Wage Gaps and Job Sorting in African Manufacturing*

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Abstract

Using matched employer-employee data from eleven African countries, we investigate if there is job sorting in African labor markets. We find that much of the wage gap associated with education is driven by selection across occupations and firms. This is consistent with educated workers being more effective at complex tasks like labor management. In all countries the education wage gap widens rapidly at high levels of education. Most of the education wage gap at low levels of education can be explained by selection across occupations. We also find that the education wage gap tends to be higher for women, except in Morocco where many poorly educated women work in the export garment sector. A large proportion of the gender wage gap is explained by selection into low wage occupations and firms.

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1. Introduction

Much attention has been devoted to human capital and its role in development (e.g. Lucas 1993, Mankiw, Romer and Weil 1992). Microeconomic studies have consistently shown that education and earnings are positively correlated, at least in activities such as manufacturing and modernized agriculture (e.g. Jamison and Lau 1982, Knight and Sabot 1990, Yang 1997). Other individual characteristics, such as experience or gender, are often found to be correlated with wages too. Still, little remains known about how labor markets in poor countries reward schooling, experience, and other individual skills. In this paper we use micro data from eleven African countries to estimate wage gaps associated with education, gender and work experience, and ask if these gaps can be attributed to a sorting process by which individuals get allocated to different types of jobs and different types of firms depending on their individual characteristics.

The idea that employment relationships result from a sorting process goes back a long way in economics – Roy (1951) is often taken as a starting point. One possible reason for sorting is that the returns to skills are heterogenous across jobs. Suppose, for example, that skills acquired through higher education raise productivity more in certain tasks than in others. Sorting of workers across jobs should result in highly educated individuals performing tasks in which they are more productive. Thanks to sorting, highly educated workers will be found in occupations and firms in which they are more productive. In contrast, if education raise productivity equiproportionally in all firms and occupations alike, there is no reason to expect highly educated workers to be sorted in specific firms or occupations. A similar reasoning applies for gender and work experience. Certain firms may require highly experienced workers, for example, and reward them accordingly. Depending on the cultural and institutional context, some jobs may be better (or worse) suited for men than women.

Documenting how significant is labour market sorting requires data on earnings, occupation and other worker characteristics, as well as firm-level characteristics. Household data do not include firm-level information and so will not be fit for purpose. Instead, we use the largest and most comprehensive matched employer-employee dataset from Africa that we are aware of, spanning eleven countries and more than 30,000 manufacturing workers.[1] Data on up to

[1] Previous studies on returns to education in Africa are typically confined to one or a few countries, see e.g. Moll (1996) on South Africa; Canagarajah and Thomas (1997) on Ghana; Krishnan, Selassie and Dercon (1998)

ten workers per firm are available, enabling us to control for unobserved firm effects in our earnings regressions. As there is a firm-level panel dimension in the data, we can allow these firm-effects to vary over time. Our estimated education wage gaps are interpretable as reflecting the combined return to education *and* to the portion of unobserved ability that is correlated with education. By the same token, the gender wage gap captures possible discrimination as well as various unobserved worker characteristics correlated with gender. Our goal is to document the magnitude of such wage gaps, and assess the importance of job sorting across firms and occupations. This is informative because it tells us where returns to ability – whether innate or acquired – are likely to be the highest.[2]

Our main null hypothesis underlying the empirical analysis is that there is no sorting by education in African labor markets. To test this hypothesis, we compare earnings regressions with and without firm and occupation controls. If the education wage gap disappears once we control for occupation, this means that sorting across occupation accounts for the education wage gap. Similarly, if the gap vanishes when we control for firm fixed effects, it implies that the gap is accounted for by sorting across firms. In contrast, if highly educated workers are equally more productive in all firms and occupations, the education wage gap should remain the same once we control for occupation and firm fixed effects.

The no sorting hypothesis is strongly rejected by the data. On average, for both men and women, more than half the education wage gap can be attributed to sorting across jobs and firms. There is also a large gender wage gap in all studied countries, women earning on average less than men. A large proportion of this wage gap is explained by selection into low wage occupations and firms. We also find that the education wage gap tends to be higher for women, except in Morocco where many poorly educated women work in the export garment sector.

on urban Ethiopia; Appleton, Bigsten and Manda (1999) on Kenya; Appleton (2002) on Uganda; and Söderbom, Teal, Wambugu and Kahyarara (2006) on Kenya and Tanzania. Most of these use household data.

[2] Distinguishing between sorting according to observable and unobservable ability is potentially interesting but beyond the scope of the paper, which is why we do not attempt to isolate the *causal* effect of schooling or other observable characteristics on earnings. Doing so would require controlling for unobserved abilty which is extremely difficult, almost certainly requiring very different data. Worker-level panel data might be useful, but would not solve all the problems. For example, worker education seldom changes once individuals reach adulthood, making identification very difficult. Even if education were time-varying, one might be concerned that a change in education is itself correlated with unobserved worker heterogeneity if primarily highly motivated workers make the effort of acquiring additional education. If the goal is to estimate the returns to schooling, some form of natural or real experiment would probably be useful, although it is hard to think of an approach that is both immune to endogeneity problems and practical.

One implication of these results is that the composition of different types of firms and jobs in the economy has a major effect on returns to ability and skills in Africa. In particular, it seems it is primarily the larger, more productive firms that can put to good use the skills workers learn in school. Seen in this light, enterprise growth in Africa may be important for strengthening the incentives to invest in schooling, and for economic development more generally.

The rest of the paper is organized as follows. The conceptual framework is presented in section 2. The data sources and survey methodology are presented in section 3. Regressions of earnings functions appear in Section 4, and conclusions are provided in Section 5.

2. Conceptual Framework

Workers with different education levels receive different wages. This is true everywhere and, as we will see, is also true in African manufacturing. There are many possible explanations for this. Most of them have to do with returns to ability.[3]

2.1. Returns to ability and job sorting

There has been much debate as to whether the education wage gap represents returns to innate ability, or to skills acquired in school, or a combination of the two. Innate ability is likely to play a role because children who are smarter to start with tend to do well in school and thus acquire more education. In this paper we make no claim regarding the returns to education. What interests us is where the education wage gap comes from. To shed light on this, we decompose the education wage gap into a portion that is common to all firms and occupations, and a portion that results from educated workers sorting themselves into better paying firms or occupations.

[3] Other possible explanations include credentialism (which can be interpreted as employers deriving utility from employing highly educated workers) and network effects in rationed labor market (e.g., educated workers having better information and access to rationed high paying jobs).

This is achieved by estimating four earnings regressions of the form:

$$\log w_{ijt} = \gamma_1 S_{ij} + \alpha_1 H_{ijt} + \varepsilon_{1ijt} \quad \text{(model 1)}$$

$$\log w_{ijt} = \gamma_2 S_{ij} + \alpha_2 H_{ijt} + u_{2jt} + \varepsilon_{2ijt} \quad \text{(model 2)}$$

$$\log w_{ijt} = \gamma_3 S_{ij} + \alpha_3 H_{ijt} + \eta_3 D_{ijt} + u_{3jt} + \varepsilon_{3ijt} \quad \text{(model 3)}$$

$$\log w_{ijt} = \gamma_4 S_{ij} + \alpha_4 H_{ijt} + \eta_4 D_{ijt} + \varepsilon_{4ijt} \quad \text{(model 4)}$$

where w_{ijt} denotes the wage of worker i in firm j at time t, S_{ij} is the education of worker i in firm j, H_{ijt} denotes a vector of worker characteristics other than education, D_{ijt} is a vector of occupational dummies and u_{jt} is a firm-specific (time-varying) effect.[4]

Estimating models (1) to (4) is the focus of this paper. By comparing the γ's across models, we get a sense of how much of the education wage gap is due to sorting across firms ($\gamma_1 - \gamma_2$), how much is due to sorting across occupations ($\gamma_1 - \gamma_4$), and how much is due to sorting across both firms and occupations ($\gamma_1 - \gamma_3$). Under the null of no sorting/equal returns to ability across firms and occupations, we have $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4$. Our dataset contains manufacturing workers only, and so all estimated wage gaps reported in the paper should be interpreted as conditional on manufacturing employment. It may be that some of the returns to skills come from selection into the manufacturing sector, however assessing this mechanism is not possible with our data. It seems to us likely that the total (unconditional) wage gap is somewhat higher than that conditional on manufacturing employment.

Although our approach is essentially descriptive, our ultimate motivation is a better understanding of what African labor markets value in high ability workers. Investment in education has been presented to developing countries – including African countries – as the solution to their problems. The empirical evidence underlying such policy recommendations comes mostly from cross-country growth regressions (e.g. Mankiw et al. 1992, Barro 1991) and from earnings regressions estimated using data collected at the household level (Knight and Sabot 1990). Yet we know relatively little about how better educated, more able workers actually help the

[4] Our data-set contains multiple observations on workers within firms. Since we observe a panel of firms over time, firm fixed effects are allowed to vary over time. Firm fixed effects control for *all* firm-level determinants of average wages.

economy.[5] Do they raise productivity in all firms alike? Or do they raise productivity more in certain firms? Are high ability workers more productive in supervision than in production?

We recognize that our decomposition analysis does not identify precisely the channels through which ability affects wages. But it provides useful impressionistic evidence. One possible channel is that there is complementarity between worker and firm productivity, so that better firms need better workers (Abowd, Kramarz, Lengermann and Perez-Duarte 2004). If this channel is important, we expect a large proportion of the education wage gap to result from high ability workers working in high-wage firms. To test this hypothesis, we check whether the education wage gap falls once we control for firm productivity through u_{2jt} – i.e., whether $\gamma_1 \gg \gamma_2$. We also recognize that, because of likely imperfections in the labour market, it will not be possible to say how much of the various wage gaps is due to an underlying productivity differential between workers with different levels of education. Firm and occupation dummies may pick up productivity effects, but they may also reflect labour market imperfections, e.g. in the form of rent sharing.

Another possible channel, discussed for instance in Azam and Lesueur (1997) and Fafchamps and Söderbom (2006), is that literacy – and intellectual ability more generally – make workers more productive in management and supervision tasks. This is because a hierarchical organization of production requires methods (accounting, reporting, written instructions) that are best undertaken by educated, highly intelligent workers.[6] If this is the case, educated workers ought to be overrepresented in supervisory and management positions where they would earn higher wages – hence we would observe $\gamma_1 \gg \gamma_4$. If both channels are at work, we expect $\gamma_3 < \gamma_2$ and $\gamma_3 < \gamma_4$.

So far we have assumed that the education wage gap is linear in years of schooling. This may be too restrictive. Early work in this area indicated that the earnings function is concave in education. This has been interpreted as evidence that low levels of education have high returns (e.g. Psacharopoulos 1994, Psacharopoulos and Patrinos 2002). Much of the recent empirical

[5] The idea that wage differentials reflect productivity differentials is supported by the analysis in Jones (2001). Nevertheless, we acknowledge that there may not always be a perfect match between wage and productivity differentials, e.g. because of labor market imperfections.

