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Wages Equal Productivity. Fact or Fiction?

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Abstract

If labor markets operated entirely frictionless, productivity premiums associated with different worker characteristics would equal the wage premiums earned by workers possessing those characteristics. Using matched employer-employee data from the manufacturing sector of three sub-Saharan countries, we evaluate to what extent the two premiums differ for four characteristics that are clearly related to human capital: schooling, training, experience, and tenure. Equality holds strongly and even surprisingly well for firms in Zimbabwe (the most developed country in the sample), but not at all in Tanzania (the least developed country), while results in Kenya are intermediate. Where equality fails, the pattern is for general human capital characteristics (schooling, experience) to receive a wage return that exceeds the productivity return, while the reverse applies to more firm-specific human capital characteristics (training, tenure). Schooling tends to be over-rewarded, even though large productivity gains are consistently associated with formal employee training programs. Wages tend to rise with experience, while productivity gains are mostly associated with tenure. We demonstrate the remarkable robustness of the findings controlling, among other things, for sampling errors, nonlinear effects, and non-wage benefits. Localized labor markets and imperfect substitutability of different worker-types provide a partial explanations for the estimated gap between the wage and productivity premiums.

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1 Introduction

In the textbook economics world, markets are the most efficient institution to allocate scarce resources. They clear all the time, equalizing demand and supply, and profit opportunities are arbitraged away. In particular, production factors are predicted to be paid the marginal productivity of the market clearing factor. In the real world, there are frictions, unobservable characteristics, adjustment costs, erroneous expectations, and maybe discrimination; all of which can distort the market equilibrium away from efficient allocation. This should not necessarily worry us, economists, as the theory is only intended to be a stylized version of reality. However, a systematic gap between costs (wages) and benefits (productivity) can provide information about crucial omissions from the theory.

A well-functioning labor market should perform at least two tasks: matching workers with firms and setting wages. The ability of the labor market to allocate workers to firms or industries with the highest productivity or the best future prospects is of particular importance for the likely effect of trade reforms, and this has been studied extensively—see Pavcnik (2002), Eslava, *et al.* (2004), and Filhoz and Muendler (2006) for studies on Latin American countries. Van Biesebroeck (2005) investigates the effectiveness of labor markets in several African countries, including the three countries studied here, in performing this task and finds that the reallocation mechanism is less effective than in the United States.

A second aspect of labor market efficiency is to determine a wage rate. If labor markets function as spot markets with minimal frictions and informational asymmetries, we would expect arbitrage to equalize the remuneration of characteristics to their productivity. Otherwise, workers are not provided with the proper incentives to invest in human capital characteristics, such as schooling or tenure. While an important issue, it has not been studied extensively because of lack of suitable data. Employee surveys do not contain information on firm level output and factor inputs necessary to assess productivity. Data sets of firms or plants generally lack information on all but a few basic characteristics of their workforce, e.g. the fraction of male workers.

Matched employer-employee data sets contain the necessary information, but these are not widely available.[1] One can use the observed employees to estimate average values of worker characteristics by employer. Hellerstein, Neumark, and Troske (1999) pioneered the approach, jointly estimating a plant level wage equation with a production function. Using U.S. administrative record information, they test for equality of the wage and productivity premiums associated with a number of characteristics. They only find a discrepancy for the gender dummy: women are estimated to be only 16% less productive than their male coworkers, but paid 45% less.

The bulk of the evidence for developed countries points towards equal wage and productivity

[1] A conference symposium in the *Monthly Labor Review* (July 1998) and the book by Haltiwanger, *et al.* (1999) provide overviews.

returns for most characteristics.[2] Most recently, using 1990 U.S. data, Hellerstein and Neumark (2004) confirms that the wage gap between males and females exceeds the productivity gap. In contrast, the lower wages for blacks are in line with productivity estimates, and even though 'some college' education only attracts a 43% wage premium while it is associated with a 67% productivity boost, the difference is not statistically significant. Similar work for France in Pérez-Duarte, *et al.* (2001) and for Israel in Hellerstein and Neumark (1999) finds no gender discrimination. The only characteristic with a wage premium significantly different from the productivity effect is age in France, older workers are overpaid, while engineers are underpaid in Israel.

For developing countries, Jones (2001) estimates a firm level production function jointly with an individual-level wage equations for Ghana.[3] She finds that women are 42% to 62% less productive and paid 12% to 15% less. No formal test is reported, but the standard errors are fairly large. Her focus is on the reward for an extra year of schooling, which is estimated to equal the productivity gain associated with education, both are 7% per year. When discrete levels of education attainment are used, the results are ambiguous. The differences in point estimates are large, but especially the coefficients in the production function are estimated imprecisely and none of the formal tests finds a statistically significant difference.[4] Bigsten, *et al.* (2000) gauge the link between wages and productivity indirectly. First, they estimate the returns to education in five sub-Saharan countries using a standard wage equation. Then, they separately estimate the production function, including lagged levels of education as a proxy for human capital. They find that the implied rate of return to human capital is very low, in particular only a fraction of the return to physical capital.

Labor market frictions are likely to be at least as important in developing countries as in more mature economies. As stressed by Fafchamps (1997) in the introduction to a symposium on "Markets in Sub-Saharan Africa", one should be careful not to assume outright that markets are efficient, regardless of the institutions required to perform their function. The contribution of this paper is foremost to provide information on the wage-productivity gap for three more sub-Saharan countries: Tanzania, Kenya, and Zimbabwe. All three countries are relatively poor, but during the sample period the GDP per capita for Zimbabwe exceeded that for Tanzania by a factor of six, while Kenya was intermediately developed. We focus on four human capital characteristics: experience, schooling, tenure, and employee training programs. The latter two are adjusted continuously while workers are in the workforce. A crucial function of the wage setting is to provide workers with the correct investment incentives for these.

Following the methodology in Hellerstein, *et al.* (1999), we compare the salary remuneration

[2] Limited to discretely measured characteristics.

[3] No details are given on the assumptions on the variance-covariance matrix when the individual and firm level data is combined. Van Biesebroeck (2007) outlines one possible set of assumptions and finds results in line with those in this paper.

[4] Many differences are large in absolute value—five of the eight estimated differentials exceed 20%—but the direction of the difference varies by schooling level.

for workers' characteristics to the contribution the same characteristics make to output. As the analysis is carried out at the firm level, the nature of the comparison is implicitly between wage bill and output differences between firms that vary in the average characteristics of their workforce. A methodological contribution of the paper is to incorporate a consistent aggregation method to the firm level when human capital for individual workers varies with continuously measured characteristics. This is particularly important when diminishing returns are allowed for. For example, we show that when a squared term on experience is included in the Mincer wage equation, one needs to include the average variance of experience within firms in the firm level wage regression.

The main findings are summarized here. In Tanzania, the poorest country of the three, the wage premiums deviate substantially and significantly from the corresponding productivity premiums. The wedge between wage and productivity returns are much smaller and all are insignificant in relatively more developed Zimbabwe. Results for Kenya, an intermediate country in level of development, are intermediate: equal remuneration can be rejected for some characteristics (e.g. experience), but not for others (e.g. schooling). The breakdown in correct remuneration is most pronounced for characteristics that contributed to general—as opposed to firm-specific—human capital: schooling and experience.

Moreover, the way in which equality fails to hold is similar for the experience-tenure and the schooling-training comparison. Contrast the pattern of wage and productivity premiums for pre-employment schooling (building mostly general skills) and formal employee training programs (building more firm-specific human capital). The productivity advantage for firms that employ a lot of 'trained' workers is large and relatively uniform across countries, ranging from 45% in Zimbabwe to 75% in Kenya. Only a fraction of these productivity gains accrue to the worker in the form of higher salary in Tanzania (only one sixteenth of the total) or in Kenya (one quarter). Trained Zimbabwean workers, however, receive a salary premium that exceeds the direct productivity gain, possibly because the effects spill over and improve the productivity of co-workers. Note that the productivity effect of training could be due to selection or to human capital building. In contrast, productivity returns to schooling are modest in Tanzania and Kenya (1.6% and 2.1% per year), even though each additional year of formal eduction is rewarded by large salary increases, 6.6% in Tanzania and even 9.4% in Kenya. In Zimbabwe, the productivity and salary premiums associated with schooling are large and of similar magnitude. Such a mismatch between productivity effects and salary compensation will provide the wrong incentives for workers, from a social point of view.

A number of robustness checks indicate that the failure for wage and productivity premiums to equalize is not driven by the way characteristics are measured, the functional form of the production function, the controls included in the equations, nor by diminishing returns to characteristics or sampling error. Unobservable components to the worker remuneration or measurement error in capital are also unlikely to cause the patterns.

Allowing for imperfect substitution between workers with high and low levels of experience reduces the gap for schooling, but the gap for experience remains. When we perform the analysis including only firms from a single geographic area in each country, the gaps diminish substantially for Kenya (Nairobi), suggesting that localized labor markets could be important, but for Tanzania (Arusha) the differences remain. We also discuss frictions in the matching process between workers and firms and long-term contracts which could in principle explain the gap between instantaneous wage and productivity returns.[5] It is unclear, however, why these issues should be disproportionately important for Tanzania.

There are several important debates in development or labor economics that would benefit from a better understanding of the relationship between wages and productivity. First, Knight and Sabot (1987) argue that the higher output growth in Kenya in the first decades since independence—relative to the otherwise similar Tanzania—can be explained to a large extent by the differential access to secondary education. They advocate increased investment in education as an important tool for development. The Tanzanian firms in this sample have, on average, a more educated workforce, but the productivity effects of schooling fall far short of the wage effects. It illustrates that higher education does not translate automatically into higher output.

Second, measurement of productivity growth relies explicitly on the equality of relative wages and relative productivity. Labor productivity growth is calculated by subtracting labor growth from output growth, weighing categories of workers by their wage shares, see for example Jorgenson and Griliches (1967). If the equality between wages and productivity fails to hold systematically in developing countries, productivity growth measures will be biased.

Third, the debate on the importance of firm specific human capital investments as captured by the return to tenure—see Topel (1991) and Altonji and Williams (2005)—is centered around the wage equation. Implicitly it is assumed that wage increases must reflect productivity advances. On the same topic, Brown (1989) finds that wage increases within a plant occur predominantly when on-the-job training is taking place. He concludes that such pattern of remuneration supports the link between wages and productivity, as opposed to contractual reasons for such a remuneration pattern as stressed by theoretical principal-agent models. Direct estimates of wage and productivity premiums would contribute useful information to this debate.

The remainder of the paper is organized as follows. The measurement framework to compare wage and productivity premiums associated with worker characteristics is introduced in Section 2. The countries and the employer-employee data are discussed next, in Section 3. Baseline results are presented in Section 4 and several checks in Section 5 illustrate the robustness of the findings. In Section 6, a number of reasons that might explain why equality fails to hold are explored. Section 7 concludes.

[5] Yet an alternative channel, profit sharing between firms and workers, is discussed by Velenchik (1997) in a study of urban labor markets in Zimbabwe. She provides evidence that profit growth has a positive coefficient in an individual wage growth regression.

