese (see subsection 3.2). Similarly, the distance to the most experienced worker is respectively 13.9 versus 14.3 years, again higher for the Senegalese where the benefits of the imitation process are found to be null. Hence, the fact that there are no benefits from learning-by-watching in the Senegalese case should be explained by other factors, beyond the workers' human capital endowments.

A first explanation could lie in strong rigidity in the fixation of wages. Another explanation may refer to the work organisational features within firms, the environment of employees contributing to intensification of the learning-by-watching process. For instance, more compartmentalized firms may leave fewer places to the emergence of peer effects. Unfortunately, we lack relevant information on the firms to know whether Senegalese firms are more partitioned²⁸. Finally, the important presence of temporary workers in firms, or firms with high labour turnover, could also explain why the diffusion of knowledge is not efficient. While the ratio of the number of full time temporary workers to the total number of full time permanent employees amounts to 27% in the Moroccan firms, it is much higher in the Senegalese firms (67%). The underlying higher turnover may well explain the divergence of knowledge diffusion efficiency between these two countries.

6. Concluding comments

Using matched worker-firm data from Benin, Morocco and Senegal, we have developed and estimated in this paper a model of on-the-job learning which accounts for two forms of informal learning within firms, i.e. learning-by-watching and learning-by-oneself. Our estimates highlight contrasted effects of informal training on earnings. The interest of the

²⁸ However, indicators of the supervision rates in firms are informative. Note that while the proportion of firms with a share of managers higher than 10 percent of the total employees amounts to 11% for Morocco, it is much higher for Senegal with 39%.

model presented consists in the estimation not only of the earnings effects of the self-learning process, but also of the speed of knowledge diffusion within firms.

We note some very important difference in the rate of knowledge diffusion respectively in Morocco and Senegal and in Benin. While the rate is comprised between 6% and 8% in the former group of countries, its value is much higher in Benin (above 50%). Less time is hence required in that country for an average worker to learn a given proportion of the firm's knowledge. Another finding is that controlling for firm characteristics significantly reduces the value of the rate of knowledge diffusion. Interestingly, the rates of return to learning-by-oneself are affected by the possibility of learning-by-watching. Both in Morocco and Senegal, the benefits of learning-by-oneself are enhanced, but the potential benefit of learning from colleagues disappears in the latter country. Moroccan estimates exhibit significant economic returns to both learning-by-watching and self-learning.

From our results, it turns out that the overall return to human capital explaining the remuneration of a given worker involves personal skill characteristics, including individual abilities to learn, but also firms' knowledge characteristics. It seems then important to consider these two sources of returns from human capital simultaneously because education policies and policies promoting vocational training may affect both worker's human capital and firm's human capital environment. In particular, assessing policies without accounting for educational and knowledge externalities within firms may largely under-estimate the benefits of such policies.

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Table 1. Composition of the sample

Number of employees per firm	Morocco				Benin				Senegal			
	Workers		Firms		Workers		Firms		Workers		Firms	
	N	%	N	%	N	%	N	%	N	%	N	%
4	40	0.5	10	1.2	28	1.8	7	3.7	128	10.0	32	17.8
5	130	1.7	26	3.2	65	4.2	13	6.9	105	8.2	21	11.7
6	180	2.4	30	3.6	84	5.4	14	7.4	156	12.1	26	14.4
7	224	2.9	32	3.9	161	10.3	23	12.2	105	8.2	15	8.3
8	320	4.2	40	4.9	216	13.8	27	14.4	200	15.6	25	13.9
9	1008	13.2	112	13.6	252	16.1	28	14.9	180	14.0	20	11.1
10	5720	75.0	572	69.6	760	48.5	76	40.4	410	31.9	41	22.8
All	7622	100.0	822	100.0	1566	100.0	188	100.0	1284	100.0	180	100.0

Sources: ICA Benin and Senegal, FACS Morocco.

Table 2. Descriptive statistics of the workers

Variables	Morocco	Benin	Senegal
Log of hourly earnings	4.050 (0.616)	5.658 (1.059)	6.590 (0.885)
Years of education	8.679 (5.428)	9.430 (4.721)	10.322 (5.661)
Years of experience off the firm	12.766 (9.300)	12.377 (7.969)	12.747 (9.280)
Years of tenure in the firm	7.435 (6.305)	6.030 (5.418)	8.981 (7.870)
Female	0.398 (0.490)	0.139 (0.346)	0.160 (0.367)
Married	0.518 (0.500)	0.687 (0.464)	0.673 (0.469)
Formal training	0.041 (0.199)	0.198 (0.399)	0.355 (0.479)
Number of observations	7622	1566	1284

Sources: ICA Benin and Senegal, FACS Morocco.