[6] Supervisory and management jobs also carry a lot of responsibility and may have to pay more to compensate for higher effort. Firms may find it optimal to pay efficiency wages (e.g. Shapiro and Stiglitz 1984, Sparks 1986, Azam and Lesueur 1997). A related possibility is that workers in skilled jobs may need to be compensated for the disaffection from fellow workers that they incur for taking on, say, a supervisory role.

evidence, however, suggests that the earnings-education profile is in fact convex.[7] Aggregate growth regressions also suggest that secondary education has higher aggregate returns than primary education (Barro and Sala i Martin 1992).

As already discussed we cannot disentangle innate ability from what is learned in school, and so we cannot establish whether returns to schooling are concave or convex. We can, however, examine which types of skills and abilities are most valuable to the manufacturing sector. Someone who has completed primary school is someone who, in spite of crowded classrooms and lack of books, is smart and determined enough to master basic literacy skills. If workers with primary education are paid more, this suggests that basic literacy skills – and the determination to learn them – are valued by manufacturing firms. If they are not, this suggests that literacy skills – and the innate ability that they signal – are not valued. We can also ask the data whether the decomposition of the wage gap varies with the education level. For instance, if we find that individuals with college education are more likely to be found in managerial position, this suggests that college education – and the innate ability it signals – are valuable in managerial tasks.

To investigate these issues more in detail, we re-estimate the models in a semi-parametric fashion by letting the coefficient of S_{ij} vary with the level of schooling. To this effect, we replace the γS_{ij} term in models (model 1) to (model 4) with education dummies $\sum_n \gamma_n M_{ijn}$ where $M_{ijn} = 1$ if $S_{ij} = n$, and 0 otherwise. We expect the difference in schooling coefficients $\gamma_{n+1} - \gamma_n$ to be largest for those skills and abilities that are most valuable to the manufacturing sector.

2.2. The gender wage gap and job sorting

A similar approach can be used to decompose the gender wage gap. To this effect, we introduce a gender dummy term θG_{ijt} in models (model 1) to (model 4). Comparing the value of the gender coefficient θ across models tell us what proportion of the gender gap is due to sorting across occupations and across firms. We also examine whether the schooling coefficients vary

[7] Kingdon and Unni (2001) report that, for urban India, returns increase with the level of education; Duraisamy (2002) finds a similar result. Belzil and Hansen (2002) report increasing marginal returns to education in the U.S., up to grade 14. Söderbom et al. (2006) document convex earnings-education profiles in Kenyan and Tanzanian manufacturing.

between men and women. To this effect, we introduce a cross-term of the form $\varphi S_{ijt}G_{ijt}$. This tells us whether the gender wage gap is larger at low or high levels of education.[8]

Many different explanations have been proposed to account for the gender wage gap (Altonji and Blank 1999). One of these explanations is that women employees as a group are penalized by the emphasis many of them put on parenting and elderly care. This is because female workers are more likely to be absent from work to care for a sick child or an elderly parent. For the same reason, they also are less likely to accept to work overtime and after hours.[9] As a result, the explanation goes, men are often preferred for positions of responsibility. If this interpretation is correct, women should receive a lower return to high ability because they are less likely than men to be promoted to management or supervisory positions. Hence for them the coefficient of schooling should be smaller. This also implies that when we control for sorting by occupation, the gender difference in schooling coefficient should disappear or at least decrease.

Another explanation for the gender wage gap is gender segregation, modeled after Becker's (1971) work on race discrimination. Underlying this explanation is the idea that, for various reasons that we need not discuss here, employers prefer a gender-homogeneous workforce, i.e., either all male or all female. The gender wage gap then arises as a result of the sorting of workers across firms that pay different wages. If this hypothesis is true, we expect the gender wage gap to be non-existent within firms. Consequently, the coefficient of the gender dummy should disappear once we control for firm fixed effects (model 2). It is also conceivable that gender segregation varies by occupation within firms, e.g., female typists and male drivers. If this is the cause for the gender wage gap, the coefficient of the gender dummy should no longer be significant once we control for occupation.

Gender segregation can affect the coefficient of schooling if male-dominated jobs require more schooling and ability. This occurs, for instance, if management and supervisory jobs are reserved for men while low skilled work is reserved for women. If this hypothesis is correct, the coefficient of S_{ij} in regressions not conditioning on occupation should be higher for men because they get

[8] Appleton, Hoddinott and Krishnan (1999) provide a detailed analysis of the gender wage gap in Ethiopia, Cote d'Ivoire and Uganda, based on household data from the mid 1980s and early 1990s. Our focus is different from theirs primarily in that we concentrate on sorting mechanisms in the labour market.

[9] If women cannot credibly commit never to take on parenting duties or to care for an elderly parent, they may be denied promotion even when they choose work over family.

selected in higher paying occupations. In this context, the difference in schooling coefficients between men and women should disappear once we control for occupation.

Yet another possibility is that, in order to compete with men for better paid jobs, women must be more qualified than men. This can arise because employers prefer male employees and are willing to incur a cost in terms of lost productivity in order to employ them – this is the Becker (1971) 'taste for discrimination' idea. Alternatively, female workers may be victim of what Arrow (1972) called 'statistical discrimination': if the population of female workers is less productive on average or has a larger variance in unobserved ability, employers will demand higher credentials from female job applicants (Coate and Loury 1993). In this case, women will be paid less on average but those with better credentials will be able to compete with men for better paid jobs, thereby raising the schooling coefficient for female workers. In this case, controlling for occupation should narrow the gender wage gap as well as the difference in schooling coefficient between men and women. Investigating these various hypotheses is the object of the rest of the paper.

3. The Data

The data used in this paper come from a variety of surveys collected over a period spanning more than a decade. They cover two North African countries – Algeria and Morocco – and nine Sub-Saharan African (SSA) countries – Burundi, Cameroon, Cote d'Ivoire, Ethiopia, Ghana, Kenya, Tanzania, Zambia, and Zimbabwe. For many of these surveys, the authors were directly involved in the design of the questionnaire, the piloting of the surveys, and/or the training of the enumerators. They are therefore quite familiar with the surveyed firms and the strengths and weaknesses of the data.

The bulk of the data from SSA was collected as part of the Regional Program for Enterprise Development (RPED) organized by the World Bank. In this program, samples of approximately 200 randomly selected manufacturing firms were interviewed in eight countries (Burundi, Cameroon, Cote d'Ivoire, Ghana, Kenya, Tanzania, Zambia, and Zimbabwe).[10] The

[10] We focus on the manufacturing sector, because most firms in this sector are privately owned and follow a for-profit motive. Other sectors are less suited for an analysis of this type. In in the African public sector, for instance, the importance of political appointments, prebendalism, and overstaffing has long been documented. (e.g. van der Gaag and Vijverberg 1989, Vijverberg 1993, Velenchik 1997a). Trade unions are also more active in the civil service and government-owned firms than in the private sector. The likely presence of market distortions

surveys started with Ghana in 1992, and most other country surveys were initiated in 1993.[11] Firms were re-interviewed three years in a row in most countries; as some firms dropped out of the sample, they were replaced with other firms with similar characteristics.[12] Four sectors of activity are covered: textile and garments; wood products; metal products; and food processing. Small as well as large firms are included in the dataset. The RPED data have been extensively analyzed and have greatly improved our understanding of manufacturing in the continent (e.g. Bigsten, Collier, Dercon, Fafchamps, Gauthier, Gunning, Oduro, Oostendorp, Patillo, Söderbom, Teal and Zeufack 2004, Bigsten et al. 2000, Bigsten et al. 2004, Mazumdar and Mazaheri 2002, Fafchamps and Söderbom 2006).

We augment the RPED data set with data from two other sources. First, we add data on Ethiopian manufacturing firms that were collected independently of RPED but using a comparable questionnaire.[13] Second, we use data from the Kenyan Manufacturing Enterprise Survey (KMES), fielded in 2000 and designed as a follow-up to the last Kenyan RPED survey.[14] This survey generates data for 1998 and 1999.

In addition to our surveys from SSA, we have data from surveys in Algeria and Morocco. Both surveys focus on enterprises employing at least 10 people and operating in the following sectors of activity: food processing (excluding bakeries), textile, garments, leather, electrical machinery, chemicals, and plastics. The Algerian data were collected in 2002 in collaboration between the government and the World Bank as part of the Investment Climate Assessment (ICA) surveys. Around 600 firms were interviewed. The Moroccan data were collected as part of the Firm Analysis and Competitiveness Surveys (FACS), carried out in 2000 jointly by the World Bank and the Ministry of Commerce, Industry and Telecommunications (Fafchamps, El Hamine & Zeufack 2002). A sample of 860 firms in the six main towns was randomly drawn

makes it difficult to interpret the correlation between education and wages. In the fast growing not-for-profit sector, the education wage gap is similarly difficult to measure given the importance of volunteer work and the practice of hiding worker remuneration in perks and in-kind advantages (e.g. Edwards and Hulme 1995, Barr, Fafchamps and Owens 2005). Earnings are also inherently hard to measure in self-employed agriculture, which characterizes much of Africa.

[11] RPED or RPED-style surveys have been conducted in other African countries as well, but the worker questionnaire was not used. Consequently, we do not have matched employer-employee data for these countries.

[12] Burundi was surveyed only once due to the rapid deterioration of the political situation following the Rwandan genocide. Cote d'Ivoire was surveyed only twice due to insufficient funding.

[13] The Ethiopian survey was coordinated by Taye Mengistae.

[14] The KMES was organized by the Centre for the Study of African Economies, University of Oxford. See Söderbom and Teal (2001) for a report based on these data.

from a census of manufacturers conducted every year by the Ministry. The Moroccan survey generates data for 1998 and 1999. The Moroccan and Algerian questionnaires are very similar in spite of using two different acronyms.[15]

As already mentioned, one unusual feature of all these data sets is that they contain matched employer-employee information. At the same time as the firms were surveyed, a sample of workers was drawn from each firm designed to cover the full range of firm employees. The objective was to have up to 10 workers from each firm where firm size allowed. To increase the informational content of the data, the worker sample was stratified according to occupational status.[16] Each worker was interviewed individually by enumerators.

The methodology used to draw samples of workers in each firm implies that manufacturing workers did not all have the same probability of being selected. Since at most 10 workers were interviewed in each firm, workers in large firms have a lower probability of being interviewed. Moreover, within each firm, enumerators were instructed to select workers from each occupational category. This means, for instance, that employees engaged in occupations that represent a small proportion of the workforce – such as managers and technical staff – have a higher likelihood of being interviewed than skilled and unskilled workers, who constitute the bulk of the workforce. To take this into account, we assign a sampling weight to each worker based on the number of employees in the firm and in his or her occupational category in the firm, so as to mimic a randomly drawn sample. Unless otherwise indicated, all analysis conducted in this paper accounts for stratification using sampling weights.