2 A measurement framework

The methodology owes a great deal to Hellerstein, *et al.* (1999). If labor markets are efficient, operate as a spot market, and firms are minimizing costs, the wage premium of a worker should equal its productivity premium. Barring imperfect information, any difference will be arbitraged away. Both premiums can be identified by jointly estimating a wage equation and production function at the firm level. As an example, assume that the average productivity of male workers exceeds the productivity of female workers by ϕ_M percentage. With perfect substitutability between men and women, which is relaxed later (see Section 6.1), the production function can be written as a function of capital and both types of labor,[6]

$$Q \;=\; A\ f(K,\ L_F +\ (1+\phi_M)L_M).$$

The first order conditions for cost minimizing input choices of the firm entail that in an efficient labor market the relative wage for both types of workers should equal their relative productivity:

$$\begin{aligned} \frac{w_M}{w_F} &= \frac{MP_M}{MP_F} = \frac{\partial Q/\partial L_M}{\partial Q/\partial L_F} \equiv 1+\phi_M \\ \lambda_M \equiv \frac{w_M - w_F}{w_F} &= \frac{MP_M - MP_F}{MP_F} \equiv \phi_M. \end{aligned} \tag{1}$$

Jointly estimating the wage (λ_M) and productivity (ϕ_M) premiums associated with each characteristic makes it possible to test for the equality in equation (1) for several characteristics individually or jointly. Traditionally, researchers have been concerned with a potential bias introduced by unobserved worker ability in the wage equation or unobserved productivity in the production function. Joint estimation should alleviate such concerns as the bias works in the same direction in both equations. The unobservables are to a large extent two sides of the same coin.[7] We are only interested in the relative magnitudes of the coefficients in each equation, which should be less affected. In the robustness checks, see Section 5.2, this is discussed further.

Discrete characteristics

Assuming the Cobb-Douglas functional form, the production function can be written in logarithms as[8]

$$\ln Q \;=\; \ln A + \alpha_K \ln K + \alpha_L \ln \tilde{L} + \epsilon_q.$$

Male and female workers are combined in the labor aggregate $\tilde{L}$, where each type of employee (L_F or L_M) is multiplied by its relative productivity level (1 or $1+\phi_M$). It will be useful to

[6] Firm and time subscripts are omitted from all equations and derivation. In the next section, the firm level panel data used for estimation is discussed‘.

[7] Frazer (2001) exploits this assumption to control for unobserved ability in the wage equation with the productivity residual.

[8] It is straightforward to generalize the methodology to other functional forms. We report results for a translog production function in the robustness checks, see Section 5.2.

rewrite $\tilde{L}$ as

$$\begin{aligned}\tilde{L} &= L_F + (1+\phi_M)L_M \\ &= L[1+\phi_M \frac{L_M}{L}].\end{aligned} \tag{2}$$

The last term is simply the fraction of male workers in the total labor force ($L = L_F + L_M$). Substituting (2) in the production function allows estimation of the gender productivity gap by nonlinear least squares from just the proportion of male workers in each firm and the usual output and input variables.

For joint estimation, we derive a firm level wage equation consistent with the Mincer (1974) model of human capital. Sticking with the earlier example, define a wage equation at the individual level as,

$$W_i = w_F F_i + w_M M_i.$$

The average wage paid to women is w_F—F_i is dummy that takes on a value of one if individual i is a women—and w_M to men. Summing over all employees at the firm gives an expression for the total wage bill,

$$\begin{aligned}W &= w_F L_F + w_M L_M \\ &= w_F[L + (\frac{w_M}{w_F} - 1)L_M] \\ &= w_F\, L\, [1 + \lambda_M \frac{L_M}{L}].\end{aligned}$$

Taking logarithms and adding an additive error, representing measurement error in the wage and unobservable worker characteristics, gives an estimable wage equation at the firm level,

$$\ln \frac{W}{L} = \ln w_F + \ln[1 + \lambda_M \frac{L_M}{L}] + \epsilon_w. \tag{3}$$

Nonlinear least squares estimation will produce an estimate of the average baseline wage (for female workers) and of the gender wage premium. The only information needed is the average wage and the proportion of male workers at the firm.

Generalizing this approach to construct a wage and production equation with workers that differ on more dimensions is limited by the data. At the very least, we want to differentiate workers by gender, experience and schooling. If each characteristic divides workers into two groups, three characteristics define eight categories of workers (unexperienced, educated males, etc.). Given that we observe a maximum of ten workers in each firm, the proportion of each firm's workforce that falls in either of the eight categories will be estimated extremely inaccurately.

If we are willing to assume that for each characteristic the relative number of workers, wages, and productivity in either group is the same for each of the four possible groups defined by the other two characteristics, we can avoid this type of dimensional problem. In effect, this is an "independence of irrelevant alternatives" assumption on the relative number of workers and the wage and productivity returns for each characteristic. We have to assume, for example, that the relative number of male to female workers, is the same in each experience-schooling category, and similarly for the relative wages and productivity by gender. If gender is indicated by M or F subscript, experience by Y or X (young versus high experience), and schooling by U or S (uneducated versus high schooling), we make three sets of assumptions for the gender variable:

$$\begin{aligned} \text{equal numbers:} \quad & \frac{L_{\mathbf{M}YS}}{L_{\mathbf{F}YS}} = \frac{L_{\mathbf{M}XS}}{L_{\mathbf{F}XS}} = \frac{L_{\mathbf{M}YU}}{L_{\mathbf{F}YU}} = \frac{L_{\mathbf{M}XU}}{L_{\mathbf{F}XU}}, \\ \text{equal productivity:} \quad & \frac{\phi_{\mathbf{M}YS}}{\phi_{\mathbf{F}YS}} = \frac{\phi_{\mathbf{M}XS}}{\phi_{\mathbf{F}XS}} = \frac{\phi_{\mathbf{M}YU}}{\phi_{\mathbf{F}YU}} = \frac{\phi_{\mathbf{M}XU}}{\phi_{\mathbf{F}XU}}, \\ \text{equal wage premium:} \quad & \frac{\lambda_{\mathbf{M}YS}}{\lambda_{\mathbf{F}YS}} = \frac{\lambda_{\mathbf{M}XS}}{\lambda_{\mathbf{F}XS}} = \frac{\lambda_{\mathbf{M}YU}}{\lambda_{\mathbf{F}YU}} = \frac{\lambda_{\mathbf{M}XU}}{\lambda_{\mathbf{F}XU}}, \end{aligned} \tag{4}$$

and similarly for all other characteristics, e.g. $L_{MY\mathbf{U}}/L_{MY\mathbf{S}} = L_{FY\mathbf{U}}/L_{FY\mathbf{S}} = ...$

These assumptions allows us to simplify the labor aggregate in the production function from eight additive terms, one for each worker category, to three multiplicative factors, one for each characteristic:

$$\begin{aligned} \tilde{L} &= L_{FYS} + (1+\phi_{FXS})L_{FXS} + (1+\phi_{MYS})L_{MYS} + ... + (1+\phi_{MXU})L_{MXU} \\ &= L\ [1+\phi_M \frac{L_M}{L}]\ [1+\phi_X \frac{L_X}{L}]\ [1+\phi_S \frac{L_S}{L}]. \end{aligned} \tag{5}$$

The assumptions on the wage premiums in (4) are customarily made in Mincer wage regressions. Aggregating as before leads to additive terms for all charateristics in the firm level log wage regression as well. Controlling for further characteristics in human capital, now requires adding additional factors to (5). With more characteristics, it becomes even more indispensable to make the assumptions, as in (4), that all ratios are equal conditional on the other characteristics. These assumptions cannot be tested, or we would have avoided making them. In the small sample of employees we observe at each firm, some ratios will obviously not be equal, but this can readily arise if only a limited number of employees are sampled.[9] The assumption of perfect substitutability between workers with different characteristics is relaxed below, in Section 6.1.

The baseline model constructed so far is

$$\ln \frac{W}{L} = \lambda_0 + \ln(1+\lambda_M \frac{L_M}{L}) + \ln(1+\lambda_X \frac{L_X}{L}) + (1+\lambda_S \frac{L_S}{L}) + \epsilon_w \tag{6}$$

$$\begin{aligned} \ln Q &= \alpha_0 + \alpha_K \ln K \\ &+ \alpha_L[\ln L + \ln(1+\phi_M \frac{L_M}{L}) + \ln(1+\phi_X \frac{L_X}{L}) + \ln(1+\phi_S \frac{L_S}{L})] + \epsilon_q \end{aligned} \tag{7}$$

where $\lambda_0 = w_{FYU}$ is the base salary for a female, inexperienced, uneducated worker. λ_M, λ_X, and λ_S are the wage premiums associated with gender, experience (high versus low), and education

[9] In some cases, enough workers are observed that the assumptions in (4) can be rejected, e.g. for some small firms all employees are sampled. To rationalize such observations, we have to invoke some measurement error.

(high versus low). Ideally we would like to weight the workers by hours worked to construct the employment fractions, but this variable is only available at the firm level averaged over the entire workforce. Equations (6) and (7) are estimated jointly with Zellner's seemingly unrelated regression estimator, allowing for correlation between the two error terms.

Continuous characteristics

Virtually all previous studies use only discrete characteristics, which require a separate additive term for each type of worker, e.g. high versus low levels of schooling: $(1 + \phi_S \frac{L_S}{L})$. If schooling were defined more finely, e.g. distinguishing between elementary (benchmark), secondary (S_s), and tertiary (S_t) education, the adjustment to the schooling term would be straightforward: $(1 + \phi_{S_s} \frac{L_{S_s}}{L} + \phi_{S_t} \frac{L_{S_t}}{L})$. Clearly, with only ten workers observed per firm, this approach has limits.

When characteristics vary continuously, such as schooling or experience, the derivation of both (firm level) equations is more complicated. Frazer (2001) demonstrates how to derive a human capital term in the production function consistent with Mincer (1974). The labor composite $\tilde{L}$ in (5) can be written as the sum over all workers L_j with each type of worker j multiplied by its human capital component. The productivity adjustment takes the form of $e^{\phi_0 + \phi_S S_j + \phi_X X_j}$, if types differ by schooling and experience. In the continuous case, ϕ_S measures how effective labor varies with schooling, $(\partial \ln \tilde{L} / \partial S)$. The productivity effect of schooling also depends on the importance of labor in production, $\partial \ln Q / \partial S = \alpha_L \phi_S$. A first order Taylor approximation of the production function with the nonlinear human capital factors produces a log-linear equation.[10] The logarithm of output is a function of capital and labor, also in logarithms, and the average schooling attainment and experience over all workers in the firm:

$$\ln Q \;\; = \;\; \alpha_0 + \alpha_K \ln K + \; \alpha_L \; [\ln \bar{L} \; + \; \phi_X \bar{X} \; + \; \phi_S \bar{S} \;] \; + \; \epsilon \qquad (7')$$

The derivation of the firm level wage equation is similar, with λ_S and λ_X capturing the (marginal) wage premiums associated with schooling and experience ($\partial \ln W_i / \partial S$ and $\partial \ln W_i / \partial X$). With continuously measured variables, arbitrarily cutoff levels are avoided. For education, plausible cutoff levels are suggested at years when degrees are conferred, but for experience or tenure the classification of workers is arbitrary. Gender and other inherently discrete characteristics can be taken into account as before, replacing $\bar{L}$ in (7′) by $L \; (1 + \phi_M \dfrac{L_M}{L})$. The limited model allowing for continuous characteristics that we take to the data is

$$\ln \frac{W}{L} \;\; = \;\; \lambda_0 + \ln(1 + \lambda_M \frac{L_M}{L}) + \lambda_X \overline{X} + \lambda_S \overline{S} + \epsilon_w \qquad (8)$$

[10] Frazer (2001) further illustrates that a second order approximation of the production function consistent with a Mincer wage regression with continuous experience and schooling measures involves the inclusion of variance and covariance terms of the characteristics by firm in the equations. Details on the derivation are in the Appendix. Because of the limited number of workers per firm in our sample (a maximum of 10), we refrain from doing so. When the returns for characteristics are modeled as quadratic instead of linear, see Section 5.3, we are forced to introduce a second order approximation.

$$\ln Q \quad = \quad \alpha_0 + \alpha_K \ln K + \alpha_L[\ln L + \ln(1 + \phi_M \frac{L_M}{L}) + \phi_X \overline{X} + \phi_S \overline{S}] + \epsilon_q. \tag{9}$$

The full models adds continuous terms for years of tenure ($\phi_T \overline{T}$) and a discrete term for the share of workers that followed a formal training program ($\ln(1 + \phi_R \frac{L_R}{L})$).