Standard deviations are in parentheses.

Table 3. Descriptive statistics of the firms

Variable names	Definitions	Morocco		Benin		Senegal	
		mean	s.d.	mean	s.d.	mean	s.d.
secteur1	Agro industry / Garment for Morocco (1 if yes)	0.370	0.483	0.206	0.405	0.345	0.476
secteur2	Chemicals and related products / Food for Morocco (1 if yes)	0.098	0.297	0.049	0.216	0.097	0.295
secteur3	Materials for construction / Textile for Morocco (1 if yes)	0.233	0.423	0.049	0.215	0.079	0.271
secteur4	Furniture / Leather for Morocco (1 if yes)	0.078	0.268	0.188	0.391	0.034	0.182
secteur5	Metallic products / Electricals for Morocco (1 if yes)	0.044	0.205	0.112	0.316	0.093	0.290
secteur6	Industry of paper and paper products / Chemicals for Morocco (1 if yes)	0.091	0.288	0.215	0.411	0.120	0.325
secteur7	Plastics products (1 if yes)	0.086	0.280	0.012	0.110	0.078	0.268
secteur8	Textiles and leather (1 if yes)			0.019	0.137	0.101	0.302
secteur9	Wood (1 if yes)			0.143	0.350	0.046	0.209
secteur10	Other (1 if yes)			0.006	0.080	0.007	0.083
export	Exporting firms (1 if yes)	0.571	0.495	0.221	0.415	0.558	0.497
pfemme	Share of female employees	0.570	2.233	0.128	0.180	0.103	0.124
size	Firm size (1: <50 employees, 2: 50<=employees<150, 3:employees>=150)	1.820	0.778	1.237	0.586	1.688	0.796
effectpermplein	Total number of permanent full-time employees	126.8	202.1	25.240	52.556	96.805	270.139
qualdominant	Qualified employees being dominant occupation (1 if yes)	0.328	0.470	0.514	0.500	0.203	0.403
pqual_mis	Qualified employees being dominant occupation missing (1 if yes)					0.038	0.192
nonqualdominant	Non qualified employees being dominant occupation (1 if yes)			0.098	0.297	0.285	0.452
pnonqual_mis	Share of Unskilled Workers missing (1 if yes)			0.008	0.087	0.038	0.192
pcadredireleve	Share of managers higher than 10% of the total employees (1 if yes)	0.110	0.313	0.734	0.442	0.391	0.488
pcadredir_mis	Share of managers missing (1 if yes)					0.038	0.192
labintensive	Highly labour intensive firms (1 if labour costs > 75% total costs)	0.023	0.151	0.046	0.210	0.003	0.056
labintensity	Labour intensity	0.265	0.201	0.143	0.406	0.116	0.152
labintensity_mis	Labour intensity missing (1 if yes)			0.522	0.500	0.215	0.411
massesal_tot_mis	Total wage costs missing (1 if yes)					0.202	0.401
etrangere	Firms with more than 75% foreign owned (1 if yes)	0.042	0.200	0.080	0.271	0.151	0.358
Klocal	% of local firm capital			86.700	29.978	80.861	36.119
Klocal_mis	% of local firm capital missing					0.004	0.062
profit	Profitable firms (1 if yes)	0.635	0.481	0.927	0.261	0.845	0.362
profit_mis	Profitable firms missing (1 if yes)			0.192	0.394	0.643	0.479
psalairepiece	Share of piece-rate pay for non qualified employees	0.005	0.061				
pabsenteism	Share of days lost due to absenteeism	0.024	0.058				
pgreve	Share of days lost due to strike	0.002	0.025				
pgreve_mis	Share of days lost due to strike missing (1 if yes)	0.229	0.420				
ppertevols	Share of days lost due to theft	0.003	0.012				
ppertevols~s	Share of days lost due to theft missing (1 if yes)	0.218	0.413				
daylostgreve	Number of days lost due to strike			0.520	4.918	0.134	1.410
daylostgreve_mis	Number of days lost due to strike missing (1 if yes)			0.110	0.313	0.061	0.239
daylostemeutes	Number of days lost due to riots			0.223	1.703	0.234	1.199
daylostemeutes_mis	Number of days lost due to riots missing (1 if yes)			0.104	0.305	0.061	0.239
daylostfamille	Number of days lost due to family events			1.377	5.574	1.305	7.242
daylostfamille_mis	Number of days lost due to family events missing (1 if yes)			0.094	0.292	0.099	0.299
valpertevols	Value of losts due to thefts, vandalism or arson					0.529	1.600
valpertevols_mis	Value of losts due to thefts, vandalism or arson missing					0.129	0.336
pertevols	Has suffer losts due to thefts, vandalism or arson			0.193	0.395		
pertevols_mis	Has suffer losts due to thefts, vandalism or arson missing			0.005	0.071		
formation	Firm provided (on- or off-the-job) formal training (1 if yes)			0.328	0.470	0.393	0.489
jourformestot	Number of days of provided formal training	130.60*	1992.86	30.033	127.531	18.777	66.082
sale	Sales of the firm the year preceding the survey**	2.5 ^E +04	5.1 ^E +04	1.7 ^E +09	9.2 ^E +09	4.2 ^E +09	1.4 ^E +10
sale_mis	Sales of the firm the year preceding the survey missing			0.032	0.176	0.090	0.286
prod	Value of the production the year preceding the survey**	2.3E+04	4.5 ^E +04	5.1 ^E +08	2.2 ^E +09	8.8 ^E +08	5.0 ^E +09
prod_mis	Value of the production the year preceding the survey missing			0.186	0.390	0.640	0.480
psyndic	Share of unionised employees			0.035	0.163	0.342	0.402
psyndic_mis	Share of unionised employees missing			0.021	0.144	0.048	0.214
pnoschool	Share of uneducated workers in permanent employees			0.096	0.201	0.107	0.165
pprimaire	Share of primary school workers in permanent employees			0.206	0.222	0.256	0.257
pcollege	Share of middle school workers in permanent employees			0.342	0.268	0.180	0.195
plycee	Share of high school workers in permanent employees			0.190	0.204	0.152	0.178