The main characteristics of the employee sample the eleven countries covered by this paper are presented in Table 1. To illustrate the importance of properly weighting the data, we show weighted (in bold) and unweighted (in italics) means for all workers characteristics.[17] If several years of data are available, all years are combined.

Average monthly earnings, expressed in US$, show remarkable variation across countries. The average (weighted) level of earnings in Cameroon is similar to that in Morocco, but more than five times higher than in Tanzania. The two CFA countries in our sample – Cameroon

[15] The ICA questionnaire is but an improved version of the FACS questionnaire.

[16] Where there is panel data, samples of workers have been interviewed again in subsequent years, but the identity of the workers differs across survey rounds. In all surveys, information on worker identifiers was not collected to protect the confidentiality of workers' responses.

[17] The standard deviation is calculated on the unweighted data.

and Cote d'Ivoire – pay higher manufacturing wages on average than the non-CFA countries in Sub-Saharan Africa. The high wages paid in these two countries may reflect the overvaluation of the currency at the time of the data collection (early 1990s).

Levels of schooling of the manufacturing workforce vary much less across countries than average earnings. In all the countries except Ethiopia, Burundi and Cote d'Ivoire, the average manufacturing worker has around 8 years of education – the equivalent of a junior high school degree. There is no apparent relationship between average wages and average schooling levels across countries. Manufacturing workers in Tanzania earn five times less than those in Morocco and Cameroon, even though they have basically the same education level on average. Moreover, Cote d'Ivoire pays higher wages although workers are less educated than in other studied countries. We also see few differences in average age, experience (proxied as age minus the year the individual left school), or length of tenure across countries, one possible exception being Burundi where workers tend to be younger, less experienced and with a shorter tenure. This probably reflects the small size of most manufacturing firms in the Burundi sample.

Turning to the composition of the sample by gender, we see that women account for 10 to 27% of the manufacturing workforce in SSA but for about 50% in Morocco where they constitute the bulk of unskilled and skilled manpower in the textile and garment sectors. Men dominate high and middle management positions in all countries.

The breakdown by occupational category varies somewhat between countries in that the level of disaggregation used in the nine RPED surveys is more detailed than that used in Morocco and Algeria. We also see that correcting for stratification does not have a major impact on the occupational breakdown in the SSA samples but has a large effect in Morocco. This is due to the fact that Moroccan firms are larger on average than SSA firms and use relatively less management (Fafchamps and Söderbom 2006).

Although it is not the focus of this paper, there is a striking contrast in the proportion of production workers in the total workforce. At one extreme, production workers represent 93% of the manufacturing workforce in Morocco. In contrast, in SSA, even if we include supervisors, technicians, and maintenance staff, they only represent between 51% (Tanzania) to 75% (Kenya) of the workforce, with a SSA average of 66%. As shown by Fafchamps and Söderbom (2006), some of this gap is due to differences in firm size – SSA firms tend to be smaller and smaller firms have proportionately more non-production personnel. The rest may be due to rent sharing and labor management difficulties (e.g. Velenchik 1997b, Bigsten et al. 2004, Mazumdar and Mazaheri 2002).

4. Econometric results

We now turn to the estimation of earnings regressions. As pointed out earlier, all regression results presented here are weighted by the size of the firm's employment in each occupational category to correct for oversampling. We also correct standard errors for clustering and stratification.[18]

As discussed in Section 2, we estimate four regression models of the form:

$$\begin{aligned}
\log w_{ijt} &= \gamma_1 S_{ij} + \theta_1 G_{ijt} + \varphi_1 S_{ijt} G_{ijt} + \alpha_1 H_{ijt} + \varepsilon_{1ijt} && \text{(model 1)}\\
\log w_{ijt} &= \gamma_2 S_{ij} + \theta_2 G_{ijt} + \varphi_2 S_{ijt} G_{ijt} + \alpha_2 H_{ijt} + u_{2jt} + \varepsilon_{2ijt} && \text{(model 2)}\\
\log w_{ijt} &= \gamma_3 S_{ij} + \theta_3 G_{ijt} + \varphi_3 S_{ijt} G_{ijt} + \alpha_3 H_{ijt} + \eta_3 D_{ijt} + u_{3jt} + \varepsilon_{3ijt} && \text{(model 3)}\\
\log w_{ijt} &= \gamma_4 S_{ij} + \theta_4 G_{ijt} + \varphi_4 S_{ijt} G_{ijt} + \alpha_4 H_{ijt} + \eta_4 D_{ijt} + \varepsilon_{4ijt} && \text{(model 4)}
\end{aligned}$$

for each of the eleven countries in our sample. For Morocco and Algeria, we have large samples so that we can comfortably estimate regressions separately for each country. Sample sizes are much smaller for Sub-Saharan Africa, unfortunately. For these countries, we increase efficiency by estimating pooled regressions in which the coefficients of worker characteristics H_{ijt} and occupation dummies D_{ijt} are constrained to be the same across countries. We do, however, allow the coefficients of the gender dummy G_{ijt}, the schooling variable S_{ijt} and their cross-term to vary across countries. We also include year-specific country dummies, except in the regressions controlling for firm-year fixed effects.

For Morocco and Algeria, we have information on whether the worker received vocational training from a previous employer. We include this information as a dummy variable as well as a cross-term between vocational training and gender.[19] Interpretation of the results concerning

[18] Given the very large number of individual effects in some regressions, including individual dummies is not a feasible option. Fixed effect regression on suvey data is implemented by differencing the data with respect to the weighted mean.

[19] We also have information on vocation training received from the current employer. This variable, however, is subject to selection bias, training being offered to very bad or very good workers, and it is ignored here.

this variable follows the same principles as for education.

In addition to gender, our earnings regressions include the standard set of controls: age, work experience, job tenure, and their square. In the Morocco sample, we also include a dummy for whether the wage figure provided by the respondent is net of taxes. In the other countries, wages are always reported net of taxes.

Detailed regression results for Sub-Saharan Africa are presented in Table 2 for models 1 to 4. Those for Morocco and Algeria are given in Tables 3 and 4, respectively. We begin by discussing the education wage gap. Education coefficients have been summarized in Table 5 to facilitate comparison. We then discuss vocational training before briefly commenting on the other regressors.

4.1. Education and Earnings

Education is strongly significant in model (1) in all countries. Column 1 in Table 5 shows that the average education wage gap for male workers over the eleven countries is 5.9%, with a minimum of 2.7% in Ghana and a the maximum of 10.5% in Zambia. Algeria and Morocco tend to have slightly lower education wage gap than SSA. Recall that all results are interpretable as conditional on manufacturing employment. The education wage gap in the entire population is likely to higher than what we observe here, as part of the return to education may be in the form of better access to relatively well paid jobs in manufacturing, professional services, and the public sector. We observe a large gender difference in the education wage gap. On average, this gap is higher for women (7.5% across all eleven countries). There is, however, a marked variation across countries. In seven of the eleven countries, the gender difference in the education coefficient is not significant at the 10% level. In three countries, the difference is significant and positive: Cote d'Ivoire, Kenya and Zimbabwe (see Table 2). In these countries the female dummy is also negative and significant, implying that women with no formal education get paid much less than men without education, and that the gender gap narrows as education increases. Indeed, in these three countries, the gender wage gap disappears for women with 10 to 12 years of education. These results are consistent with the idea that women must be better educated in order to compete with men for better paid jobs, perhaps because of statistical discrimination.

In contrast, in Morocco, the gender difference in the education wage gap is negative and strongly significant. At the same time, the gender dummy is positive, indicating that women with no schooling get paid significantly more than men without education. Estimated coefficients indicate that above 3 years of schooling the gender wage gap becomes negative; a positive female wage gap exists only for workers with very little education. This result is consistent with the idea that female workers in Morocco are not selected for jobs that require a high level of education.

Comparing models 1 and 2 in Table 5 tells us how much of the education wage gap is due to sorting among firms. On average across the eleven countries, the sorting of male workers across firms accounts for less than 20% of the gap. This percentage, however, varies dramatically across countries – from a high of 74% in Ghana to a low of -14% in Zimbabwe. In all countries we can reject at the 1% level the hypothesis that $\gamma_2 = 0$: the positive education wage gap for male workers is not entirely due to sorting among firms.

The picture is different for female workers. The magnitude and significance of the gender dummy fall in most countries once we control for firm fixed effects. This suggests that the gender wage gap is due in large part to sorting among firms – perhaps because of gender segregation by employers. Sorting among firms also accounts for a larger proportion of the education wage gap for women: once we control for firm fixed effects, the coefficient of schooling for women falls by a third on average over the eleven countries. Morocco again stands out as an exception, with the schooling coefficient rising for women after we control for firm fixed effects. This means that educated women tend to work in firms that on average pay less to their workforce. After controlling for selection among firms, the education wage gap is very similar for men and women – 4.8% versus 5.0% on average over the eleven countries. In model 2, the gender difference in the education coefficient is significantly positive in only two countries – Algeria and Kenya – while it is significantly negative in Morocco and Burundi.

Turning to model (3) in Table 5, we observe a further fall in the coefficient on education for male and female workers. We find that, within the same firm, workers in management positions receive wages that are 86% (Algeria) to 179% (Morocco) higher than those of skilled production workers, our reference category.[20] Those in middle management and administrative positions receive wages on average 25% to 82% higher than those of unskilled workers while unskilled workers are paid on average 11% to 21% less than skilled workers. In all cases, Morocco displays

[20] Percentage difference = exp(log difference) - 1.

the strongest wage differences by occupation.

Part of these wage differences reflect differences in education, since the coefficient of education in model 3 captures wages differences across workers who are in similar occupations in the same firm. On average across the eleven countries, sorting across firms and occupations accounts for over half of the total education wage gap in manufacturing. In one country, Ghana, the coefficient of schooling is no longer significant, suggesting that, in that country, sorting by firm and occupation accounts for all the education wage gap. Ghana is also the country in which the education wage gap is the lowest. In contrast, in Zimbabwe and Burundi, the schooling coefficients are virtually identical whether we control for selection or not. This suggest that there are probably large difference across countries regarding what mechanism drives returns to education and ability in manufacturing. It is not immediately clear what drives these differences.

In Morocco, a special case in our sample as far as gender is concerned, the gender difference in the education wage gap is no longer significant in model 3. This is consistent with the idea that in that country the gender wage gap is due to women being confined to low paying firms and occupations – mostly production workers in the textile and garment sectors.