3 Data

<u>*Countries*</u>

The three countries included in the sample—Tanzania, Kenya, and Zimbabwe—are middle-sized former British colonies in East Africa that differed substantially in level of development.[11] Although the World Bank classified all three as low income, their GDP per capita (in PPP in 1992) ranged from \$395 in Tanzania, less than half the \$1089 of Kenya, to a level almost six times as high in Zimbabwe (GDP per capita of \$2459). The differences are smaller comparing the U.N. human development index, which also takes education and life expectancy into account, but the ordering is the same. In the 1992 ranking (published in 1994), Tanzania occupies the 148th place with 0.306, putting it in the low development category. Kenya and Zimbabwe rank rather closely at places 125 and 121, with scores of 0.434 and 0.474, near the bottom of the medium development group.[12]

[Table 1]

The different development levels of the countries is mirrored in the share of workers employed in industry.[13] Only 4.7% of employment in Tanzania is in industry, while it is almost twice as high in Zimbabwe (8.6%) and intermediate in Kenya (7.3%). In Tanzania, the transition from agriculture to other sectors had only just begun; agriculture comprised almost half the workforce at the end of the 1990s. In Kenya, the transformation was in full swing; the employment share of agriculture declined from 42% in 1975 to 27.5% by the sample period. Zimbabwe, in contrast, has seen a stable 18.5% of its workforce employed in agriculture for the last 25 years.

Given that Zimbabwe is much more advanced in its industrial transformation, it is not surprising that it far surpasses the other two countries in GDP per capita. The difference in labor productivity in industry is even more stark. While industry workers in Kenya produce twice as much as Tanzanian workers, Zimbabwe's output per worker outstrips Tanzania by a factor of

[11] Unfortunately, only three countries could be included in the analysis. A partial analysis was possible with data from Cameroon (almost as developed as Zimbabwe) and Burundi (even less developed than Tanzania), but the sample sizes are smaller, some variables (e.g. capital) are measured less accurately, and other variables (e.g. training in Burundi) are missing. Results for these countries are in between the extremes of Tanzania and Zimbabwe. The failure of the equalities to hold exactly is more pronounced for Burundi than Cameroon: the p-values for the joint test in Table 2(a) were respectively 0.03 and 0.22.

[12] Canada topped the ranking with a score of 0.932 and Guinea closed it with a score of 0.191.

[13] Manufacturing employment that matched manufacturing value added was not available for Tanzania in 1992.

1 to 7 and Kenya 1 to 4. It underscores the importance of developing a strong manufacturing sector. World Bank (2000) statistics show that manufacturing workers in Tanzania earn on average 3.5 times more than agricultural workers, while the ratio stands at 5.7 in Kenya and even at 9.9 in Zimbabwe.

Infrastructure statistics, from the World Bank Development Report, confirm the different levels of development of the three countries. Zimbabwe has 22km of paved highways per 1000 km^2 of land, while the corresponding numbers for Kenya and Tanzania are 15km and 4km. The same ranking is preserved in kilometers of railroad by area, at respectively eight, five, and four kilometers, or airports per million inhabitants, 1.4 in Zimbabwe, 0.6 in Kenya and 0.3 in Tanzania. In fact, almost any conceivable statistic that one expects to be correlated with development produces the same ranking: access to clean water, telephone penetration, school enrollment, infant mortality, etc.[14]

Tanzania and Kenya each counted approximately 25 million inhabitants, while Zimbabwe only had 10 million in 1992. The manufacturing sector, which we will focus on, is more evenly sized because of its much greater importance in Zimbabwe. All countries count between 126,000 and 188,000 manufacturing workers. A stratified sample of manufacturing firms in three consecutive years provides the micro data used in the analysis.

Firms

The firm level data was collected between 1992 and 1995 by three different research teams, coordinated by the Regional Program of Enterprise Development at the World Bank.[15] Firms were sampled to give the firm of each manufacturing worker equal probability to be included in the sample—an implicit stratification by employment size. Approximately 200 firms were surveyed each year in each country, covering four broadly defined manufacturing sectors: food processing, textile and clothing, wood and furniture, and metal and equipment. A maximum of 10 employees per firm were interviewed each year.[16] While firms could be linked over time as a panel, this was not possible for the workers.

The resulting sample is an unbalanced panel of firms with, on average, 110 to 183 observations per year in each country. In the first year, the firms employed 19,383 to 58,108 workers and 619 to 1206 of them were interviewed. A large fraction of the manufacturing sector is covered by this sample. The value added produced by the sample firms amounts to 31% of official manufacturing GDP in Tanzania, 17% in Kenya, and 26% in Zimbabwe. The share of manufacturing workers that are employed by firms included in the sample is substantially lower in the first two countries,

[14]Only life expectancy at birth gives a reverse ranking, but this is due to the staggering HIV infection rate, affecting one third of the adult population in Zimbabwe and almost one sixth in Kenya.

[15]The firm level data for the three countries is available online at http://www.csae.ox.ac.uk/datasets/main.html, which is maintained by the Centre for the Study of African Economics at the University of Oxford. On the same site is also a data appendix with information on the survey, the sampling frame, and the variable construction.

[16]In Zimbabwe, workers were only interviewed in the first and second year.

as large firms tend to have higher labor productivity (Van Biesebroeck, 2005). The stratified sampling yielded significantly larger than average firms. The absence of reliable firm censuses in these countries makes it impossible to compare with the universe, but the average firm size in these countries is surely smaller than in the U.S. manufacturing sector, where firms employed on average 61 workers in 1993 (OECD, 1995).

The differences in level of development between the countries are equally apparent when we compare the firms in the sample, see Van Biesebroeck (2005) for a more elaborate comparison. The median firm in Tanzania achieved only 38% of the labor productivity of the median firm in Kenya, while labor productivity in Zimbabwe is 42% higher than in Kenya. Total factor productivity numbers show similar differences when capital intensity is taken into account. The median firm in Kenya is twice as productive as in Tanzania, but achieves only two thirds of the productivity level of the median firm in Zimbabwe. The salary differences between the countries match the labor productivity differences rather well. Workers in Tanzania earn 27.4% of the average salary in Zimbabwe, while the labor productivity at their employers stands at 26.8%. Salaries in Kenya, on average \$120, are slightly below what one would predict from the relative labor productivity, which would imply a salary of approximately \$140. The statistics for the sample confirm that Zimbabwe is by far the most developed country of the three, while Tanzania is lagging far behind.

The following variables will be used in the analysis. Value added, the output measure, is total sales minus raw materials, intermediate inputs and energy. Labor input is the total number of full-time employees and hours is the average monthly hours worked per worker, which is only available at the firm level. Capital is the replacement value of the plant and equipment at the end of the year. Nominal variables are deflated with GDP deflators from the World Bank (2000). Summary statistics for the first year of the sample are in Table 1.

Workers

The remainder of Table 1 provides averages and standard errors for the worker level variables. The number of workers interviewed in each firm averages around six and varies between one and seventeen, but only for a few Tanzanian firms more than ten workers are included. The monthly salary is deflated with the same deflator as value added. Schooling is measured both continuously, in years, and as the fraction of employees that completed some high school. As we separately observe age, years of schooling, and graduation year we can calculate a labor force experience variable. Tenure is the number of years with the current employer. In addition to the continuous variables in years, a discrete variable measuring the proportion of workers in the firm with higher than median experience and tenure is reported as well. The training dummy captures completion of any formal training program, excluding on-the-job training, but including training received at former employers.

Workers in Zimbabwe work on average in larger firms, are slightly older, stay longer with the same firm and are more likely to receive (or choose to enroll in) formal training once they are employed. The sample of workers in Kenya is the most dominated by males. In Tanzania, workers receive the lowest salaries, but paradoxically they have the highest years of schooling.

Information on productivity is only available at the firm level and individual wages have to be aggregated to carry out the comparison with productivity. Identification of the wage and productivity premiums associated with worker characteristics comes from correlation across firms of the composition of the workforce and average salaries or output. The working paper version, Van Biesebroeck (2003), shows results for the employee level wage equation to confirm that the aggregation does not obscure how an individual's characteristics are rewarded.[17]

Individual wage regression with least squares capture both variation within and between firms. For example, the higher salary for male workers can be the result of men getting on average higher salaries than women within a given firm or men can be disproportionately employed in firms that pay higher salaries, a between effect, even without differential pay by gender. When we separately identify the magnitude of both effects, we find that in almost all cases they work in the same direction. Two variables warrant caution: the gender dummy in Tanzania and Zimbabwe, and tenure in Zimbabwe.

The average male worker receives a higher salary in all three countries. In Tanzania and Zimbabwe, this is solely the result of higher wages for men within firms. The pay differential is reduced by sorting of men towards lower-paying employers. Comparing average earnings across firms will show a negative wage premium for men, because firms that employ a high proportion of men pay lower salaries on average, even though men employed in those firms still earn more than their female coworkers. This complicates the interpretation of the gender dummy.

A positive coefficient on tenure can be the result of firms raising salaries for employees with high tenure. On the other hand, workers could choose to stay for a longer time with employers that offer high pay in general. Both interpretations are plausible, but only the second one is backed up by the data in Zimbabwe. In each of the three countries, the between-firm effect—which is what we will pick up with the firm level regressions—dominates the total.

4 Results

The estimation results by country for equations (8) and (9) with continuously measured experience and schooling are in Table 2(a). The corresponding results for discrete characteristics, in Table 2(b), will be discussed below. In each specification, hours worked and time, industry, and location dummies are added as controls to both the wage equation and production function. The input coefficients in the production function are estimated precisely and the point estimates are plausible. Returns to scale are estimated to be moderately increasing, but only in Kenya

[17] A full survey of the returns to education estimated from Mincer wage regressions in sub-Saharan Africa is in Appleton, Hoddinott, and Mackinnon (1996).

do they significantly exceed unity (at the 5% level). The relative importance of capital and the labor aggregate is estimated rather similarly in each country. The fit for the production function is notably better, with R-squares at least twice as high as for the wage equation. In contrast, standard errors on the human capital characteristics are invariable lower in the wage equation, although the difference is slight for Zimbabwe.