puniv	Share of higher educated workers in permanent employees		0.147	0.178	0.125	0.131
propmoins30	Share of <30 years old workers		0.345	0.234	0.203	0.210
prop30_45	Share of 30-45 years old workers		0.515	0.228	0.493	0.255
propplus45	Share of >45 years old workers		0.130	0.154	0.212	0.213
	Number of observations	822		188		180

Sources: ICA Benin and Senegal, FACS Morocco.

*: Number of on-the-job day trainees.

** : in local currencies.

Standard deviations are in parentheses. To avoid dropping firm observations with missing values in the factor analysis, we use the modified zero-order regression method described in Maddala (1977): observations with missing information are set to zero and we include in the analysis a dummy variable for the missing observations.

The factor analysis (PCA) includes the following firm variables:

Morocco: secteur1, secteur2, secteur3, secteur4, secteur5, secteur6, secteur7, export, pfemme, size, psalairepiece, qualdominant, pcadredireleve, labintensive, etrangere, profit, pabsenteism, pgreve, pgreve_mis, ppertevols, ppertevols_mis, jourformestot, sale, prod.

Benin: secteur1, secteur2, secteur3, secteur4, secteur5, secteur6, secteur7, secteur8, secteur9, secteur10, export, pfemme, size, effecperplein, qualdominant, nonqualdominant, pnonqual_mis, pcadredireleve, labintensive, labintensity, labintensity_mis, etrangere, Klocal, profit, profit_mis, daylostgreve, daylostgreve_mis, daylostemeutes, daylostemeutes_mis, daylostfamille, daylostfamille_mis, pertevols, pertevols_mis, formation, jourformestot, sale, sale_mis, prod, prod_mis, psyndic, psyndic_mis, pnoschool, pprimaire, pcollege, plycee, puniv, propmoins30, prop30_45, propplus45.

Senegal: secteur1, secteur2, secteur3, secteur4, secteur5, secteur6, secteur7, secteur8, secteur9, secteur10, export, pfemme, size, qualdominant, pqual_mis, nonqualdominant, pnonqual_mis, pcadredireleve, pcadredir_mis, labintensive, labintensity, labintensity_mis, massesal_tot_mis, etrangere, Klocal, Klocal_mis, profit, profit_mis, daylostgreve, daylostgreve_mis, daylostemeutes, daylostemeutes_mis, daylostfamille, daylostfamille_mis, valpertevols, valpertevols_mis, formation, jourformestot, sale, sale_mis, prod, prod_mis, psyndic, psyndic_mis, pnoschool, pprimaire, pcollege, plycee, puniv, propmoins30, prop30_45, propplus45.