Finally we turn to model 4 in which we control for occupation but not for firm fixed effects. We see that, for male as well as female workers, selection among occupations accounts on average for one third of the education wage gap. Put differently, one third of the wage difference is achieved because educated workers tend to be selected in better paid occupations. Results also indicate that the wage premium paid to workers in management and administrative or support staff positions is nearly always larger when we do not control for firm fixed effect. This suggest that firms that hire more management and administrative or support staff also pay higher wages to all workers on average. This result is consistent with the observation by Fafchamps and Söderbom (2006) that larger firms in SSA and Morocco need to motivate production workers and supervisors by paying higher wages.

We have seen that a non-negligible proportion of the education wage gap is due to sorting among firms. To investigate whether wage differences are driven by firm size and capital-labor ratio, we regress the estimated firm-level fixed effects $\widehat{u}_{jt}$ in the earnings regression on the log of capital and employment and sectoral dummies. The estimated model is of the form:

$$\widehat{u}_{jt} = \alpha \log L_{jt} + \beta \log K_{jt} + \tau M_{jt} + \varepsilon_{jt}$$

where $\widehat{u}_{jt}$ is the estimated fixed effect for firm j in year t from model 2, L_{jt} is total employment in firm j at time t, K_{jt} is capital stock, and M_{jt} is a vector of sectoral and year dummies. To save on degrees of freedom, we again pool the SSA observations but include country-year dummies.

Results are presented in Table 6. They show that larger firms, in terms of total employment (all regressions) and capital stock (Morocco and Algeria), pay higher wages to all workers. This is a standard result (Oi and Idson 1999).[21] Taken together with our earlier findings, we see that part of the education wage gap results from the fact that better educated workers are hired by firms that are larger and more capital intensive. We also find some very large sector and country dummies, suggesting that some of the wage differences across firms are related to technology.

4.2. Vocational training and earnings in Algeria and Morocco

A similar decomposition analysis can be applied to wage gaps attributable to vocational training, for which we have data only for Morocco and Algeria. To reduce the risk of endogeneity bias, we only consider vocational training received from a previous employer, not from the current employer. Since only a small proportion of surveyed workers report receiving such training, results should be treated with caution.

We find a large vocational training wage gap in Morocco – around 45% for men and 32% for women (Table 3, model 1). The gender difference, however, is not significant – possibly because of the small number of workers who received such training. The vocation training wage gap is much lower in Algeria – 2.3% for men and 4.9% for women – and insignificant.

By comparing models 1, 2 and 3 for Morocco, we see that, as in the case of education, around one fifth of the vocational training wage gap is due to sorting between firms and one third to sorting across occupations. It therefore appears that returns to vocational training manifest themselves in ways similar to those of education and ability.

[21] Fafchamps and Söderbom (2006) investigate the reason for this relationship in African manufacturing.

4.3. Tenure and experience

Tables 2 to 4 also provide information regarding wage gaps due to work experience, length of tenure, and age. All of these variables enter the regressions with a quadratic term and so partial effects will vary. Since these variables are used here primarily as controls, we only describe the results briefly.

We begin with the relationship between wages and years of tenure, summarized in the first panel of Table 7 for various values of tenure. These estimates are interpretable as showing the wage-tenure relationship, holding all other factors constant, including age and general experience. Of course, as a worker gains one more year of tenure, his or her age and general experience increases by one year as well, but we ignore the latter effect for the moment. In model 1 (first column) we find the usual declining marginal returns to tenure for the Sub-Saharan Africa manufacturing firms but constant returns in Algeria and increasing returns in Morocco. This, however, arises because of a strong positive relationship between length of tenure and average firm wage: firms that pay better wages also retain workers longer. This is immediately apparent by comparing results for models 1 and 2: once we control for unobserved firm heterogeneity (model 2), all three samples display the usual falling marginal effects of length of tenure. The effect appears strongest in Morocco which, as we have seen, also has the widest wage disparity across occupation categories. Within firms, wage gaps attributable to tenure result from promotion across occupational categories – most commonly, from unskilled to skilled production worker. Indeed, marginal returns to tenure fall in most cases once we control for occupation (model 3).

Turning to general experience, we compute the combined wage gap associated with age and time spent in the labour market, where the latter is proxied as age minus the year the individual left school.[22] We do this by adding up the partial effects of age and experience implied by the regressions, evaluated at age and experience as indicated in the second panel of Table 7, ignoring the tenure effect. For example, comparing an individual in SSA aged 20 with one year of experience to someone with the same observable characteristics except he or she is aged 19 and has no work experience, the predicted wage gap is about 4% in favour of the more experienced

[22] Labour market experience is *not* perfectly collinear with age, education, and tenure, as some individuals may take longer to finish their education than others.

worker. The most striking finding here is that earnings rise much more quickly amongst the young in SSA than in Algeria and Morocco. The wage gaps in SSA take the form of selection across firms: once we control for unobserved firm heterogeneity, the experience wage gaps fall, suggesting that firms that pay more on average also tend to employ older workers. One possible explanation is that firms that pay more are those seeking to hire more workers; consequently, they are also the firms that hire older, more experienced workers. We find that experience wage gaps fall once we control for occupation, a finding consistent with the idea that, as they age, SSA workers get promoted to better paid occupational categories. The pattern is similar for Algeria and Morocco, except that wages increase more slowly with experience than for SSA.

5. Non-parametric estimation

The results presented so far demonstrate that a large fraction of the education wage gap arises through sorting among firms and occupations. What these results do not clarify, however, is whether sorting affects the wage gap from different levels of education differently. To elucidate this point, we now turn to a non-parametric approach. In this approach, we replace the variable 'years of education' with yearly dummies and re-estimate all four models, with no education defined as the reference category. Estimated coefficients, which indicate the log wage premium over no education, are presented graphically together with 95% confidence intervals.

Given the smaller number of available observations for Sub-Saharan Africa, we divide the data into three sub-groups: West Africa (Cameroon, Cote d'Ivoire, and Ghana), poor East Africa (Burundi, Ethiopia and Tanzania) and southern Africa plus Kenya (Kenya, Zambia and Zimbabwe). These groupings are partly based on geography, partly on levels of development. Of the three groups, the second is by far the poorest in terms of GDP per capita while the West African countries in our sample tend to be better off. Results for the three groups are presented in Figures 1, 2 and 3. Figures 4 and 5 present estimate education coefficients for Algeria and Morocco, respectively.[23]

We focus first on coefficient estimates from model 1. From the figures, we see that the primary education dummies are typically not significantly different from zero in Sub-Saharan

[23] The underlying regressions, which are not shown in order to conserve space, contain female-education interaction terms. All figures referred to in this section are constructed with these interaction terms set to zero, i.e. they are interpretable as showing the earnings functions for men.

and Moroccan manufacturing. For Algeria we find positive and significant coefficients associated with primary education, although the effect is not significant for two years of primary education. These results seem to suggest that, with the possible exception of Algeria, basic literacy and numeracy skills, by themselves, are not particularly crucial for African manufacturing. This is not entirely surprising, given that most manufacturing is concentrated in light industries like textile and garment where the use of sophisticated machinery is rare.

In the context of African labor markets, comparing illiterate workers to those with partial primary education may underestimate the return to primary education. This is because illiterate workers in manufacturing may have a high innate ability but have been deprived of a chance to go to school. In contrast, those with a small amount of primary education may have had access to school but insufficient native ability to justify spending more time in school. Such a situation would generate a negative correlation between innate ability and education when comparing the two groups of workers, and this negative correlation may counterbalance the positive effect of education, resulting in a zero wage gap between the two groups. Without data on innate ability we cannot investigate this possibility directly. But massive rationing out of primary education for a large proportion of children would be needed to compensate for those children who did not attend school because they were less able. In the studied countries, with the possible exception of Ethiopia, enrollment levels in primary education are reasonably high, so the rationing effect is probably not strong enough to explain our results.

In contrast, the coefficients of secondary and tertiary education dummies are very high in all regressions, although the shape of the curve varies across countries and specifications. In Morocco, Algeria and the third SSA group (Kenya, Zambia and Zimbabwe – Figure 3), the curve follows a relatively straightforward pattern, rising steadily above 8 years of schooling – and even accelerating markedly above 12 years of education in Morocco. This suggests that, in these countries, academic skills in math and English/French and high-level vocational skills are useful to the manufacturing sector. In the first two SSA groups (Figures 1 and 2) returns are high after secondary schooling, however marginal returns are very low, possibly even negative, between 8 and 12 years of education.[24]

[24] Negative returns seem to imply that students have an incentive to stop their education since staying longer in school appears to lower their wage in absolute terms, unless they manage to complete a college degree. This interpretation may be misleading, however, because the earnings functions estimate here are conditional on workers

Turning to model 2, we see that in all cases the estimated earnings functions become flatter as a result of controlling for firm-year fixed effects. This confirms that a large share of the education wage gap come from selection across firms. For Algeria and Morocco, once we control for unobserved firm heterogeneity schooling variables become non-significant for up to 9 years of schooling. This means that the education wage gap at lower levels of education (primary and lower secondary) results entirely from selection across firms. A somewhat similar result is observed in Figure 3, albeit with up to 7 years of schooling only.

We now consider model 3. As anticipated, we note a further flattening in the earnings function in all regressions. This again confirms that a proportion of the education wage gap takes the form of selection across occupations. The same general conclusion obtains if we consider model 4. We note a fall in the education wage gap at higher education levels, suggesting that selection across occupations accounts for a larger share of education wage gap among post-secondary graduates. This interpretation is confirmed if we compare models 1 and 4. In this case, the coefficients of lower education dummies remain by and large unchanged while those of higher education dummies fall. The education wage gap between 9 and 13 years of schooling (end of secondary school) thus manifest itself primarily through better chances of obtaining middle management and support staff positions.

The results presented here suggest that returns to basic literacy and numeracy are not particularly strong in African manufacturing. Moreover, a large share of the wage gap at lower education levels comes from selection across firms, in the sense that firms paying more to all workers attract a disproportionate share of workers with some primary education. Within firms, workers tend to be paid the same irrespective of their years of primary and lower secondary education. This suggests that lower education serves primarily as a screening mechanism: better paying firms seem to insist on some primary education as a way of selecting high productivity workers – possibly because basic literacy and numeracy skills facilitate labor management, possibly because it signals higher ability. Conditional on being recruited in the firm, however, primary education is not rewarded. It therefore does not appear that basic literacy and numeracy are important to the success of African manufacturing. This interpretation is confirmed

being in manufacturing. It is conceivable that completion of secondary school opens the door to civil service jobs where pay is better. Given the data at our disposal, we cannot pursue this possibility further.

by observing that Morocco, which is by far the most successful manufacturing exporter in our sample, employs many illiterate and poorly educated workers in its competitive export sector (Fafchamps 2006).

In contrast, basic academic skills and vocational high level skills are highly rewarded in the labor market, generating in general a convex curve with an inflection point around 10-12 years of education. Furthermore, we find that a large share of the wage gap for higher education workers comes from selection across occupations. This suggests that higher education is valued because it imparts skills that are valuable in management and administrative positions.