The coefficients on the gender dummy tend to be estimated imprecisely with varying signs and magnitudes. Firms that employ a high proportion of men are more productive in Kenya, but as discussed earlier, it might be because men are more productive or because they tend to work for more productive firms. Regardless of the cause, differences in pay by gender do not correspond well to productivity differences. Perhaps surprisingly for Africa, the results suggest that men are underpaid, relative to their productivity, although the differences are not statistically significant. P-values for a Wald test for equality between the gender coefficients in the wage equation and production function—testing the equality in equation (1)—are reported at the bottom of Table 2(a). Only for Kenya can we reject equality, and even there only at a 10% significance level. In the following specifications, the coefficients on the gender dummies are unstable and we will not focus much on them.

[Table 2]

The returns to experience and schooling in the wage equation, on the other hand, are precisely estimated and correspond well to the results at the individual level, see Van Biesebroeck (2003). Salaries rise substantially with experience in Tanzania and Kenya, but not in Zimbabwe, where education is rewarded higher than in the two other countries. At least compared to the productivity premiums, the wage premiums are estimated similarly in the three countries. The effects of experience and education in the production function both rise with the level of development. In Tanzania, experience contributes negatively to productivity, while higher education contributes nothing. In Kenya, there is no discernable effect of experience on production, while schooling contributes positively, although not in proportion to the wage premium paid for education. In Zimbabwe, the individual return—in the form of higher salary—and the return to the firm—higher output—associated with experience and schooling are very close.

The gaps between the salary and productivity premium for experience and schooling are largest in Tanzania, at respectively 4.4% and 6.1%, and they are also sizeable in Kenya, at 2.6% and 4.0%. In Zimbabwe, the gaps are 0.8% and 1.4% and equality of the returns cannot be rejected at all with a formal statistical tests. The p-values are 0.36 and 0.67. In the two less developed countries, equality of the returns to experience can firmly be rejected, even at a 1% significance level. The same holds for schooling in Tanzania (at a 10% significance level), but not in Kenya. The different findings cannot simply be attributed to less precisely estimated coefficients for Zimbabwe, which has only slightly higher standard errors. The joint test for equality of the returns to each of the three characteristics confirms the pattern. In Tanzania, by far the least developed economy, the p-value of the Wald test for joint equality is only 1%. In

Kenya, the p-value still tends towards rejection at 5%, largely due to the high wage premium for experience that is not backed up by any productivity gains. In Zimbabwe, none of the differences between the estimated coefficients is even remotely statistically significant, and the same is true for the joint test.

As mentioned, the largest discrepancy between the wage and productivity premium is for experience. In the two least developed countries, workers get substantial pay increases over their career, which are not backed up by any discernible productivity effect. In Tanzania, productivity is even estimated to decline with experience, which could represent an age effect. The wage premium for schooling exceeds its effect on productivity in each country, but the extent differs widely. An extra year of schooling raises the average salary in Tanzania by 5.9% even though there is no productivity effect to speak of. In Kenya, the return to schooling is much larger, 9.1%, which exceeds the productivity it brings the employer by more than half. In Zimbabwe, the excess return to schooling is kept to a moderate 1.4% per year, less than a quarter of the average productivity gain associated with an extra year of schooling.

Including tenure and training in the wage equation and production function, identifies additional instances where characteristics are rewarded differently from their productivity effect. The estimates are reported in Table 3(a). The coefficients on the gender dummy have changed somewhat, but are still estimated inaccurately. Experience is still rewarded with higher salary increases than the productivity effect warrants, especially in Tanzania, to some extent in Kenya, but not at all in Zimbabwe. The wage premium associated with schooling increases slightly in the poorest two countries, while some of the effect in Zimbabwe is taken over by the new variables, most likely training. The gap in wage and productivity premium associated with schooling decreases for Tanzania, but it increases for Kenya. Only in Zimbabwe are the two premiums similar, as before.

[Table 3]

The first added variable, tenure, measures the number of years an employee has been with his current employer. Even conditional on experience, an extra year of tenure raises the wage by 1.7% in Zimbabwe. This closely matches the corresponding increase in output (1.6%). The gap between the individual and firm return is, again, largest in Tanzania and intermediate in Kenya. The same pattern holds for formal training. In the two least developed countries, workers that have received training are paid more, but they receive only a fraction of the benefit a firm reaps from training. In Zimbabwe, the wage premium for workers exceeds the productivity effect. Combined with a higher return to tenure than to experience, the compensation patterns will help to reduce worker turnover, especially of those valuable employees that received training. This is borne out by a cursory look at the correlation between training and tenure at the individual level. Controlling for experience, workers with training had half a year higher tenure with their current employer, and the difference is statistically significant. The relationship is particularly strong in Zimbabwe.

It is illuminating to compare the size and composition of the year on year salary and productivity increases across countries. A Tanzanian employee that remains with the same employer will see his salary grow by 0.6% per year on average, while the salary increase would be higher if he changed employers. The productivity of workers is estimated to decline by almost 3% per year and this is hardly influenced by job changes. In Kenya, salaries for loyal employees increase by 3.2% a year, approximately one sixth more than for workers that change employers, even though there is very little productivity growth, 1% if a worker does not change employers, none otherwise. In Zimbabwe, the wage and productivity increases match remarkably well and they mostly accrue with tenure, not with general labor market experience. When we control for tenure, training, and education, the wage return to experience is virtually nil in Zimbabwe.

A joint test for the hypothesis that for the four observable human capital components—experience, schooling, tenure, and training—wage premiums equal productivity premiums follows the same pattern as the joint test with the restricted set of variables in Table 2(a). Equality is rejected for Tanzania at the 5% significance level. For Kenya, it can only be rejected if we are willing to tolerate a 15% significance level. The hypothesis can never be rejected for Zimbabwe.

Relative to their productivity effects, experience and schooling are over-rewarded in the two poorest countries, while the reverse is true for training and tenure. Workers will be expected to underinvest in the latter two characteristics. In Zimbabwe, tenure and training (in addition to schooling) carry the highest reward, but both also bring large productivity gains. Training is rewarded even more than the direct productivity effect seems to warrant. This is not necessarily inefficient as firms might benefit from spillover effects to other employees or, alternatively, the higher salary associated with training helps to retain the most experienced workers, who are paid slightly below their marginal productivity.

It is noteworthy to point out that training is consistently associated with large productivity effects. The point estimates on the training variables in the production function are uniformly large in Tables 3(a) and (b), but estimated imprecisely. The effects range from 42% (Zimbabwe) to 75% (Tanzania and Kenya). It is impossible to know whether this constitutes human capital accumulation—training boosting productivity directly—or selection—firms can selectively offer training to their best employees or disproportionately choose to hire or retain workers that received training. It is striking that these "trained" workers do not receive much of a salary boost in Tanzania or Kenya, even though the point estimate for their productivity contribution is higher than in Zimbabwe. While the quality of training programs could vary by country, at least the productivity effects are similar. In the vast quantity of research summarized in the last two-volume *Handbook of Development Economics* and the last three-volume *Handbook of Labor Economics* there is only a short discussion of on-the-job training in the chapter by Gibbons and Waldman (1999), focussing on selection. This is in sharp contrast with the many chapters evaluating the effects of formal education. Training seems a topic worthy of further research, especially in the developing country context.

We can group the more firm-specific aspects of human capital—tenure and training—and the more general human capital attributes—experience and schooling—and perform separate tests for equality of wage and productivity premiums. This clearly identifies the general characteristics as the cause of rejection in the lesser developed countries. Firms in each country seem to reward firm-specific characteristics at least somewhat in relation to their productivity, all p-values are around 0.60, although it should be noted that the effects of training are estimated especially imprecisely for Tanzania and Kenya. The differences between countries are limited to the general characteristics, with a p-value of 0.03 for Tanzania, 0.16 for Kenya, and 0.99 for Zimbabwe. Grouping characteristics differently—schooling and training (learning), on the one hand, and experience and tenure (over time), on the other—points again to the importance of experience. The failure to equalize returns to general characteristics is driven mostly by experience, not by schooling.

Much of the sensitivity analysis in the next section will focus on the wage-productivity gap for experience: a very large difference for Tanzania (5.0%), intermediate for Kenya (2.7%), and almost perfect equality for Zimbabwe (0.1%). The underlying pattern is that over time salaries increase with general experience in Tanzania and Kenya, but with firm-specific tenure in Zimbabwe. Productivity is more closely related to tenure than experience in each country. If firms are cost-minimizing and labor markets work efficiently, differences between wage and productivity effects should be arbitraged away. We will investigate a number of alternative explanations for the disparities in returns in Section 6.

5 Robustness checks

In this Section we present several robustness checks that leave the general pattern of the results unchanged: the extent to which characteristics, especially experience, are rewarded in line with their productivity contribution is negatively related to the level of development of the country. In turn we look at discrete definitions for all human capital characteristics (5.1), translog production function and additional controls (5.2), diminishing returns on schooling and experience (5.3), sampling error (5.4), and we discuss potentially important unobservables (5.5).

5.1 Discrete variables

Qualitatively the same and quantitatively very similar results are obtained when experience and schooling are measured as discrete variables at the individual level. For experience or tenure, we measure the proportion of the workforce in each firm above or below the median (interviewed) worker for that country. For schooling, we measure the proportion of workers in each firm that at least attended secondary school, but not necessarily finished it. The results with the limited set of characteristics are in Table 2(b) and for the full model, adding tenure and training, in Table 3(b). When discrete (dummy) variables are used for all characteristics, it is not necessary to rely on a Taylor approximation for the firm-level production function.

The main results go through, some even become stronger. Equality of wage and productivity premiums is strongly rejected in Tanzania, the least developed country in the sample. The striking negative effect of experience on productivity also remains, but it now becomes weaker as the tenure variable is introduced, as expected. In Kenya, the rejection of equality is more strongly than using continuous variables and equality can again not be rejected in Zimbabwe. Relative to the earlier results, the premiums in the wage and production equations are still similar in Zimbabwe, although not as alike as in Table 2. The extent to which joint equality of the return to characteristics can be rejected decreases with the level of development in the country and the rejection is the strongest for experience.

The full model results with discrete characteristics confirm both earlier conclusions. It emerges even more strongly than before that the probability of rejection decreases with the level of development. The p-value for a joint test for equality of all returns, excluding the gender dummy, goes from 0.00 in Tanzania, to 0.04 in Kenya, and 0.65 in Zimbabwe. This tendency holds most strongly for more general human capital characteristics (p-values are 0.01, 0.02, and 0.93, respectively) or for the variables that measure the accumulation of human capital over time (p-values are 0.00, 0.05, and 0.75).

5.2 Production function

We next investigate the robustness of the results to a more flexible specification of the production function. The results in the top panel of Table 4 uses a translog instead of Cobb-Douglas production function. The labor aggregate is unchanged ($\log \tilde{L}$), but quadratic and interaction terms with capital are included. Only in Kenya are the second order terms jointly significant. It is no surprise then that the results go through relatively unchanged.

[Table 4]

Hellerstein and Neumark (2004) estimate a similar model using the semi-parametric Olley-Pakes approach to control for the endogeneity of unobserved productivity in the production function. Their results are virtually unchanged using this methodology compared to simple least squares. Similarly, Fox and Smeets (2007) find that the coefficients on worker characteristics in the production function are barely affected when the estimation method is changed from least squares to the Olley-Pakes semi-parametric estimator. The same is true in our sample, but to conserve space these results are not reported here (they are available upon request).