Table 4. Estimates of the log of hourly earnings

A. Without controls of firm heterogeneity

Variables	Morocco		Benin		Senegal	
	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)
Constant	3.443*** (34.55)	3.177*** (32.37)	4.156*** (35.03)	3.773*** (28.47)	5.594*** (52.73)	5.087*** (44.16)
Years of education	-0.018*** (4.85)	-0.006* (1.80)	0.055*** (3.07)	0.067*** (3.82)	0.011 (0.92)	0.027** (2.39)
Years of education ² (/10)	0.026*** (11.43)	0.026*** (11.61)	0.026*** (3.04)	0.025*** (3.02)	0.014*** (2.72)	0.017*** (3.33)
Years of experience off the firm	0.005** (2.51)	0.016*** (8.27)	0.041*** (5.16)	0.056*** (6.99)	0.007 (1.15)	0.025*** (4.08)
Years of experience off the firm ² (/10)	-0.002*** (3.86)	-0.003*** (6.38)	-0.008*** (3.90)	-0.010*** (5.02)	-0.002 (1.27)	-0.004** (2.51)
Female	-0.105*** (9.00)	-0.078*** (6.84)	-0.061 (0.90)	-0.061 (0.92)	-0.074 (1.21)	-0.016 (0.28)
Married	0.171*** (14.12)	0.062*** (4.79)	0.240*** (4.72)	0.083 (1.54)	0.407*** (9.45)	0.169*** (3.65)
Receipt of formal training	0.260*** (9.50)	0.263*** (9.89)	0.069 (1.24)	0.030 (0.55)	0.086* (1.86)	0.058 (1.30)
Years of tenure in the firm		0.034*** (7.35)		0.061*** (2.83)		0.050*** (3.16)
Years of tenure in the firm ² (/10)		-0.012*** (3.47)		-0.020 (1.17)		-0.009 (0.83)
Years of tenure in the firm (/100)		0.003*** (3.53)		0.004 (1.07)		0.001 (0.44)
Observations	7622	7622	1566	1566	1284	1284
R-squared	0.43	0.46	0.37	0.40	0.42	0.48

B. With controls of firm heterogeneity

Variables	Morocco		Benin		Senegal	
	(1C)	(1D)	(2C)	(2D)	(3C)	(3D)
Constant	3.242*** (41.21)	3.292*** (35.63)	4.682*** (39.01)	4.049*** (31.18)	5.421*** (54.05)	5.153*** (46.13)
Years of education	-0.002 (0.71)	-0.001 (0.26)	-0.027* (1.67)	0.037** (2.09)	0.011 (1.12)	0.020* (1.89)
Years of education ² (/10)	0.018*** (8.93)	0.018*** (8.64)	0.037*** (5.02)	0.028*** (3.39)	0.013*** (3.06)	0.017*** (3.39)
Years of experience off the firm	0.013*** (8.62)	0.013*** (7.45)	0.025*** (3.74)	0.047*** (6.09)	0.013** (2.54)	0.024*** (4.16)
Years of experience off the firm ² (/10)	-0.002*** (5.74)	-0.002*** (5.38)	-0.004** (2.33)	-0.008*** (4.18)	-0.001 (0.94)	-0.004*** (2.59)
Female	-0.066*** (6.79)	-0.065*** (5.89)	-0.045 (0.77)	0.034 (0.51)	-0.032 (0.65)	0.035 (0.61)
Married	0.048*** (4.64)	0.059*** (4.85)	0.024 (0.55)	0.119** (2.32)	0.081** (2.11)	0.171*** (3.82)
Receipt of formal training	0.024 (0.86)	0.134*** (5.27)	0.014 (0.23)	0.042 (0.76)	0.089** (2.30)	0.043 (1.00)
Years of tenure in the firm	0.036*** (8.47)	0.029*** (6.58)	0.058*** (2.99)	0.057*** (2.74)	0.034** (2.31)	0.048*** (3.10)
Years of tenure in the firm ² (/10)	-0.014*** (4.58)	-0.011*** (3.32)	-0.040*** (2.67)	-0.024 (1.45)	-0.003 (0.35)	-0.014 (1.31)
Years of tenure in the firm (/100)	0.002*** (3.86)	0.002*** (3.36)	0.009*** (2.87)	0.005 (1.35)	-0.000 (0.23)	0.002 (0.91)
Observations	7622	7622	1566	1566	1284	1284
R-squared	0.51	0.52	0.36	0.46	0.46	0.52

Sources: ICA Benin and Senegal, FACS Morocco.