6. Conclusion

We have estimated the education wage gap in African manufacturing using employer-employee matched data on eleven countries. Results indicate that this gap can be divided into three parts: sorting across firms, sorting across occupations within firms, and the rest from higher wages paid to better educated workers in the same firm and occupation. On average across the eleven countries, sorting across firms and jobs accounts for more than half of the education wage gap. The evidence suggests that most of the relationship between ability and earnings operates through job selection. This is an interesting finding, particularly if firms are using education as a signal so that more able workers are being sorted into more productive firms. If this is the case, the potential benefits of education are twofold: education may have a direct effect on firm productivity by providing workers with productivity-enhancing skills; and education may have an indirect effect on firm productivity by enabling firms to identify more able workers, thereby increasing allocative efficiency.

As anticipated, we observe a significant gender wage gap. Once we control for firm heterogeneity, the magnitude and significance of the gender dummy fall in most countries, suggesting that the gender wage gap is due in large part to sorting among firms – perhaps because of gender segregation by employers. While on average the education wage gap is higher for women, in seven of the eleven countries the difference is not significant. In three of the remaining countries, the difference is significant and positive but the female dummy is negative and significant: women on average get paid less than men but the gap is lower for educated women – and even disappears for women with 10 to 12 years of education. This suggests that, while women are able to compete with men for well-paid jobs at higher levels of education, at lower levels of education women are at a disadvantage relative to men, perhaps because of statistical discrimination.

Morocco, which is the country in our sample with the largest share of female employment in manufacturing, displays a different pattern. The gender difference in the education coefficient is negative and strongly significant while the gender dummy is positive. The net effect is positive only for women with very little education. At higher levels of education, women get paid less than men.[25] Furthermore, in this country we find that the gender difference in the education coefficient is no longer significant once we control for occupation and firm heterogeneity. This is consistent with the idea that in Morocco the gender wage gap is due to women being confined to low paying firms and occupations – mostly production workers in the textile and garment sectors.

The above decomposition of the education and gender wage gaps is useful for two reasons. First, it describes the market signals sent to workers of different gender and education levels in African manufacturing. Presumably, if the education earnings gap is larger in certain firms or occupations, educated workers will seek out those jobs. Secondly, provided we are willing to assume that earnings are correlated with productivity, the pattern of relationship between wages and education level is indicative of the way by which skills and ability raise productivity. For instance, sorting by occupation affects primarily the coefficient of high levels of education in the earnings regression (i.e., above 9th grade). In contrast, sorting across firm affects all education levels but, in most countries, it accounts for all the education wage gap of workers below 9th grade – i.e., workers with less than primary education are paid the same as uneducated workers in the same firm. A similar pattern is observed for vocational training received from previous employers. These results suggest that there are firms that require smarter and better educated workers on the shop floor. These firms pay more to all workers, which suggests that these firms are more productive. They also tend to be larger and more capital intensive. Other firms – especially small ones – hire workers with little or no education, many of them women, and pay them low wages.

[25] In the Moroccan data, the average gender wage gap in the raw data is between 0.09 and 0.16 among individuals with 5 years of education or less; around 0.20 for indivduals with 6-14 years of education; and 0.44 for for those with more than 14 years of education. Thus this result is not driven by the functional form of the earnings function, or by inappropriate extrapolation.

An immediate implication of these observations is that the size distribution of firms and the relative importance of high productivity and low productivity firms within the manufacturing sector have a major effect on returns to ability and skills. One possible interpretation is that it is only the larger, more productive firms that can put to good use the skills workers learn in primary and lower secondary school. Alternatively, high paying firms may rely on primary and lower secondary schooling as a screening device: relative to illiterate production workers, workers with some education are likely to have higher ability on average. We suspect that the second explanation is the correct one. Indeed, once we control for firm heterogeneity, wages are the same for workers with or without primary education. In contrast, if low-level education raised worker productivity in high paying firms, they would be paid more and this would show up in the education coefficient.

A different pattern is observed for higher levels of education, i.e., upper secondary and post-secondary. For workers at this level of qualification, the education wage gap comes primarily from selection into better paid occupations, i.e., management and record keeping tasks. This is in agreement with our initial expectations: workers who are smarter and highly educated are essential to certain tasks such as labor management, record keeping, and the operation and maintenance of machinery. What the analysis suggests is that the level of education necessary for these tasks is quite high – above 9th grade. This is particularly striking because the average level of education is quite low in the studied countries, so that even low levels of education signal reasonably high ability. Compared to Africa where the overwhelming majority of the work force works in agriculture and other forms of self-employment, in developed economies a large proportion of the total labor force is engaged in labor management, record keeping, and the operation and maintenance of machinery. An extraordinarily high ability thus does not appear necessary to undertake these tasks. Putting these two observations together suggests that the skills that workers learn in high school and college are essential for management and supervision tasks.

More work is needed to ascertain the respective roles that labor management and machine operation play in firm productivity. In particular, do educated workers raise firm productivity because they help better manage other workers or because they help better manage the machinery? Fafchamps and Söderbom (2006) examine the role of labor management in raising productivity. They conclude that labor management plays a critical and largely underestimated role. These issues deserve more research.

As a final remark, it is important to acknowledge that this paper has not sought to investigate whether job sorting achieves an efficient allocation of workers in our samples, or whether African labor markets are more – or less – allocatively efficient than labor markets elsewhere. We have taken job sorting as a given and examined the relationship between wage gaps and job sorting. Testing whether African labor markets achieve some measure of allocative efficiency would be a useful endeavor, but it is beyond the scope of this paper.

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Table 1: Descriptive Statistics: Weighted and unweighted means, and standard deviations

	Algeria	**Burundi**	**Cameroon**	**Côte d'Ivoire**	**Ethiopia**	**Ghana**	**Kenya**	**Morocco**	**Tanzania**	**Zambia**	**Zimbabwe**
Monthly earnings (US$)	**208.7**	**98.0**	**274.2**	**158.4**	**95.3**	**75.4**	**86.8**	**270.8**	**52.1**	**102.0**	**135.2**
	203.8	*95.8*	*283.6*	*158.1*	*99.8*	*78.2*	*92.9*	*328.3*	*52.0*	*111.0*	*130.4*
	[135.9]	[92.0]	[204.9]	[98.3]	[88.5]	[59.9]	[77.5]	[373.0]	[48.0]	[91.6]	[91.3]
Years of education	**10.3**	**4.9**	**8.7**	**6.0**	**6.5**	**9.5**	**8.6**	**7.9**	**8.2**	**7.2**	**8.3**
	10.2	*4.8*	*8.7*	*5.9*	*6.4*	*9.7*	*8.8*	*8.7*	*8.2*	*7.4*	*8.2*
	[4.7]	[5.0]	[3.9]	[4.1]	[3.1]	[3.4]	[3.1]	[5.4]	[3.3]	[2.1]	[2.5]
Age	**39.2**	**31.3**	**33.9**	**34.7**	**29.7**	**34.0**	**33.6**	**33.2**	**34.7**	**33.8**	**36.2**
	36.4	*32.1*	*34.2*	*35.3*	*30.6*	*34.3*	*34.3*	*34.7*	*35.4*	*34.1*	*36.8*
	[10.4]	[9.4]	[7.5]	[8.4]	[10.8]	[10.1]	[9.5]	[8.8]	[10.1]	[9.7]	[10.5]
Years of tenure	**12.1**	**4.8**	**6.2**	**6.9**	**6.1**	**6.9**	**7.5**	**7.0**	**7.3**	**6.3**	**9.5**
	7.9	*5.4*	*6.6*	*7.7*	*7.0*	*7.0*	*8.2*	*7.2*	*8.0*	*6.7*	*10.3*
	[8.3]	[6.3]	[6.1]	[6.7]	[7.1]	[6.8]	[7.4]	[6.4]	[7.1]	[6.7]	[8.1]
Years of experience	**21.4**	**14.7**	**14.5**	**17.4**	**11.8**	**16.4**	**16.5**	**18.0**	**17.0**	**15.8**	**19.5**
	18.5	*15.8*	*14.9*	*18.1*	*12.7*	*16.4*	*17.1*	*18.7*	*17.4*	*16.0*	*20.1*
	[12.6]	[10.8]	[8.7]	[9.6]	[11.1]	[10.6]	[10.5]	[11.1]	[11.0]	[10.4]	[11.3]
Female	**19.5%**	**11.9%**	**14.9%**	**10.0%**	**26.9%**	**21.8%**	**14.6%**	**50.5%**	**23.1%**	**19.6%**	**18.0%**
	20.4%	*10.3%*	*14.0%*	*8.5%*	*27.3%*	*19.6%*	*14.2%*	*39.3%*	*21.9%*	*19.3%*	*15.7%*
Received training in previous job	**12.1%**							**1.6%**			
	11.0%							*2.4%*			
First job	**20.1%**							**44.1%**			
	25.0%							*40.7%*			
Wage reported net of taxes	**100.0%**							**31.5%**			
	100.0%							*34.8%*			
Management		**0.2%**	**8.1%**	**4.9%**	**2.4%**	**5.1%**	**4.2%**		**20.9%**	**10.2%**	**4.7%**
		0.9%	*8.5%*	*4.2%*	*2.7%*	*7.3%*	*5.0%*		*18.6%*	*11.6%*	*3.1%*
Administration		**17.6%**	**20.3%**	**18.4%**	**10.9%**	**16.6%**	**11.4%**		**17.5%**	**13.5%**	**17.3%**
		13.2%	*17.8%*	*12.4%*	*7.7%*	*14.3%*	*10.7%*		*13.7%*	*14.3%*	*9.0%*

Note: Weighted means are shown in **bold**, unweighted means in *italics*, standard deviations (unweighted) in []. The table continues on the next page.

Table 1 continued.