Instead, the results in the bottom panel of Table 4 are for additional controls added to both equations. We include state and foreign ownership dummies to capture some firm heterogeneity and control for the fraction of unionized workers and family members, whose presence is possibly not orthogonal to the firms' remunerations practices.[18] In addition, we also include (log) capital

[18]We follow the usual practice in the labor literature of not including occupation variables in the wage equation. A fraction of the return to human capital characteristics will be realized through changes in occupation, which

in the wage equation. Note that the same controls that have been included throughout—hours worked and time, industry, and location dummies—are maintained. The drawback of including these extra variables is that we loose 8% of the firms in the sample, especially in Kenya.

Even though these additional controls tend to be jointly significant in most equations, p-values for the F-tests are reported at the bottom of Table 4(b), the main findings go through unchanged. Equality of wage and productivity premiums is strongly rejected in Tanzania, tenuous in Kenya, but cannot be rejected in Zimbabwe. The most notable difference is that schooling is now underrewarded in Kenya and Zimbabwe, but the gap still decreases with the level of development, respectively 4.5%, 3.1%, and 2.1% per year. The firm level controls have the expected effect and the signs are invariably the same in both equations: negative for state ownership and positive for foreign ownership. Tellingly, family members receive higher salaries in Tanzania and Kenya, even though firms that employ a high fraction of family have lower productivity. The gap is significant with a p-value of 2% in both countries. In contrast, in Zimbabwe family members receive 17% higher salary, but are also estimated to be 7% more productive. This gap is not significantly different at all (p-value is 80%).

5.3 Diminishing returns

A shortcoming of the previous analysis is the imposition of linear effects on the continuous variables. The small sample makes it hard to identify nonlinearities precisely, but one would certainly expect the returns to schooling and experience to be concave. An extra difficulty is that in the aggregation from the individual to the firm level, a first order approximation was made. In order for the quadratic and interaction terms in the returns to schooling and experience to make it into the estimating equation, a second order approximation is necessary.

At the individual level, human capital—and hence the wage rate—can be modeled to evolve according to

$$\ln W_i = \lambda_0 + \lambda_M M_i + \lambda_X X_i + \lambda_S S_i + \tfrac{1}{2}\lambda_{XX} X_i^2 + \tfrac{1}{2}\lambda_{SS} S_i^2 + \lambda_{XS} X_i S_i \qquad (10)$$

The Appendix contains the details how to derive a second order approximation for the production function and to aggregate wages to the firm level in a way consistent with a Mincer model of human capital at the individual level, as equation (10). Most importantly, in addition to the squared and interaction terms of average schooling and experience, it requires the inclusion of the average variances and covariance for experience and schooling within each firm in the regression. These terms are missing in the firm level production function estimated by Jones (2001).

Estimation results are in Table 5. Changes relative to the benchmark results in Table 2(a) are modest. The R-squares for the regressions hardly increase when quadratic terms are included. The effect of experience is estimated to be concave and increasing, except for the production function in Tanzania, as before, where it is negative but at a diminishing rate. The same concave

are obviously endogenous.

increasing pattern holds for schooling, except for the wage equation in Kenya. In the majority of cases, education and experience are estimated to be complements, although few coefficients are statistically significant.

The rejection of equality of wage and productivity effects is more likely for Tanzania and Kenya than for Zimbabwe, but the p-values become a lot larger. Unfortunately, this is not because of closer estimates of wage and productivity effects, but mostly because of less precise estimates.

For Tanzania, the mismatch between the two premiums is now much more pronounced for experience than for schooling. The point estimates on the linear terms are as dissimilar as before and the quadratic terms also have opposite signs in the wage and production equations. The schooling results are somewhat closer. The difference in linear terms is unchanged, but they are estimated much less precisely, and the quadratic terms are very similar. The results for Kenya are opposite. Allowing for diminishing returns almost entirely eliminates the discrepancy in returns to experience. The p-value in the joint test for equality of all experience terms is only as low as 0.15 because of the interaction term with schooling. However, the effect of schooling in both equations is now entirely unrelated.

[Table 5]

It is impossible to attach any firm conclusions given the imprecision of the estimates. Nevertheless, it is striking how similar the wage and productivity effects remain for Zimbabwe. It is the only country for which the signs on all coefficients, including the quadratic and interaction terms, are the same in both equations. The only noticeable difference is that schooling has a less pronounced effect on productivity, less strongly increasing and less concave, than on wages. Evaluating the marginal returns to schooling and experience at the sample averages, gives results that are close to the linear estimates. The average wage effect of a year of schooling in Zimbabwe is 8.5%, while the productivity effect is 8.5%. In Tanzania, the two effects are +1.6% and -0.6%, while the corresponding effects for Kenya are +6.7% and -1.8%. Similar discrepancies arise for the average experience effects, but now Tanzania has by far the biggest gap. Enforcing linearity of the effects does not seem to be the driving force behind the rejections in the poorer countries.

5.4 Sampling error

Till now we have treated the average employee-characteristics per firm as known, even though they were estimated from a subsample of workers. It would be useful to know how sensitive the results are to sampling of workers.[19] Would the conclusions still hold if we had drawn a

[19]For 8% of the firms, all employees are observed and sampling is not an issue. On average, 30% of a firm's employees are interviewed, but the distribution is right-skewed. For half of all firms, we observe less than 18% of the workers and for one out of ten firms, less than 2% of the workforce.

different sample of workers from each firm to calculate the average characteristics? We check the robustness of the results using two different approaches.

The first method extends the approach in Hellerstein, *et al.* (1999) to deal with continuous variables. Different samples of workers are repeatedly drawn from the implied universe of employees, constructed to be consistent with the estimated proportions for each characteristic. For example, a firm with 100 employees from which 6 men and 4 women were actually sampled, is assumed to have a total of 60 male and 40 female workers. From this universe of 100 workers, samples of 10 workers are drawn without replacement and the proportion of male workers in each sample is used in new estimations. For continuous variables, schooling and experience, we sample without replacement from the smoothed cumulative distribution function of the observed sample of employees.

The samples are generated independently for all characteristics and firms, drawing for each firm a hundred times the same number of workers as found in the original sample. For firms where all employees are observed, the observed averages are used in each simulation. Using each of the hundred simulated samples, the wage and production equations are estimated as in Table 2(a). The top panel of Table 6 contains the average coefficient estimates and standard deviations across all simulations. The average and standard deviation for the p-value of the Wald test for equality of all coefficients is also calculated, as well as the fraction of simulated samples where the p-value is below the 5% significance level.

[Table 6]

The original findings are virtually unchanged. In 99 of the samples, the joint test is rejected for Tanzania, in only 59 of the Kenyan samples, and never for Zimbabwe. The nature of the differences also remains the same. In the two poorer countries experience and schooling are rewarded more than their contribution to output. In Zimbabwe, the remuneration matches the productivity gain rather well and when they differ, characteristics tend to be underrewarded. The variability of the gender differentials is exacerbated in the simulations.

The simulations confirm the previous findings, but it is not the ideal experiment. Assuming that the estimated averages are the true underlying means, we verified whether the results are robust to different possible samples of workers. However, we would like to know what the results would look like if the true means were used instead of the estimates. The observed averages are consistent with a whole range of underlying true means, but not all values are equally likely, given the observed sample of workers.

We can use Bayes' law to calculate, for example, the probability that any randomly generated number between 0 and 1 represents the true proportion of male workers in the firm, given the observed sample of workers. The probability that the true mean differs from the observed mean by a certain amount is a decreasing function of the proportion of workers that are observed. If the majority of all employees in the sample are observed, the true proportion of male workers in that firm cannot differ a lot from the observed proportion. For discrete variables, we can calculate this probability exactly for any (randomly generated) difference. For continuous variables, we can calculate the probability that the true average lies in any interval, which we draw randomly with constant width for each characteristic.[20] We simply use Bayes' law and the distribution of the estimated mean. The law of large numbers tells us that the mean of any i.i.d. random variable is normally distributed in the limit. From a set of observations we can consistently estimate the mean and variance of the underlying random variables, and hence the first two moments of the distribution of the mean.[21]

The product of the probability for each of the three characteristics is then used as weight on the firm in the SUR estimation. Firms for which all employees are observed, 8% of the sample, receive a constant weight of one. As in the first experiment, we draw 100 samples and the average estimation results are reported in the bottom panel of Table 6.

The results for the second experiment are again similar to those in Table 2(a). Rejection of the joint hypothesis is still unanimous for Tanzania. The results for Kenya and Zimbabwe are found to differ less than in the observed sample, but rejection of the joint hypothesis is still more likely for Kenya. The average p-value for Zimbabwe drops to only 13%, even though the hypothesis can only be rejected at a 5% significance level in 4 of the 100 samples, compared to 57 for Kenya. Relative to the previous simulations, the standard deviations of the estimated coefficients are higher.

5.5 Unobservables

We should not conclude that markets work inefficiently in Africa, simply because they look different from Western markets. Often, they simply adjusted to the specific circumstances, such as information asymmetries, enforcement problems, and geographic isolation. For example, Benjamin (1995) points out that some of the agricultural economics literature prematurely concluded in favor of inefficient markets to explain an inverse relationship between labor productivity and farm size. Properly accounting for unobservable land quality, which was estimated to be higher for smaller farms, completely eliminated the inverse productivity-size relationship.

Even more than for empirical work in developed countries, one should be aware of data limitations. Unobservables like non-wage compensation or measurement errors in capital are potentially problematic. In the current context, both of these measurement problems are likely to work against finding the pattern documented.

Non-wage compensation is likely to rise with skill, just as in developed countries. In Africa, this takes the form mostly of payments in kind, which tend to be more important in the least

[20] We use a different width for the three characteristics, as their observed variance in the sample differs a lot, but is almost constant across countries.

[21] Its standard deviation is the estimated standard error over the square root of the number of workers interviewed.

developed countries, like Tanzania. Approximately 60% of the firms in the sample report how much in kind payments they make. In some cases it is zero and in almost all instances it amounts to less than 10% of total compensation. Adding payments in kind to the dependent variable of the wage regression increases the premiums associated with schooling and experience slightly in Tanzania, with little change for Kenya and Zimbabwe. This exacerbate the excess wage premium for Tanzania, relative to the productivity premium.[22]

A second variable prone to measurement error is the capital stock. Throughout, the output elasticity with respect to capital is estimated slightly higher for Tanzania (0.24-0.25) than for Zimbabwe (0.21-0.23). It is possible that the capital coefficient estimate for Tanzania is upward biased. If the human capital measures are positively correlated with physical capital, as in developed countries, such an upward bias could translate in a downward bias of the human capital coefficients. However, the difference is relatively small. Running the regressions for the three countries as a system, enforcing uniform capital and labor coefficients, had very little impact on the estimated skill premiums.

6 Possible explanations

6.1 Imperfect substitution between characteristics

An important maintained assumption is the perfect substitutability between all types of workers. If this is relaxed, the marginal product of a male worker, for example, will depend on the share of male workers already employed and on other characteristics of the workforce. We now explore whether allowing for imperfect substitutability between workers with different levels of experience changes the results. Recall that this characteristic had the greatest gap between wage and productivity premiums in most previous tables.