Regressions (A) and (B) are OLS, (C) are fixed effects models, and (D) are OLS estimates with firm factors. Absolute value of t statistics are in parentheses, significance levels being respectively equal to 1% (***), 5% (***) and 10% (*). All regressions also include dummies for occupation.

Table 5. Structural estimates of the learning-by-watching model

Variables	Morocco		Benin		Senegal	
	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)
Constant	3.260*** (33.42)	3.365*** (36.47)	2.964*** (19.69)	3.951*** (26.83)	4.854*** (39.36)	5.216*** (45.94)
Years of education	-0.021*** (4.95)	-0.008* (1.95)	0.142*** (14.07)	0.015 (0.73)	0.065*** (7.52)	0.004 (0.32)
Years of education ² (/10)	0.033*** (13.13)	0.021*** (8.96)	-0.002* (1.78)	0.039*** (4.01)	0.002 (1.07)	0.025*** (4.14)
Years of experience off the firm	0.015*** (7.24)	0.011*** (5.88)	0.053*** (6.47)	0.043*** (5.25)	0.029*** (4.40)	0.030*** (4.87)
Years of experience off the firm ² (/10)	-0.003*** (5.67)	-0.002*** (4.29)	-0.010*** (4.71)	-0.007*** (3.59)	-0.004*** (2.89)	-0.005*** (3.30)
Female	-0.073*** (6.38)	-0.064*** (5.82)	0.020 (0.30)	0.033 (0.48)	0.009 (0.15)	0.056 (1.00)
Married	0.074*** (5.74)	0.074*** (6.14)	0.067 (1.28)	0.120** (2.37)	0.191*** (4.28)	0.183*** (4.22)
Receipt of formal training	0.243*** (9.13)	0.129*** (5.06)	0.029 (0.53)	0.017 (0.31)	0.049 (1.13)	0.044 (1.05)
δ_s	0.069*** (5.83)	0.061*** (2.69)	0.548*** (4.81)	0.054*** (4.28)	0.430*** (3.74)	0.142*** (3.07)
δ_e	0.026 (1.19)	0.001 (0.02)	0.023* (1.78)	0.009 (0.47)	0.150*** (2.75)	0.120** (2.05)
$\alpha_5 \delta_i$	0.014*** (3.53)	0.019** (2.42)	0.053*** (5.83)	0.040*** (4.34)	0.023** (2.25)	0.025 (1.41)
$\alpha_6 \delta_i^2$	0.000 (0.51)	-0.000 (0.79)	-0.001*** (4.51)	-0.001*** (3.17)	-0.000 (0.20)	-0.000 (0.70)
n	0.063*** (3.50)	0.036* (1.90)	0.585*** (2.79)	0.492** (2.17)	0.076*** (2.61)	0.035 (1.45)
Observations	7622	7622	1566	1566	1284	1284
R-squared	0.46	0.52	0.42	0.47	0.50	0.53

Sources: ICA Benin and Senegal, FACS Morocco.

Regressions (A) and (B) are estimated using non-linear least squares, models (B) including firm factors. Absolute value of t statistics are in parentheses, significance levels being respectively equal to 1% (***), 5% (**), and 10% (*). All regressions also include dummies for occupation.