	Algeria	Burundi	Cameroon	Côte d'Ivoire	Ethiopia	Ghana	Kenya	Morocco	Tanzania	Zambia	Zimbabwe
Commercial / Sales		**13.8%**	**6.2%**	**7.0%**	**8.6%**	**4.2%**	**4.9%**		**5.1%**	**8.0%**	**8.2%**
		10.3%	*5.7%*	*4.7%*	*6.1%*	*3.1%*	*3.9%*		*3.7%*	*7.2%*	*4.2%*
Supervisor		**2.7%**	**5.1%**	**6.0%**	**4.2%**	**11.1%**	**10.9%**		**6.4%**	**15.9%**	**13.0%**
		2.2%	*5.8%*	*5.5%*	*4.7%*	*10.0%*	*10.8%*		*6.7%*	*13.7%*	*13.4%*
Technician		**0.0%**	**6.5%**	**5.4%**	**2.1%**	**3.7%**	**2.5%**		**4.1%**	**2.7%**	**1.5%**
		0.0%	*6.1%*	*5.1%*	*2.4%*	*3.0%*	*2.3%*		*3.8%*	*2.5%*	*0.7%*
Maintenance		**2.7%**	**3.5%**	**3.1%**	**0.5%**	**2.0%**	**4.3%**		**4.0%**	**2.8%**	**4.5%**
		3.1%	*3.7%*	*3.0%*	*1.1%*	*2.0%*	*3.0%*		*3.2%*	*2.2%*	*3.0%*
Skilled production		**62.1%**	**42.9%**	**28.2%**	**50.7%**	**29.9%**	**33.6%**		**23.3%**	**19.9%**	**14.8%**
		69.6%	*44.4%*	*35.0%*	*51.6%*	*35.5%*	*38.0%*		*30.7%*	*18.5%*	*21.8%*
Unskilled production		**0.0%**	**1.3%**	**20.6%**	**13.6%**	**18.0%**	**12.1%**		**9.8%**	**18.6%**	**25.0%**
		0.0%	*1.6%*	*24.3%*	*16.0%*	*16.2%*	*15.0%*		*8.6%*	*21.7%*	*36.9%*
Apprentice		**0.0%**	**0.2%**	**0.1%**	**2.5%**	**0.0%**	**0.8%**		**0.0%**	**0.0%**	**0.6%**
		0.0%	*0.2%*	*0.1%*	*2.0%*	*0.0%*	*0.4%*		*0.0%*	*0.0%*	*0.8%*
Craft		**0.0%**	**2.7%**	**0.7%**	**0.0%**	**8.1%**	**11.1%**		**3.0%**	**4.4%**	**3.1%**
		0.0%	*2.3%*	*0.8%*	*0.0%*	*6.5%*	*7.1%*		*2.7%*	*3.4%*	*2.3%*
Support staff		**0.8%**	**3.1%**	**5.6%**	**4.5%**	**1.2%**	**4.3%**		**5.9%**	**4.0%**	**7.2%**
		0.6%	*3.7%*	*4.9%*	*5.6%*	*2.0%*	*3.9%*		*8.3%*	*5.0%*	*4.6%*
Upper management	**0.4%**							**0.3%**			
	3.8%							*4.5%*			
Middle management	**4.1%**							**1.5%**			
	14.1%							*9.3%*			
Skilled workers	**51.7%**							**50.1%**			
	52.1%							*39.6%*			
Unskilled worker	**37.1%**							**43.3%**			
	18.4%							*30.4%*			
Support and administrative staff	**6.4%**							**4.8%**			
	11.5%							*16.2%*			
Observations	6,448	319	1,664	1,319	1,192	1,934	5,092	15,700	1,462	2,476	1,117

Note: Weighted means are shown in **bold**, unweighted means in *italics*.

Table 2: Earnings regressions for manufacturing workers in Sub-Saharan Africa

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Education								
Kenya	0.060	**13.37**	0.037	**10.56**	0.023	**7.08**	0.037	**9.78**
Burundi	0.091	**9.93**	0.092	**13.26**	0.085	**12.00**	0.080	**8.64**
Côte d'Ivoire	0.043	**8.25**	0.032	**8.31**	0.013	**3.58**	0.021	**4.26**
Ethiopia	0.082	**8.12**	0.067	**9.31**	0.043	**6.80**	0.058	**6.34**
Cameroon	0.054	**12.00**	0.043	**12.11**	0.027	**7.63**	0.037	**8.68**
Zambia	0.105	**12.44**	0.074	**9.03**	0.034	**4.91**	0.058	**7.36**
Tanzania	0.051	**7.20**	0.046	**6.52**	0.013	**2.15**	0.024	**3.69**
Zimbabwe	0.042	**3.50**	0.048	**5.83**	0.041	**5.52**	0.031	**2.95**
Ghana	0.027	**3.11**	0.010	**2.14**	0.005	1.11	0.018	**2.06**
Female dummy variable								
Kenya	-0.499	**-4.61**	-0.362	**-4.92**	-0.263	**-4.15**	-0.354	**-3.53**
Burundi	0.169	0.78	0.184	0.96	0.200	0.99	0.151	0.72
Côte d'Ivoire	-0.382	**-2.36**	-0.270	-1.49	-0.392	**-2.16**	-0.511	**-3.07**
Ethiopia	-0.422	**-3.21**	-0.307	**-3.18**	-0.348	**-3.92**	-0.420	**-3.01**
Cameroon	0.007	0.04	0.095	0.84	0.030	0.30	-0.062	-0.44
Zambia	-0.110	-0.58	-0.054	-0.38	-0.256	**-1.72**	-0.281	-1.35
Tanzania	-0.273	**-2.29**	-0.171	**-1.81**	-0.159	**-1.98**	-0.239	**-2.23**
Zimbabwe	-0.641	**-1.74**	0.056	0.31	-0.001	-0.01	-0.648	**-1.95**
Ghana	-0.298	**-2.32**	0.038	0.52	-0.045	-0.64	-0.350	**-2.62**
Female x education								
Kenya	0.043	**3.81**	0.034	**4.59**	0.022	**3.49**	0.025	**2.40**
Burundi	-0.025	-1.29	-0.033	**-2.09**	-0.038	**-2.35**	-0.032	-1.64
Côte d'Ivoire	0.039	**2.19**	0.031	1.58	0.042	**2.07**	0.047	**2.57**
Ethiopia	0.018	1.09	0.005	0.37	0.008	0.64	0.012	0.69
Cameroon	0.004	0.25	-0.010	-0.86	-0.006	-0.57	0.002	0.15
Zambia	0.030	1.26	0.016	0.90	0.037	**1.90**	0.045	1.68
Tanzania	0.012	0.88	0.003	0.26	0.003	0.29	0.007	0.56
Zimbabwe	0.061	**1.73**	-0.008	-0.40	-0.012	-0.63	0.050	1.59
Ghana	0.010	0.76	-0.007	-1.03	-0.001	-0.18	0.014	1.01
Worker characteristics								
Age	0.089	**12.77**	0.057	**11.61**	0.043	**9.81**	0.073	**10.85**
Age squared	-0.001	**-8.54**	0.000	**-6.55**	0.000	**-5.84**	-0.001	**-7.85**
Work experience	-0.016	**-4.56**	-0.009	**-3.81**	-0.004	**-1.88**	-0.010	**-2.87**
Work experience^2	0.000	0.78	0.000	-0.13	0.000	-1.02	0.000	0.07
Length of job tenure	0.016	**5.61**	0.009	**4.08**	0.006	**3.10**	0.013	**4.90**
Job tenure squared	0.000	**-1.73**	0.000	-0.81	0.000	-0.41	0.000	-1.66

The table continues on the next page.

Table 2 continued

	Model 1		Model 2		Model 3		Model 4	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Occupation codes[(a)]								
Management					0.679	**32.46**	0.728	**23.64**
Administration					0.221	**14.35**	0.364	**15.77**
Commercial / Sales					0.127	**5.91**	0.215	**6.45**
Supervisor					0.287	**17.34**	0.391	**15.64**
Technician					0.250	**8.84**	0.359	**9.40**
Maintenance					0.132	**6.00**	0.255	**7.13**
Unskilled production					-0.124	**-7.16**	-0.070	**-2.71**
Apprentice					-0.498	**-7.02**	-0.265	**-2.15**
Craft					0.039	**1.74**	0.143	**4.78**
Support staff					-0.206	**-9.16**	-0.103	**-3.37**
Country dummies	Yes		n.a.		n.a.		Yes	
Country x year dummies	Yes		n.a.		n.a.		Yes	
Firm x year fixed effects	No		Yes		Yes		No	
Observations	16155		16155		16155		16155	
R-squared (within)	0.530		0.203		0.331		0.591	

Note: All regressions are weighted by worker population in each firm and occupation. Standard errors are corrected for clustering by firm and stratification by occupation. n.a. = not applicable.
[(a)] Skilled production worker is the omitted category.

Table 3: Earnings regressions for manufacturing workers in Morocco

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Education	0.045	**10.84**	0.039	**7.01**	0.015	**5.32**	0.027	**7.80**
Female	0.070	**2.06**	0.000	-0.01	-0.074	**-3.08**	-0.022	-0.75
Female x education	-0.023	**-5.90**	-0.014	**-4.80**	-0.003	-1.21	-0.010	**-3.05**
Female x training	-0.097	-0.85	-0.141	**-2.05**	-0.101	-1.39	-0.029	-0.28
Received training from previous employer	0.371	**4.69**	0.290	**5.20**	0.165	**2.80**	0.239	**4.33**
Worker characteristics								
Age	-0.013	-0.95	-0.004	-0.45	-0.004	-0.75	-0.009	-1.09
Age squared	0.000	**1.73**	0.000	**2.12**	0.000	**1.88**	0.000	1.18
Work experience	0.016	**3.04**	0.015	**2.82**	0.012	**4.50**	0.016	**4.27**
Work experience^2	0.000	**-3.20**	0.000	**-5.18**	0.000	**-5.72**	0.000	**-3.22**
Length of job tenure	0.012	**2.31**	0.018	**5.52**	0.014	**5.20**	0.012	**2.50**
Job tenure squared	0.000	1.56	0.000	**-1.82**	0.000	-1.27	0.000	1.63
First job	-0.049	**-2.02**	-0.049	**-3.30**	-0.048	**-3.91**	-0.063	**-3.13**
Wage reported net of taxes	-0.134	**-5.53**	-0.116	**-2.99**	-0.084	**-2.48**	-0.134	**-6.14**
Occupation codes[(a)]								
Upper management					1.026	**25.03**	1.030	**17.72**
Middle management					0.671	**23.85**	0.841	**20.49**
Unskilled worker					-0.242	**-19.11**	-0.207	**-8.79**
Support and administrative staff					-0.027	-1.28	0.095	**2.85**
Current year	0.014	0.61	n.a.		n.a.		0.014	0.66
Firm x year fixed effects	No		Yes		Yes		No	
Observations	13700		13700		13615		13615	
R-squared (within)	0.319		0.264		0.486		0.471	

Note: All regressions are weighted by worker population in each firm and occupation. Standard errors are corrected for clustering by firm and stratification by occupation. n.a. = not applicable.
[(a)]Skilled worker is omitted category.