The most straightforward approach would be to introduce two labor aggregates, one for each experience level (Y or X), in the Cobb-Douglas production function:

$$\ln Q = \alpha_0 + \alpha_K \ln K + \alpha_X \ln \tilde{L}_X + \alpha_Y \ln \tilde{L}_Y + \epsilon_q \tag{11}$$

$$\ln \tilde{L}_k = \ln L_k + \ln(1 + \phi_{kM} \frac{L_{kM}}{L_k}) + \phi_{kS} \overline{S}_k \qquad x = Y,\ X, \tag{12}$$

for schooling measured continuously. Data constraints force us, as before, to assume that the fraction of male workers is the same in each experience category maintaining the assumptions in (4): $L_{XM}/L_X = L_{YM}/L_Y = L_M/L$. Similarly, average schooling attainment is assumed constant across experience categories as well. The elasticity of substitution between each type of workers and between both types of workers and capital is unity. The output elasticities of each input, α_K, α_Y, and α_X, capture the relative importance of capital, unexperienced, and experienced workers in the production function.

[22]Full results are not reported, but available upon request. Only including firms that report payments in kind reduces the sample and might entail a selection bias.

An more general approach is to aggregate the two labor aggregates using the C.E.S. functional form. While capital and (aggregate) labor still have unitary elasticity of substitution, the elasticity of substitution between the different labor components can be estimated freely. The production function becomes

$$\ln Q \quad = \quad \alpha_0 + \alpha_K \ln K - \frac{\alpha_L}{\rho} \ln(\alpha_X \tilde{L}_X^{-\rho} + (1-\alpha_X)\tilde{L}_Y^{-\rho}) + \epsilon_q.$$

The constant elasticity of substitution between the two labor types is $\sigma = \frac{1}{1+\rho}$. If the weights of the two experience categories sum to one, returns to scale still equal $\alpha_K + \alpha_L$. In principle, it is straightforward to extend this approach and include more than two levels of experience. In practice, it is impossible to calculate average schooling and fraction of males separately for more narrowly defined experience levels and the extra categories will not really yield a richer model.

The results are in the top panel of Table 7. The test for equality of returns to experience has to be carried out differently than before. Dividing the cost minimizing first order conditions for both types of experience, gives the following relationship: $\frac{\alpha_X}{1-\alpha_X}\left(\frac{L_X}{L_Y}\right)^{-\frac{1}{\sigma}} = \frac{w_X}{w_Y}$. The relative productivity of high versus low experience workers now varies across firms, depending on the relative share of workers in each experience category. The reported p-value is for the test evaluated at the mean ratio for each experience class.

[Table 7]

The estimates close mimic the results from Table 2(a). This is not surprising, as the two types of labor are estimated to be close substitutes, in Zimbabwe even perfect substitutes. The joint test is significantly more likely to reject equality of returns in Tanzania and Kenya than in Zimbabwe, which is still driven by the return to experience. In Tanzania, the premiums for gender and schooling are estimated somewhat closer, but in Kenya the reverse is true. It is interesting to note that the weight of more experienced workers in the production function increases with the development level of the country, which would be expected if production technology is more advanced in richer countries.

In Zimbabwe, experienced workers are perfect substitutes for young workers and their only slightly higher relative weight $\frac{0.541}{1-0.541} = 1.18$ matches their only slightly higher wages relatively well. In the other two countries, the higher wage return to experience combined with a lower weight of experienced workers in the production function would lead cost minimizing firms to hire a lot more unexperienced workers. In the test, the equalizing effect of a higher ratio of low to high experienced workers is dampened by the inverse of the elasticity of substitution. Both types of workers are estimated to be rather close substitutes, hence, a much higher ratio than observed would be required to rationalize the estimated wage effects. In sum, imperfect substitutability fails as an explanation for the rejection of equal wage and productivity returns.

The bottom panel of Table 7 reports results for a similar exercise, but now workers with high or low schooling level are considered imperfect substitutes. For both Kenya and Zimbabwe the elasticity of substitution is now estimated at infinity, indicating the Cobb-Douglas production function is most appropriate. The p-values for the joint test for equality of the schooling and experience premiums displays the same pattern as before: a clear rejection for Tanzania (p-value is 0%) and failure to reject for Zimbabwe (p-value is 43%), with results for Kenya intermediate (p-value is 4%).

Ideally, we would like to perform additional robustness checks on the definition of the human capital characteristics. The limited number of workers interviewed per firm preclude us from defining the discrete schooling categories more finely or use more than two levels of experience or tenure. Similarly, we cannot define the fraction of male workers or average years of experience separately for high and low educated workers. At least the robustness of our findings when continuous or discrete definitions of the characteristics are used is encouraging.

6.2 Localized labor markets

One feature of labor markets in developing countries that might help explaining the failure of wage premiums to match productivity effects is the segregation of economic activities by geographic area. If workers rarely migrate between different cities and daily commuting is limited because of poor transportation infrastructure, pooling firms that operate in different areas can produce misleading results. Reardon (1997) surveys some evidence that suggests localized labor markets are likely to be important in Africa.

The small sample size makes it impossible to run the regressions separately for all cities. Location dummies are included in all previous regressions, but this might not suffice to control for local effects. If the relative wage rate for workers with high and low education varies by region the wage differentials will only match productivity differences if firms are equally representative in all areas. Given the concentration of manufacturing activities in only a few cities, this is unlikely to be the case. Alternatively, if areas differ in the relative abundance of different types of workers, this will give rise to differences in relative wages and firms will adjust their input mix.

One solution is to perform the analysis on the sample of firms located in the major city of each country. Nairobi, the capital of Kenya, is one of the most important manufacturing centers of East Africa and 350 of the 544 observations, 64% of the Kenyan sample, are located here. In Tanzania, the main center of manufacturing activity is Arusha, near the border with Kenya, rather than the capital Dar es Salaam. 41% of all firms in the sample are located there. In Zimbabwe, manufacturing activity is less concentrated than in the other countries. Still, 42% of the firms in the RPED sample are located in the capital, Harare.

[Table 8]

The estimation results on the limited samples are in Table 8. For Arusha (Tanzania), the gap between wage and productivity effects is slightly larger. The smaller sample yields less precise estimates and increases the p-value for the tests of equality of effects. Nevertheless, for most variables, especially for experience, we still reject equality and the same conclusion holds for the joint test. Local labor markets do not seem to be an explanation for the excess wage return to the different characteristics.[23]

The results for Nairobi (Kenya) indicate that for experience the gap is cut in half, from 2.9% to 1.4%. The point estimates for schooling and gender changed very little. As the rejection of equality was mainly driven by the excess wage return to experience, the joint test for equality of all three effects now has a p-value of 0.25 and we fail to reject joint equality. Here, the local labor market explanation seems to have some explanatory power. However, two things have changed. On the one hand, limiting the sample to firms in a single city makes arbitrage easier and the effects of isolated labor markets should disappear. On the other hand, the manufacturing centers tend to be much richer and more developed than the smaller cities. Nairobi is a lot more developed than the rest of the country. Few detailed local statistics are available, but the U.N. estimates that Nairobi alone generates 45% of Kenyan GDP.

For Zimbabwe, equality can never be rejected, even though the productivity effect of experience is estimated substantially higher and higher than the wage effect. The joint test for equality of the returns to all three characteristics gives the same ranking across the three countries as before: rejection is negatively correlated with the level of development in the country.

6.3 Long term contracts

One potential explanation for the difference between the wage and productivity premiums for experience is the presence of long term contracts. In Tanzania, and to a lesser extent in Kenya, older workers earn more than their contemporaneous productivity warrants, while the reverse is true for younger workers. A similar pattern was found in France, see Pérez-Duarte *et al.* (2001). If contracts in the economy are such that pay is backloaded over the workers' careers, wage effects at any given time might differ from productivity effects if the effects are identified from differences across firms.

A detailed analysis of wage profiles over a worker's career is beyond the scope of this paper, but the individual wage regressions in the working paper version Van Biesebroeck (2003) sheds some light on this issue. Using standard panel data techniques, the total experience premium is decomposed into within and between firm effects. Comparing across countries clearly shows that the decreasing experience premium with the level of development is driven predominantly by the between firm effect, picking up selection rather than career effects. Salary increases with experience within the same firm are similar, ranging from 1.1% in Zimbabwe to 1.9% in Tanzania. Between firm differences in the remuneration of a year of experience vary much more, from zero to 4.1% in the two respective countries. Long term career concerns seem to explain only a fraction of the experience premium gap.

[23]The same conclusion is obtained for the full model that includes tenure and training, as in Table 3(a).

It remains puzzling why individual firms would systematically over-reward experience. It makes firms with an older than average workforce particularly uncompetitive. It would also make more sense if these long term effects were associated with tenure, but paradoxically we find the reverse. Workers with high tenure are paid less than their productivity warrants, controlling for general labor market experience, especially in Tanzania. It is also puzzling why these long term contact would be important in a very poor country as Tanzania, but not in a more advanced economy as Zimbabwe.

6.4 Matching

If the labor market does not operate as a spot market with perfect information, one would also expect to find differences in wage and productivity premiums. For example, if workers are matched with firms and bargain over the surplus of the match, we should not expect to see the relative productivity match the relative wage perfectly. Firms will make wage offers that lie between the worker's outside alternative (potentially very low) and the worker's productivity. Even in such an equilibrium, it is not obvious why workers in Tanzania and Kenya are systematically paid more than their experience and schooling level warrants. These characteristics are readily observable and it is hard to rationalize firms offering salaries that exceed productivity.

One explanation might be that the benchmark workers—young, uneducated women—are paid less than their productivity warrants and that more educated or older workers have a better bargaining position, bringing their salary closer to their productivity level. All effects discussed so far were always relative to the benchmark worker. There is some evidence for this in Tanzania. Note that the constant term in the wage equation is related to the labor input coefficient in the production function. The first order condition for the benchmark worker gives $w_0 = \alpha_L Q/L$ or in logarithms $\lambda_0 = \ln \alpha_L + \ln(Q/L)$. For Tanzania we can reject that this expression holds with equality at a 1% significance level, evaluated at the average or median firm, indicating that the benchmark category of workers is paid less than the productivity level. Therefore, higher wages for educated or experienced workers can be rationalized by a better bargaining position of such workers, without requiring any productivity effects.

This still requires an explanation of why the extent to which less skilled workers have low bargaining power is negatively correlated with the level of development of the country. A more detailed study of the operation of local labor markets would be needed to explore this further. It is not unlikely that in a poor agriculture-focused economy the outside options for unskilled manufacturing workers are especially bad, but we do not have evidence for this. At least it offers a way to rationalize the observed wage-productivity gaps while maintaining cost minimizing behavior on the part of firms. Other institutional, social, or cultural considerations can lead firms to offer wage profiles over workers' careers or salary differences between household members that drive a wedge between the contemporaneous productivity effect and salary remuneration.

7 Conclusions

A couple of findings are worth reiterating. First, wage premiums associated with a number of characteristics do not always match their productivity contributions and this failure is more pronounced for some countries than for other. Equality of the two premiums is much more likely to be rejected in the poorest economy we study, Tanzania, than in the relatively richer country, Zimbabwe. This pattern is very robust.

Second, a lot of attention in the development literature is devoted to education. Rightfully so, because the rewards in terms of higher salary and output are important and we only capture a part of them in this analysis. It is nevertheless of concern that the wage increases associated with more education significantly exceed the productivity gains they bring in the least developed countries. It is still instructive to realize that the returns to education—privately and to the employers—are highest in the most developed country. Education is important, but the benefits do not materialize automatically.