Table 6. Structural estimates of the learning by oneself and others model

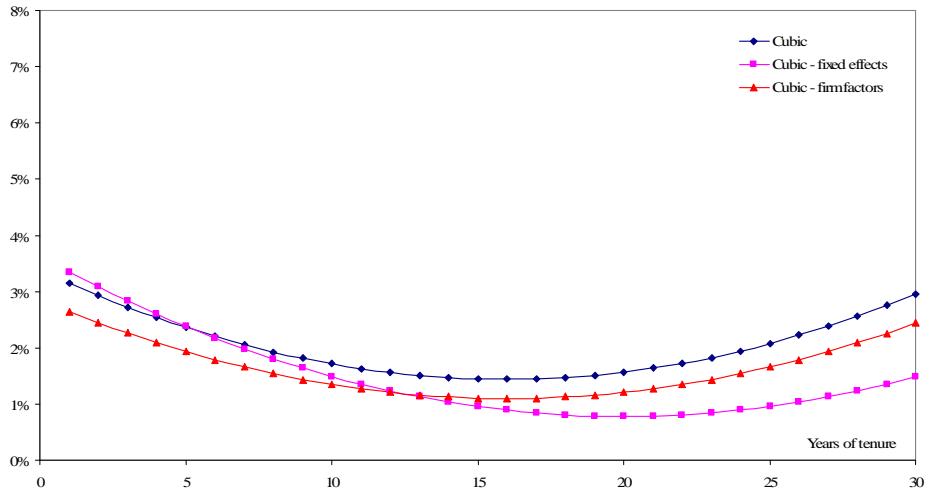
Variables	Morocco			Senegal		
	(1A)	(1B)	(1C)	(2A)	(2B)	(2C)
Constant	2.324*** (25.26)	3.187*** (32.54)	3.298*** (35.81)	4.200*** (45.48)	5.028*** (46.52)	5.190*** (51.32)
Years of education	-0.001 (0.19)	-0.008** (2.12)	-0.004 (1.08)	0.033*** (3.03)	0.028* (1.94)	0.017 (1.22)
Years of education ² (/10)	0.018*** (8.51)	0.027*** (11.69)	0.020*** (9.04)	0.015*** (3.09)	0.021*** (3.32)	0.024*** (3.93)
Years of experience off the firm	0.013*** (7.13)	0.015*** (7.79)	0.014*** (7.47)	0.028*** (4.68)	0.037*** (5.67)	0.032*** (5.19)
Years of experience off the firm ² (/10)	-0.002*** (5.07)	-0.003*** (6.23)	-0.003*** (5.59)	-0.004*** (2.82)	-0.006*** (3.82)	-0.005*** (3.31)
Female	-0.064*** (5.82)	-0.077*** (6.77)	-0.064*** (5.81)	0.185*** (3.63)	0.168*** (3.24)	0.197*** (3.93)
Married	0.063*** (5.24)	0.061*** (4.73)	0.061*** (4.99)	0.187*** (4.16)	0.171*** (3.72)	0.170*** (3.82)
Receipt of formal training	0.136*** (5.32)	0.265*** (9.94)	0.134*** (5.26)	0.119*** (2.81)	0.127*** (2.96)	0.115*** (2.74)
δ_s		0.376*** (4.32)	0.228** (1.98)		0.070*** (3.26)	0.161** (2.40)
δ_e		0.761*** (3.31)	0.247 (1.50)		0.084*** (2.91)	0.107 (1.55)
$\alpha_5\delta_t$		0.050 (0.23)	-0.239*** (2.88)		-0.001 (0.09)	-0.018 (0.66)
$\alpha_6\delta_t^2$		-0.015 (1.12)	0.005*** (2.86)		0.000 (1.46)	0.000 (0.79)
n		0.012 (1.11)	0.040*** (2.78)		0.242 (1.37)	0.041 (1.28)
g	0.013*** (19.42)	0.032*** (3.08)	0.050*** (3.60)	0.011*** (8.88)	0.021*** (3.65)	0.018** (1.96)
Observations	7622	7622	7622	1284	1284	1284
R-squared	0.52	0.46	0.52	0.50	0.48	0.52

Sources: ICA Benin and Senegal, FACS Morocco.

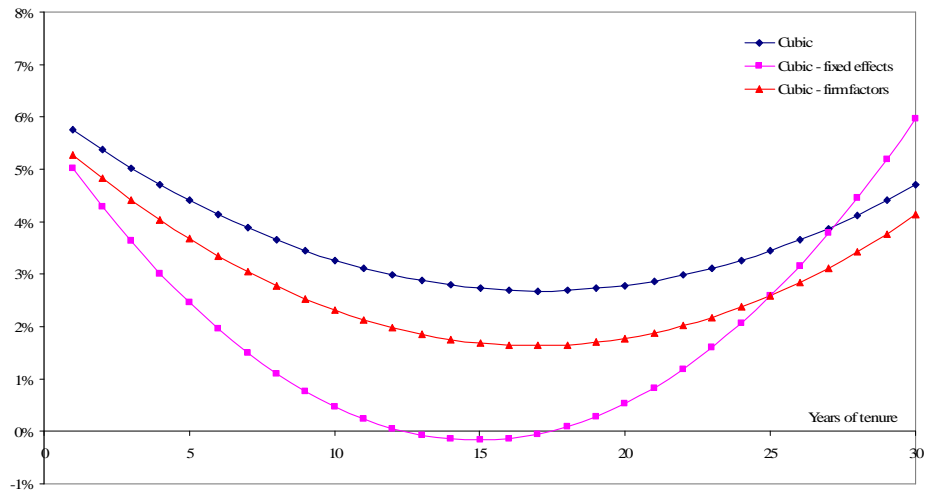
All regressions are estimated using non-linear least squares, models (A) and (C) including firm factors. Absolute value of t statistics are in parentheses, significance levels being respectively equal to 1% (***), 5% (**) and 10% (*). All regressions also include dummies for occupation.