Table 4: Earnings regressions for manufacturing workers in Algeria

	Model 1		Model 2		Model 3		Model 4	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Education	0.052	**10.34**	0.036	**9.70**	0.018	**5.37**	0.030	**7.82**
Female	-0.189	**-3.02**	-0.243	**-5.62**	-0.217	**-4.92**	-0.196	**-3.59**
Female x education	0.003	0.57	0.007	**2.25**	0.007	**1.98**	0.004	1.02
Female x training	0.026	0.34	0.021	0.35	0.035	0.69	0.027	0.41
Received training from previous employer	0.023	0.54	-0.001	-0.04	-0.015	-0.52	0.002	0.07
Worker characteristics								
Age	0.021	**2.41**	0.024	**3.10**	0.022	**3.13**	0.015	**1.73**
Age squared	0.000	**-2.71**	0.000	**-2.63**	0.000	**-2.74**	0.000	**-2.20**
Work experience	0.014	**2.91**	0.006	1.52	0.004	1.03	0.012	**2.70**
Work experience^2	0.000	0.44	0.000	0.32	0.000	0.13	0.000	-0.29
Length of job tenure	0.006	**1.98**	0.014	**5.35**	0.012	**4.71**	0.006	**2.32**
Job tenure squared	0.000	0.00	0.000	**-2.51**	0.000	**-2.33**	0.000	-0.27
First job	-0.037	**-1.99**	-0.043	**-2.25**	-0.044	**-2.36**	-0.043	**-2.44**
Occupation codes[a]								
Upper management					0.623	**14.77**	0.575	**10.68**
Middle management					0.220	**12.46**	0.268	**7.26**
Unskilled worker					-0.143	**-7.33**	-0.187	**-5.61**
Support and administrative staff					-0.053	**-3.09**	-0.067	**-2.76**
Current year	0.050	**2.22**	n.a.		n.a.		0.054	**2.68**
Firm x year fixed effects	No		Yes		Yes		No	
Observations	6448		6448		6448		6448	
R-squared (within)	0.314		0.271		0.346		0.383	

Note: All regressions are weighted by worker population in each firm and occupation. Standard errors are corrected for clustering by firm and stratification by occupation. n.a. = not applicable.
[a]Skilled worker is omitted category.

Table 5: Education Wage Gap in African Manufacturing

		Model 1	Model 2	Model 3	Model 4
Algeria	Men	5.2%	3.6%	1.8%	3.0%
	Women	5.5%	4.3%	2.5%	3.5%
Burundi	Men	9.1%	9.2%	8.5%	8.0%
	Women	6.5%	5.9%	4.8%	4.8%
Cameroon	Men	5.4%	4.3%	2.7%	3.7%
	Women	5.8%	3.3%	2.1%	3.9%
Cote d'Ivoire	Men	4.3%	3.2%	1.3%	2.1%
	Women	8.2%	6.4%	5.4%	6.8%
Ethiopia	Men	8.2%	6.7%	4.3%	5.8%
	Women	10.0%	7.2%	5.0%	7.0%
Ghana	Men	2.7%	1.0%	0.5%	1.8%
	Women	3.7%	0.3%	0.4%	3.2%
Kenya	Men	6.0%	3.7%	2.3%	3.7%
	Women	10.4%	7.1%	4.5%	6.2%
Morocco	Men	4.5%	3.9%	1.5%	2.7%
	Women	2.1%	2.5%	1.2%	1.7%
Tanzania	Men	5.1%	4.6%	1.3%	2.4%
	Women	6.3%	4.9%	1.6%	3.1%
Zambia	Men	10.5%	7.4%	3.4%	5.8%
	Women	13.5%	9.0%	7.1%	10.3%
Zimbabwe	Men	4.2%	4.8%	4.1%	3.1%
	Women	10.3%	4.1%	3.0%	8.1%
Average	Men	5.9%	4.8%	2.9%	3.8%
	Women	7.5%	5.0%	3.4%	5.3%

Note: Estimates are based on the regression results shown in Tables 2-4.

Table 6: Regression firm fixed effects on firm characteristics

	Morocco		Algeria		SSA	
	Coef.	**t-stat.**	Coef.	**t-stat.**	Coef.	**t-stat.**
Capital	0.043	**6.21**	0.010	**1.79**	4.6E-04	0.09
Labor	0.048	**4.92**	0.038	**2.78**	0.117	**12.92**
Sector dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		n.a.	
Country x year dummies	n.a.		n.a.		Yes	
Country dummies	n.a.		n.a.		Yes	
R-squared	0.142		0.109		0.540	
Observations	1425		666		2753	

Table 7: Returns to employer-specific tenure and general experience

A. Effect of an additional year of tenure (experience effect ignored)						
	Years		**model 1**	**model 2**	**model 3**	**model 4**
SSA	1		1.5%	0.9%	0.6%	1.3%
	10		1.2%	0.8%	0.6%	1.0%
	20		0.9%	0.7%	0.5%	0.7%
	30		0.6%	0.6%	0.5%	0.4%
Morocco	1		1.2%	1.8%	1.4%	1.2%
	10		1.7%	1.4%	1.2%	1.7%
	20		2.3%	0.9%	1.0%	2.3%
	30		2.9%	0.5%	0.8%	2.9%
Algeria	1		0.6%	1.3%	1.2%	0.6%
	10		0.6%	1.1%	0.9%	0.6%
	20		0.6%	0.8%	0.7%	0.5%
	30		0.6%	0.5%	0.4%	0.5%
B. Effect of an additional year of experience (tenure effect ignored)						
	Age	Experience				
	Years	**Years**				
SSA	20	1	4.2%	3.1%	2.5%	3.6%
	30	11	2.8%	2.2%	1.8%	2.3%
	40	21	1.3%	1.3%	1.0%	0.9%
	50	31	-0.1%	0.5%	0.2%	-0.4%
Morocco	20	1	1.7%	1.9%	1.3%	1.2%
	30	11	1.6%	1.7%	1.1%	1.0%
	40	21	1.5%	1.5%	0.8%	0.7%
	50	31	1.4%	1.2%	0.5%	0.5%
Algeria	20	1	2.3%	2.0%	1.6%	1.8%
	30	11	1.8%	1.5%	1.1%	1.3%
	40	21	1.3%	1.0%	0.7%	0.8%
	50	31	0.8%	0.6%	0.2%	0.3%

Note: Estimates are based on the regression results shown in Tables 2-4.