Third, a crucial aspect of remuneration practices is the trade-off between paying workers for general experience versus firm-specific tenure. This mirrors a similar trade-off between general pre-employment education and training programs for employees. In Tanzania, and to a lesser extent in Kenya, general skills (experience and schooling) are rewarded relatively more than firm-specific skills (tenure and training) even though the latter are associated with larger productivity gains. In Zimbabwe, all wage premiums match the productivity gains that are associated with them, and even more interestingly, the returns to firm-specific investments are higher than in the other countries. A richer model of human capital accumulation and remuneration is needed to understand these relationships better.

Inefficiencies in the labor market are one explanation for the wage-productivity discrepancies, but there are others. We have shown that localized labor markets could be important and that allowing for diminishing returns and imperfect substitutability between skills lowers some of the gaps. Long term contracts or especially weak bargaining power of unskilled workers in poor countries could also be part of the explanation. A more in-depth study of local labor market practices is needed to sort out these effects.

Table 1: Summary statistics

	Tanzania		Kenya		Zimbabwe	
Population	27.1m		25.0m		10.3m	
% employed in industry	4.9%		7.3%		8.6%	
Manufacturing workers[a]	126,312		177,738		18,7937	
Workers in sample firms[b]	19,383		21,090		58,108	
Workers in the sample[b]	1,018		1,206		619	
GDP/capita (PPP)	395		1089		2459	
VA/empl. in industry (USD)	983		1705		7049	
Median LP in sample[c]	38		100		142	
Median TFP in sample[c]	54		100		143	
Monthly wage (USD)	55.9	(58.6)	117.0	(322.2)	203.3	(261.3)
Share of GDP covered	0.31		0.17		0.26	
Share of labor force covered	0.15		0.12		0.31	
Number of firms	113		183		110	
Value added (log)	11.0	(2.52)	10.0	(2.62)	9.92	(2.29)
Capital stock (log)	11.5	(3.15)	10.3	(3.13)	9.19	(2.64)
Employment (log)	3.01	(1.62)	3.16	(1.73)	4.50	(1.56)
Hours worked (log)	3.85	(0.23)	3.83	(0.15)	3.82	(0.17)
Employment	106.2	(311.1)	99.8	(270.5)	275.6	(594.9)
Workers interviewed per firm	5.6	(3.2)	6.2	(3.4)	5.6	(2.6)
Monthly salary (log)	9.59	(0.53)	7.85	(0.65)	6.68	(0.75)
Male (%)	0.79	(0.40)	0.87	(0.34)	0.84	(0.36)
Experience (years)	16.4	(10.4)	16.1	(9.8)	19.9	(10.8)
Schooling (years)	12.4	(4.8)	11.5	(3.8)	11.0	(3.6)
Tenure (years)	7.8	(6.9)	7.9	(7.2)	10.3	(8.2)
Experience (% high)	0.49	(0.33)	0.47	(0.32)	0.45	(0.33)
Schooling (% high)	0.28	(0.30)	0.49	(0.34)	0.57	(0.31)
Tenure (% high)	0.41	(0.36)	0.41	(0.33)	0.46	(0.37)
Received training (%)	0.09	(0.29)	0.12	(0.32)	0.21	(0.41)

Sources: World Bank (2000) and own calculations for the sample statistics, [a] UNIDO, 1991
[b] in first year; [c] relative to Kenya, see Van Biesebroeck (2005)

Notes: Aggregate statistics refer to 1992, unless indicated, and firm and worker level statistics refer to the first year of the survey, 1992 for Tanzania and 1991 for the other two countries.

Table 2: (a) Joint estimation of wage and production equations, limited continuous characteristics

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Labor		0.828		0.779		0.816
		(.078)***		(.055)***		(.066)***
Capital		0.241		0.292		0.218
		(.037)***		(.034)***		(.040)***
Male	0.148	0.839	0.030	1.828	-0.015	-0.007
	(.135)	(.731)	(.123)	(1.11)*	(.214)	(.267)
Experience	0.020	-0.024	0.029	0.003	0.007	0.015
	(.004)***	(.014)*	(.004)***	(.012)	(.007)	(.009)*
Schooling	0.059	-0.002	0.091	0.051	0.080	0.066
	(.009)***	(.034)	(.011)***	(.030)*	(.023)***	(.031)***
Observations	316	316	544	544	210	210
R^2	0.31	0.69	0.32	0.81	0.37	0.88
Test for equality of coefficients (p-value)						
Male ($\lambda_M - \phi_M$)	0.34		0.09		0.48	
Experience ($\lambda_A - \phi_A$)	0.00		0.01		0.36	
Schooling ($\lambda_S - \phi_S$)	0.07		0.16		0.67	
Joint test	0.01		0.04		0.36	

Notes: Joint estimation (SUR) of the wage equation and production function at the firm level. The sample for Tanzania covers three years, 1992-1994, for Kenya also three years, 1991-1994, and for Zimbabwe two years, 1991-1992. Controls in both equations include hours worked and time, industry, and location dummies. Standard errors are in parentheses; *** indicates significance at 1% level, ** 5%, * 10%.

Table 2: (b) Joint estimation of wage and production equations, limited discrete characteristics

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Labor		0.799		0.775		0.820
		(.076)***		(.058)***		(.065)***
Capital		0.240		0.296		0.215
		(.035)***		(.033)***		(.040)***
Male	0.388	0.902	0.185	1.869	0.147	0.270
	(.174)**	(.845)	(.137)	(1.04)*	(.288)	(.410)
Experience	0.280	-0.494	0.151	-0.207	0.523	0.716
	(.109)***	(.155)***	(.087)*	(.159)	(.297)*	(.427)*
Schooling	0.746	0.161	0.452	0.148	1.650	1.320
	(.138)***	(.365)	(.112)***	(.232)	(.556)***	(.635)**
Observations	316	316	544	544	210	210
R^2	0.32	0.69	0.35	0.81	0.41	0.89
Test for equality of coefficients (p-value)						
Male ($\lambda_M - \phi_M$)	0.54		0.10		0.78	
Experience ($\lambda_A - \phi_A$)	0.00		0.04		0.67	
Schooling ($\lambda_S - \phi_S$)	0.12		0.21		0.65	
Joint test	0.00		0.04		0.77	

Note: Estimation as in Table 2(a).

Table 3: (a) Joint estimation of wage and production equations, full set of continuous characteristics

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Labor		0.796		0.758		0.808
		(.084)***		(.070)***		(.066)***
Capital		0.251		0.292		0.213
		(.041)***		(.039)***		(.040)***
Male	0.213	0.981	0.313	2.664	-0.106	0.239
	(.166)	(0.98)	(.193)*	(1.99)	(.190)	(.434)
Experience	0.026	-0.024	0.027	0.000	0.005	0.004
	(.006)***	(.019)	(.006)***	(.020)	(.009)	(.014)
Schooling	0.066	0.016	0.094	0.021	0.105	0.101
	(.010)***	(.038)	(.013)***	(.041)	(.021)***	(.036)***
Tenure	-0.020	-0.005	0.005	0.009	0.016	0.017
	(.008)***	(.026)	(.009)	(.026)	(.012)	(.018)
Received training	0.043	0.695	0.196	0.748	0.782	0.452
	(.170)	(.841)	(.148)	(.587)	(.232)***	(.327)
Observations	268	268	375	375	210	210
R^2	0.26	0.69	0.34	0.80	0.40	0.88
Test for equality of coefficients (p-values)						
Joint test—without male		0.05		0.15		0.90
Joint test—firm specific HC		0.59		0.63		0.62
Joint test—general HC		0.03		0.16		0.99
Joint test—learning		0.30		0.11		0.62
Joint test—over time		0.03		0.25		0.97

Notes: Estimation as in Table 2(a). Information on training is missing for some firms in Tanzania and in the last year for all Kenyan firms, hence the smaller sample sizes.

Table 3: (b) Joint estimation of wage and production equations, full set of discrete characteristics

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Labor		0.768		0.811		0.835
		(.080)***		(.070)***		(.067)***
Capital		0.260		0.292		0.232
		(.041)***		(.039)***		(.040)***
Male	0.566	1.254	0.853	2.718	-0.055	0.095
	(.240)**	(1.17)	(.303)***	(1.99)	(.218)	(.350)
Experience	0.297	-0.398	0.355	-0.187	0.270	0.424
	(.146)**	(.215)*	(.147)**	(.249)	(.265)	(.401)
Schooling	0.835	0.190	0.958	0.193	2.133	2.330
	(.162)***	(.404)	(.168)***	(.317)	(.640)***	(1.02)**
Tenure	-0.033	-0.231	0.310	0.523	0.784	1.028
	(.104)	(.281)	(.141)**	(.474)	(.309)***	(.496)**
Received training	-0.068	0.754	0.061	0.610	0.840	0.418
	(.158)	(.810)	(.136)	(.512)	(.262)***	(.312)
Observations	268	268	375	375	213	213
R^2	0.34	0.69	0.38	0.80	0.45	0.88
Test for equality of coefficients (p-values)						
Joint test—without male		0.00		0.04		0.65
Joint test—firm specific HC		0.53		0.52		0.47
Joint test—general HC		0.01		0.02		0.93
Joint test—learning		0.22		0.12		0.47
Joint test—over time		0.00		0.05		0.75

Note: Estimation as in Table 3(a).

Table 4: Joint estimation of wage and production equations, two robustness checks

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
(a) Translog production function						
Male	0.126	1.213	0.027	1.283	-0.215	0.107
	(.138)	(1.14)	(.122)	(.666)*	(.147)	(.295)
Experience	0.020	-0.031*	0.026	-0.003	0.006	0.009
	(.004)***	(.016)	(.004)***	(.010)	(.187)	(.009)
Schooling	0.059	-0.014	0.090	0.051	0.070	0.074
	(.011)***	(.037)	(.011)***	(.026)*	(.021)***	(.031)**
Observations	316	316	544	544	210	210
R^2	0.31	0.69	0.32	0.82	0.49	0.89
Test for equality of coefficients (p-values)						
Experience ($\lambda_X - \phi_X$)	0.00		0.01		0.79	
Schooling ($\lambda_S - \phi_S$)	0.05		0.15		0.91	
Joint test—without male	0.00		0.02		0.97	
Test whether second order production function coefficients are jointly significant (p-values)						
	0.33		0.02		0.25	
(b) Additional controls in (Cobb-Douglas) production function and wage equation						
Male	0.090	0.885	0.146	2.079	-0.346	-0.036
	(.138)	(.820)	(.129)	(1.38)	(.109)***	(.283)
Experience	0.018	-0.037	0.014	-0.011	0.006	0.009
	(.005)***	(.015)**	(.004)***	(.013)	(.007)	(.011)
Schooling	0.059	0.014	0.041	0.072	0.038	0.059
	(.013)***	(.039)	(.011)***	(.035)**	(.021)*	(.034)*
Observations	297	297	485	485	206	206
R^2	0.34	0.67	0.49	0.81	0.57	0.88
Test for equality of coefficients (p-values)						
Experience ($\lambda_X - \phi_X$)	0.00		0.04		0.73	
Schooling ($\lambda_S - \phi_S$)	0.25		0.38		0.51	
Joint test—without male	0.00		0.03		0.81	
Test whether additional controls are jointly significant (p-values)						
	0.03	0.00	0.00	0.02	0.00	0.07

Estimation as in Table 2(a), adding second order terms—$\log^2(\tilde{L})$, $\log^2(K)$, and $\log(\tilde{L}) * \log(K)$—to the production function in (a) and additional controls—foreign and state ownership dummies, the fraction of the workforce that is unionized or a family member, and capital—to both equations in (b).