Figure 1. Rates of return to tenure – Mincer earnings regressions

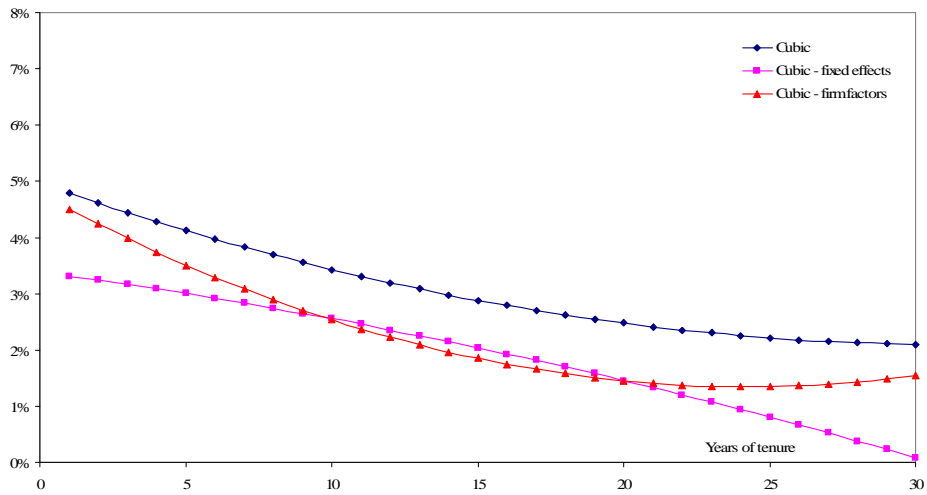
A. Morocco



B. Benin

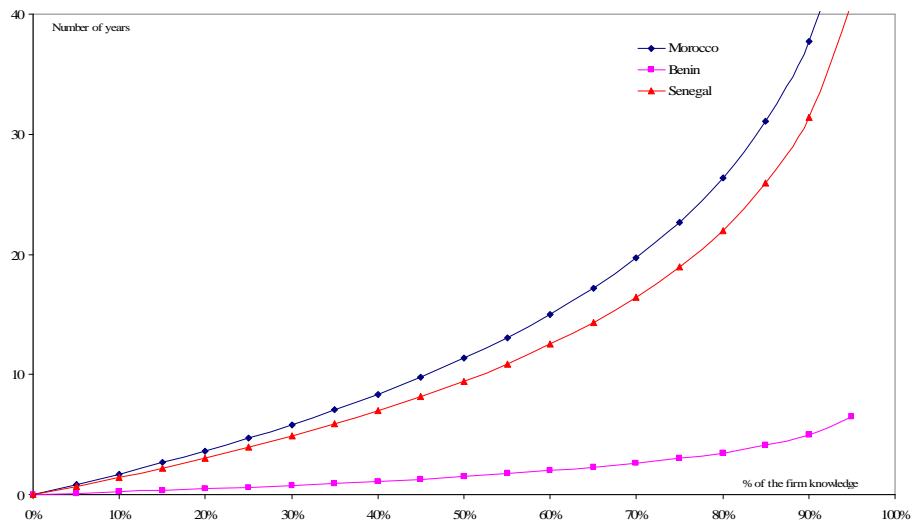


C. Senegal



Sources: ICA Benin and Senegal, FACS Morocco.