Figure 1: Earnings-Education Profiles in Côte d'Ivoire, Cameroon and Ghana

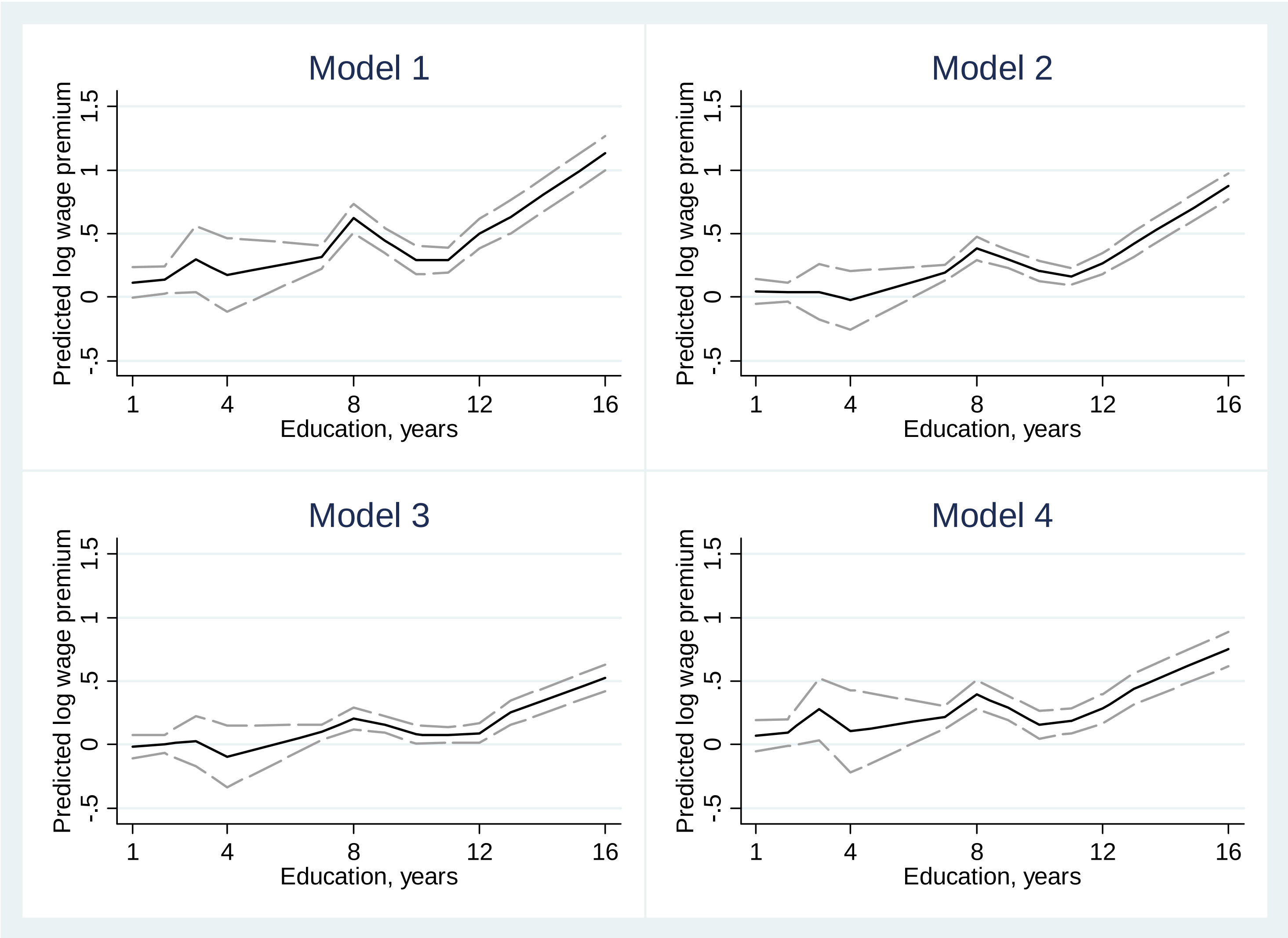

Figure 2: Earnings-Education Profiles in Burundi, Ethiopia and Tanzania

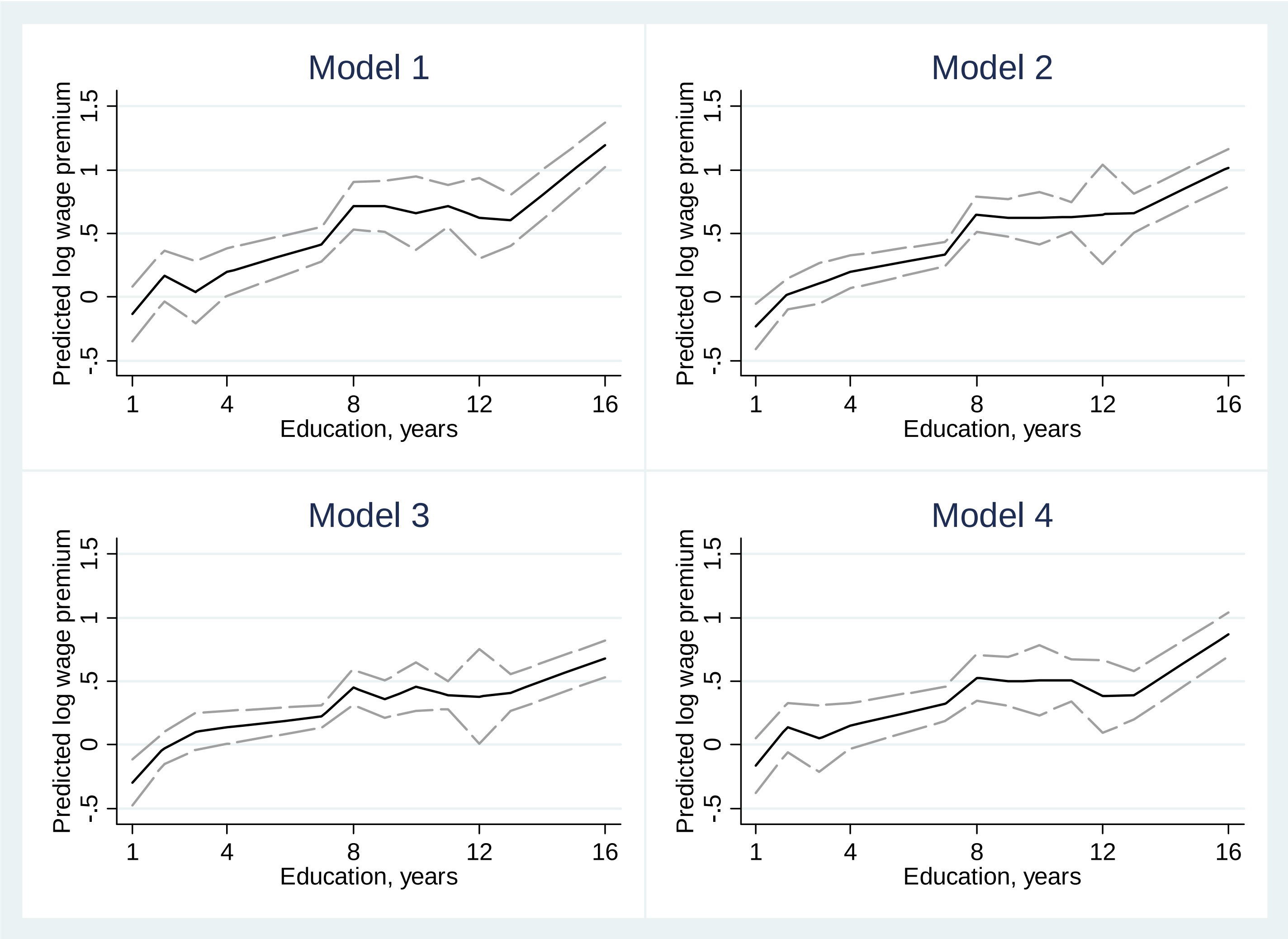

Figure 3: Earnings-Education Profiles in Kenya, Zambia and Zimbabwe

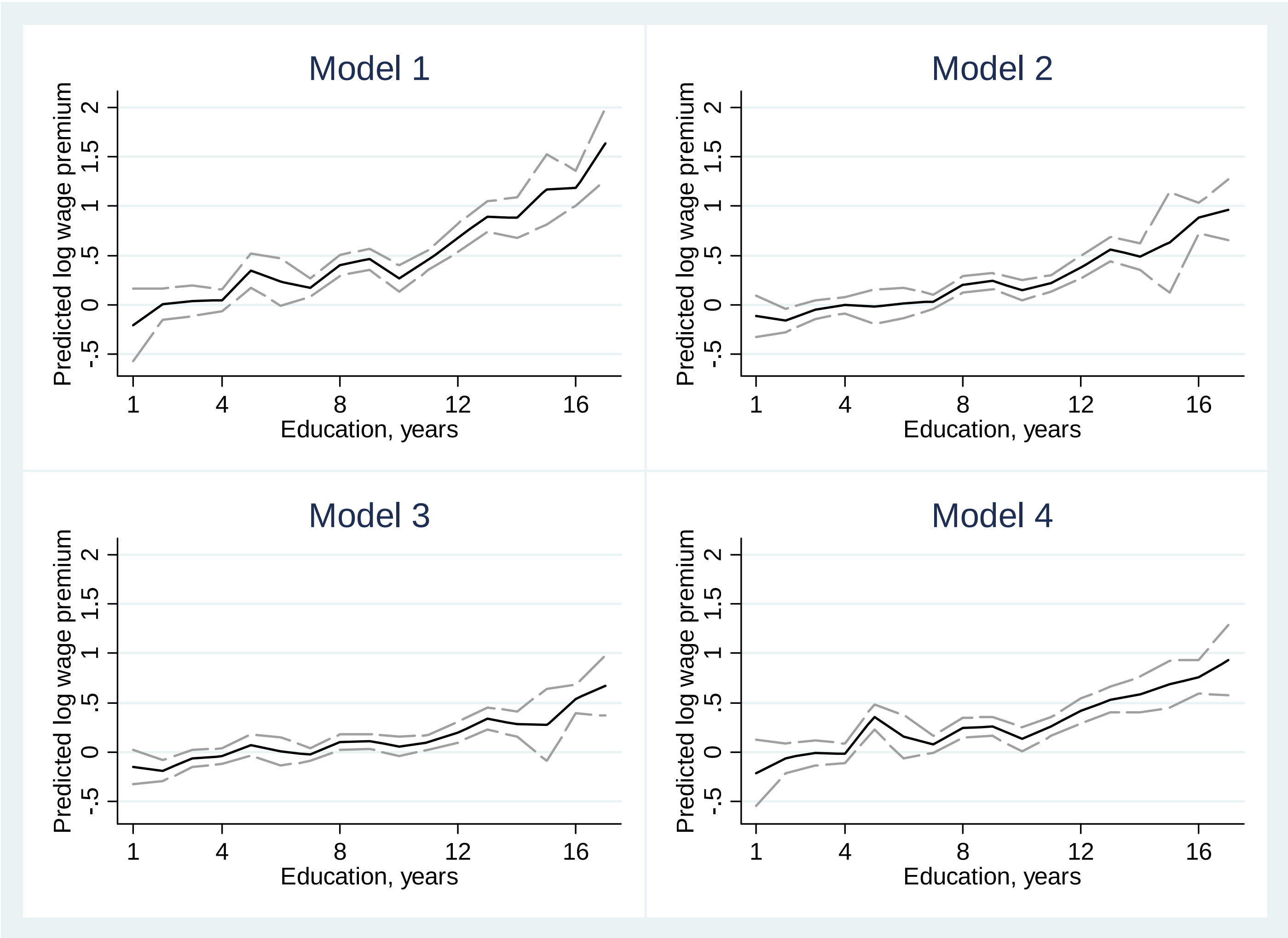

Figure 4: Earnings-Education Profiles in Algeria

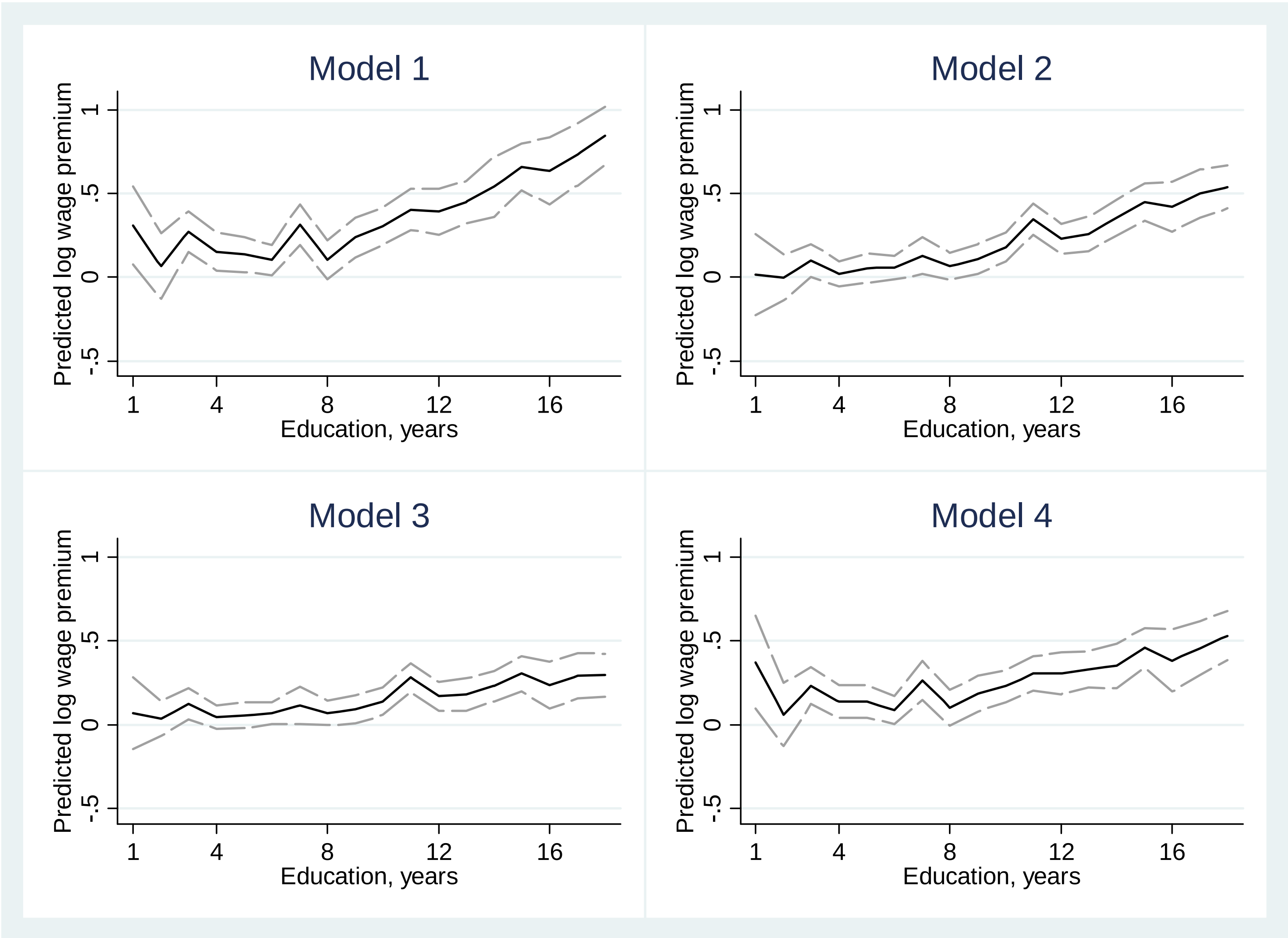

Figure 5: Earnings-Education Profiles in Morocco