Table 5: Joint estimation of wage and production equations with diminishing returns and interaction between schooling and experience

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Male	-0.011	1.480	-0.117	2.254	-0.089	0.146
	(.135)	(1.31)	(.113)	(1.56)	(.175)	(.402)
Experience	0.001	-0.046	0.053	0.062	0.068	0.064
	(.014)	(.021)**	(.013)***	(.027)**	(.013)***	(.026)***
Experience^2 ($\times$ 100)	-0.019	0.012	-0.153	-0.219	-0.817	-0.697
	(.037)	(.092)	(.047)***	(.115)*	(.126)***	(.263)***
Schooling	0.065	0.011	-0.007	0.086	0.067	0.018
	(.044)	(.117)	(.037)	(.076)	(.052)	(.100)
Schooling^2 ($\times$ 100)	-0.131	-0.138	0.353	-0.102	-0.184	-0.047
	(.200)	(.296)	(.181)*	(.456)	(.681)	(1.10)
Experience $\times$ Schooling	0.217	0.035	0.233	-0.603	0.040	0.365
($\times$ 100)	(.132)*	(.361)	(.190)	(.349)*	(.226)	(.485)
Observations	316	316	544	544	210	210
R^2	0.30	0.70	0.34	0.80	0.39	0.87
Test for equality of coefficients (p-values)						
Joint test – linear terms	0.08		0.20		0.83	
Joint test – all excluding male	0.31		0.24		0.69	
Joint test – schooling terms	0.79		0.12		0.77	
Joint test – experience terms	0.18		0.15		0.84	

Estimation as in Table 2(a), including variance, covariance, and squared terms, as derived in the Appendix.

Table 6: Joint estimation of wage and production equations on simulated samples, sensitivity analysis for sampling error

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
(a) New samples are drawn from the implied universe of workers:						
Male	0.179	0.627	0.026	1.526	-0.003	0.282
	(.042)***	(.106)***	(.050)	(.160)***	(.126)	(.155)*
Experience	0.016	-0.021	0.020	-0.005	0.003	0.005
	(.002)***	(.005)***	(.002)***	(.005)	(.004)	(.005)
Schooling	0.048	-0.001	0.071	0.046	0.082	0.073
	(.003)***	(.009)	(.004)***	(.012)***	(.010)***	(.016)***
Test for equality of coefficients (p-value)						
average	0.0008	(.011)	0.059	(.050)	0.600	(.237)
Proportion below 5%	0.99		0.59		0.00	
(b) New samples are drawn and weighted consistent with the observed means for male, experience, and schooling						
Male	0.327	1.523	0.037	0.650	0.033	0.293
	(.024)***	(.054)***	(.048)	(0.112)***	(.041)	(.069)***
Experience	0.023	-0.071	0.033	0.008	0.020	0.041
	(.002)***	(.007)***	(.002)*	(.005)*	(.003)***	(.004)***
Schooling	0.087	-0.031	0.104	0.037	0.116	0.190
	(.003)***	(.014)**	(.007)***	(.020)*	(.010)***	(.014)***
Test for equality of coefficients (p-value)						
average	0.000	(.000)	0.059	(.059)	0.133	(.067)
Proportion below 5%	1.00		0.57		0.04	

In brackets are the standard deviations of the coefficient estimates across simulations.
See text, Section 5.4, for details on the simulations. Sample sizes are as in Table 2(a).

Table 7: Joint estimation of wage and production equations with imperfect substitutability

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
(a) Imperfect substitution between high-low experience						
Male	0.242	0.586	0.035	1.923	0.045	0.368
	(.141)*	(.631)	(.124)	(1.14)*	(.230)	(.470)
Schooling	0.053	0.001	0.088	0.052	0.063	0.069
	(.009)***	(.031)	(.011)***	(.030)*	(.020)***	(.030)**
Experience (high vs. low)	0.344		0.669		0.032	
	(.117)***		(.137)***		(.187)	
Weight for high-experience		0.352		0.459		0.541
		(.074)***		(.047)***		(.065)***
Elasticity of substitution		5.957		3.035		∞
		(9.38)		(1.46)**		–
Observations	316	316	544	544	210	210
R^2	0.29	0.69	0.31	0.81	0.37	0.89
Test for equality of coefficients (p-values)						
Experience ($\lambda_X - \phi_X$)	0.00		0.00		0.63	
Schooling ($\lambda_S - \phi_S$)	0.09		0.25		0.85	
Joint test—without male	0.00		0.00		0.89	
(b) Imperfect substitution between high-low schooling level						
Male	0.294	1.030	0.427	2.358	-0.090	0.505
	(.162)*	(.889)	(.182)**	(1.38)*	(.176)	(.465)
Experience	0.013	-0.025	0.021	-0.006	0.010	0.020
	(.004)***	(.014)*	(.004)***	(.011)	(.007)	(.010)**
Schooling (high vs. low)	0.665		1.038		0.867	
	(.150)***		(.153)***		(.346)**	
Weight for high-schooling		0.538		0.590		0.738
		(.056)***		(.059)***		(.054)***
Elasticity of substitution		2.758		∞		∞
		(1.37)**		–		–
Observations	316	316	544	544	210	210
R^2	0.32	0.69	0.35	0.81	0.50	0.89
Test for equality of coefficients (p-values)						
Experience ($\lambda_X - \phi_X$)	0.01		0.02		0.32	
Schooling ($\lambda_S - \phi_S$)	0.01		0.10		0.21	
Joint test—without male	0.00		0.04		0.43	

Estimation as in Table 2(a), except for imperfect substitutability between workers and CES production function. Tests for equality of wage and productivity premium for experience in (a) and schooling in (b) are evaluated at the sample mean. See Section 6.1 for details.

Table 8: Joint estimation of wage and production equations, limited to firms in the principal city

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Male	-0.042	0.948	0.034	1.976	0.770	1.002
	(.189)	(1.13)	(.152)	(1.19)*	(.861)	(1.22)
Experience	0.019	-0.034	0.023	0.009	0.013	0.033
	(.008)**	(.021)*	(.006)***	(.013)	(.015)	(.020)*
Schooling	0.052	-0.010	0.107	0.072	0.128	0.118
	(.015)***	(.040)	(.015)***	(.035)**	(.041)***	(.055)**
Observations	127	127	350	350	88	88
R^2	0.18	0.73	0.20	0.84	0.30	0.87
Test for equality of coefficients (p-value)						
Male ($\lambda_M - \phi_M$)	0.37		0.10		0.85	
Experience ($\lambda_A - \phi_A$)	0.01		0.30		0.36	
Schooling ($\lambda_S - \phi_S$)	0.12		0.34		0.86	
Joint test	0.05		0.25		0.43	

Estimation as in Table 2(a), limited to firms in the principal manufacturing city in the country: Arusha in Tanzania, Nairobi in Kenya, and Harare in Zimbabwe.

Appendix: Second order approximation of the production function

Following the derivation in Frazer (2001), the productivity adjusted labor aggregate $\tilde{L}$ for a firm with L workers that is consistent with a Mincer model of human capital with diminishing returns on education and experience can be written as

$$f(S_1, ..., S_L, X_1, ..., X_L, M_1, ..., M_L) = \ln \Big(\sum_{i=1}^{L} e^{\phi_M M_i + \phi_X X_i + \phi_S S_i + \frac{1}{2}\phi_{XX} X_i^2 + \frac{1}{2}\phi_{SS} S_i^2 + \phi_{XS} X_i S_i} \Big),$$

where the summation is over all workers in the firm. We write down the terms in a second order Taylor expansion of this function that contain schooling. Similar terms for experience and gender are omitted as their treatment is identical.

$$\begin{aligned}
f(S_1, ..., S_L, X_1, ..., X_L, M_1, ..., M_L) &= f(0, ..., 0) && (13)\\
&+ \sum_{i=1}^{L} S_i \Big(\frac{\partial f}{\partial S_i}|_{(0,...,0)} \Big) && (14)\\
&+ \sum_{i=1}^{L} \sum_{j \neq i}^{L} S_i S_j \Big(\frac{\partial^2 f}{\partial S_i \partial S_j}|_{(0,...,0)} \Big) && (15)\\
&+ \sum_{i=1}^{L} S_i^2 \Big(\frac{\partial^2 f}{\partial S_i^2}|_{(0,...,0)} \Big) && (16)\\
&+ \sum_{i=1}^{L} \sum_{j \neq i}^{L} S_i X_j \Big(\frac{\partial^2 f}{\partial S_i \partial X_j}|_{(0,...,0)} \Big) && (17)\\
&+ \sum_{i=1}^{L} S_i X_i \Big(\frac{\partial^2 f}{\partial S_i \partial X_i}|_{(0,...,0)} \Big) && (18)\\
&+ \ldots
\end{aligned}$$

Straightforward algebra yields the following results:

$$\begin{aligned}
(13) &= \ln(Le^0) = \ln L\\
(14) &= \sum_{i=1}^{L} S_i \Big[\frac{e^{\phi_M M_i + \phi_X X_i + \phi_S S_i + \frac{1}{2}\phi_{XX} X_i^2 + \frac{1}{2}\phi_{SS} S_i^2 + \phi_{XS} X_i S_i}}{f(S_1, ..., X_1, ..., M_1, ...)} (\phi_S + \phi_{SS} S_i + \phi_{XS} X_i) \Big]_{(0,...,0)}\\
&= \sum_i S_i \frac{e^0}{Le^0} \phi_S = \phi_S \overline{S}\\
(15) &= -\frac{\phi_S^2}{L^2} \sum_i \sum_{j \neq i} S_i S_j\\
(16) &= \Big(-\frac{\phi_S^2}{L^2} + \frac{\phi_S^2}{L} + \frac{\phi_{SS}}{L} \Big) \sum_i S_i^2\\
(17) &= -\frac{\phi_S \phi_X}{L^2} \sum_i \sum_{j \neq i} S_i X_j
\end{aligned}$$

$$(18) \quad = \quad \Big(-\frac{\phi_S\phi_X}{L^2}+\frac{\phi_S\phi_X}{L}+\frac{\phi_{XS}}{L}\Big)\sum_i S_iX_i.$$

The same calculations can be performed for the derivatives with respect to X_i. Substituting all terms and using the fact that $\sum_i\sum_j S_iS_j = L^2\bar{S}^2$, $var(S) = \frac{1}{L}\sum_i S_i^2 - \bar{S}^2$ and that $cov(S,X) = \frac{1}{L}\sum_i S_iX_i - \bar{S}\bar{X}$ gives

$$\begin{aligned} f(S_1,...,S_L,X_1,...,X_L,M_1,...,M_L) \quad \approx \quad & \phi_S\overline{S}+\phi_S^2 var(S)+\phi_S\phi_X cov(S,X) \\ & + \phi_{SS}\underbrace{\frac{\sum_i S_i^2}{L}}_{(\overline{S_i^2})}+\phi_{XS}\underbrace{\frac{\sum_i S_iX_i}{L}}_{(\overline{S_iX_i})}+\ldots. \end{aligned}$$

To introduce this labor aggregate in the estimation, we need to calculate the variance and covariance of schooling and experience by firm, as well as the average of schooling and experience squared. For gender, rather than taking the derivatives, we use the assumptions in (4) which leads to a term $\ln(1+\phi_M\frac{L_M}{L})$ in the estimating equation, as before. This amounts to factoring out the gender effect from the $f(.)$ function before taking the second order approximation of the remainder.

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