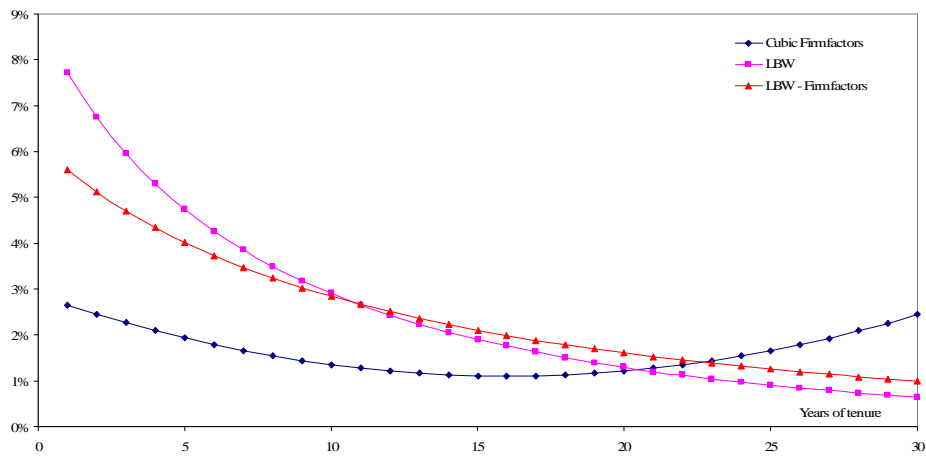
Figure 2. Time needed to accumulate the firm knowledge



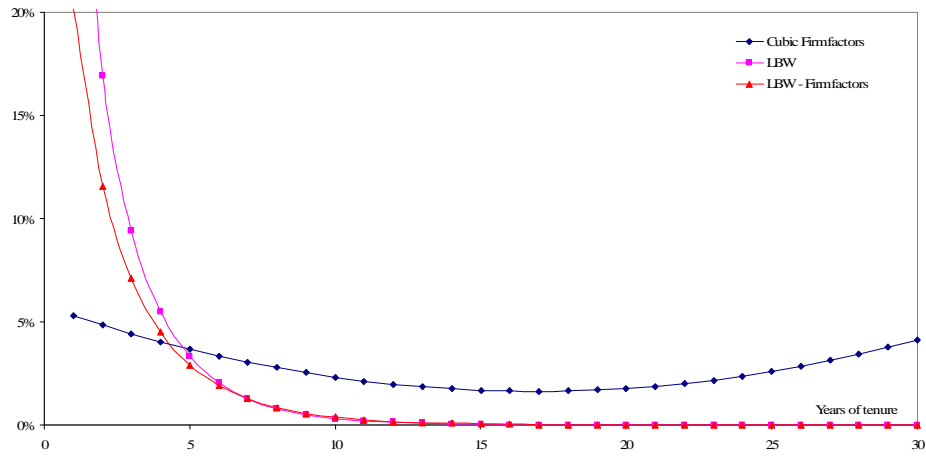
Sources: ICA Benin and Senegal, FACS Morocco.

Figure 3. Rates of return of tenure – learning-by-watching models

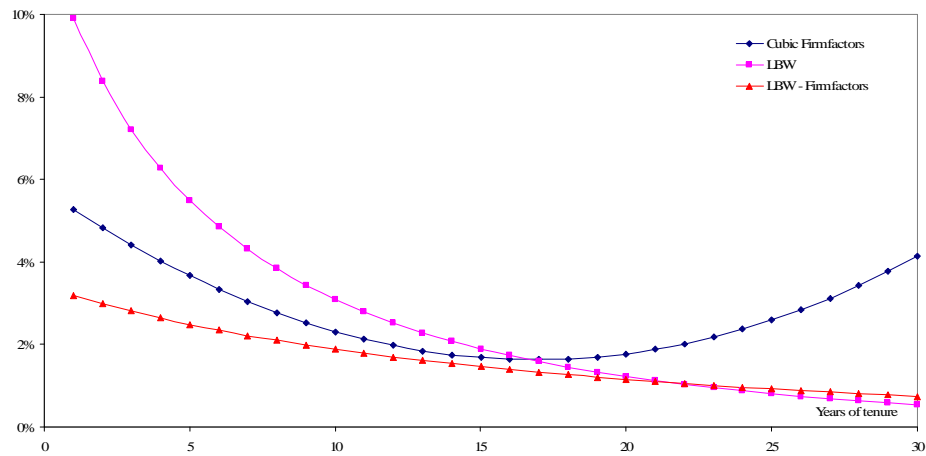
A. Morocco



B. Benin



C. Senegal



Sources: ICA Benin and Senegal, FACS Morocco.