Wages Equal Productivity. Fact or Fiction?

Johannes Van Biesebroeck*

University of Toronto and NBER

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Abstract

Using a matched employer-employee data set of manufacturing plants in three sub-Saharan countries, I compare the marginal productivity of different categories of workers with the wages they earn. In each country, I observe approximately 135 firms and an average of 5.5 employees per firm. Under certain conditions, the wage premiums for worker characteristics should equal the productivity benefits associated with them. I find that equality holds strongly in Zimbabwe (the most developed country in the sample), but not at all for Tanzania (the least developed country). Results for Kenya are intermediate. Differences between wage and productivity premiums are most pronounced for characteristics that are clearly related to human capital, such as schooling, training, experience, and tenure. Moreover, where the wage premium differs from the productivity benefit, general human capital tends to receive a wage return that exceeds the productivity return, and the reverse holds for more specific human capital investments. Schooling tends to be over-rewarded, even though most of the productivity benefit comes from job training. Wages tend to rise with experience, even though productivity is mostly increasing in tenure. Sampling errors, nonlinear effects, and non-wage benefits are rejected as explanation for the gap between wage and productivity effects. Localized labor markets and imperfect substitutability of different worker-types provide a partial explanation.

*Department of Economics, University of Toronto, 150 St. George Street, Toronto, ON M5S 3G7, Canada, jovb@chass.utoronto.ca. Seminar participants at the University of Illinois, Kellogg School of Management, and Catholic University of Louvain provided useful suggestions. Funding by the Connaught Foundation is gratefully acknowledged.

1 Motivation

In the textbook economics world, markets are the most efficient institution to allocation scarce resources. They clear all the time, equalizing demand and supply, opportunities are arbitraged away, and all production factors are paid their marginal productivity. In the real world, there are frictions, unobservable characteristics, adjustment costs, erroneous expectations, and maybe even 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, I will present evidence that the extent to which the theory fails a reality check is negatively correlated with the degree of economic development of a country. In particular, I will show that the less developed a country is, the less equal the remuneration for workers' characteristics is to the marginal contributions the same characteristics make in production. The elements omitted from the theory have predictive power with respect to the level of development.[1]

A well-functioning labor market should perform at least two tasks; matching firms and workers and setting wages. It should allocate workers to enterprises with highest productivity or the best future prospects. Through reallocation of workers between firms or industries, the labor market can provide a positive contribution to aggregate productivity growth. Van Biesebroeck (2005) investigates the effectiveness of labor markets in several African countries 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 such that characteristics are rewarded at their marginal products. If labor markets function as spot markets without imperfect information and firms maximize profits or minimize costs, we would expect differences to be arbitraged away. If differences remain, workers are not provided with the correct incentives to choose the optimal level of investment in human capital characteris-

[1]Only three countries are included in this analysis, but the patterns are very consistent across characteristics and the results are robust to different specifications. I believe the results will generalize to other countries. A partial analysis with data from Cameroon (almost as developed as Zimbabwe) and Burundi (even less developed than Tanzania) confirms the patterns I describe here. I did not include those countries in the full analysis because the data was deemed less reliable, the sample size too small, and information on some variables missing.

tics, such as schooling or tenure. Previous papers comparing wage and productivity returns in developed countries—Hellerstein, Neumark, and Troske (1999) and more recently Hellerstein and Neumark (2004) for the United States, Prez-Duarte, Crepon, and Deniau (2001) for France, and Hellerstein and Neumark (1999) for Israel—find equal wage and productivity returns for almost all characteristics.

In this paper, I investigate the pattern of rewards to different worker characteristics using individual- and plant-level data for three African countries that vary significantly by level of development. I find that in the most developed economy, Zimbabwe, characteristics are rewarded at their marginal productivity, while such equality can be firmly rejected for the least developed economy, Tanzania. In the country with an intermediate level of development, Kenya, the results are also intermediate. Equal remuneration can be rejected for some characteristics, e.g. experience, but not for others, e.g. schooling. Making the same comparison using a richer set of characteristics reveals that the breakdown in correct remuneration for less developed economies is most pronounced for characteristics that contributed to general—as opposed to firm-specific—human capital: schooling and experience.

More developed countries somehow manage to reward worker characteristics such that the return to the firm matches the return to the worker. With equal private and social returns, investment in human capital will be optimal without need for subsidies. One of the most illuminating examples of the different reward structure across countries is provided by the return to formal training, taken during employment. The productivity boost a firm enjoys for training its workers is large and relatively uniform across countries, ranging from 44% in Zimbabwe to 77% in Kenya. The benefit in higher salary to the workers, on the other hand, is less uniform. Workers with training only get a paltry 4.5% salary increase in Tanzania, 17% in Kenya, while Zimbabwean trainees receive a 78% salary boost. Less than one tenth of the plant-level gains accrue to the worker in Tanzania and less than a quarter in Kenya. In Zimbabwe, workers receive more than the direct productivity gain they produce, possibly because the effects spill over and improve the productivity of co-workers. It will be much easier for Zimbabwean employers to retain these highly productive employees and to motivate others to participate in productivity-boosting training programs.

As pointed out 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. At the same time, one should also 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. I will perform several specification checks for the results, exploring alternative explanations such as localized labor markets, imperfect substitutability between workers, and sampling error for the discrepancy between wage and productivity effects.

From a policy perspective, an investigation into the link between wages and productivity is important for at least two reasons. On the one hand, 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 plants 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. Another policy implication is regarding the measurement of productivity growth. In most developed countries, growth in labor productivity is calculated by subtracting labor growth from output growth, with labor calculated as a weighted average of several worker types each weighted by their share in wages, see for example Jorgenson and Griliches (1967). The motivation is that relative wages should equal relative productivity. If this equality fails to hold in developing countries, productivity growth measures will be biased.

I start by introducing the countries and the employer-employee matched data in Section 2. In Section 3, the reward for different characteristics is analyzed at the individual-level. Mincer wage regressions are estimated using different controls, different sets of explanatory variables, and exploiting different sources of variations. The remainder of the analysis is conducted at the plant-level. The measurement framework to compare wage premiums for worker characteristics to the productivity effects is introduced in Section 4. The previous literature is surveyed in Section 5 and labor market efficiency is tested in Section 6. Several robustness checks in Section 7 investigate the cause for the failure of wages to reflect productivity differences. Section 8 concludes.

2 Data

The three countries included in the sample are middle-sized former British colonies in East Africa that obtained independence in the early 1960s. The World Bank classifies all three as low income, even though they differ substantially by level of development. One way to gauge this is from the GDP per capita (in PPP), which stood at $477 in Tanzania in 1991, less than half of the $1092 obtained in Kenya, and only slightly more than one fifth of the GDP per capita of Zimbabwe. The differences are smaller comparing the human development index, calculated by the United Nations, which also takes education and life expectancy into account. In the most recent ranking, Tanzania occupies the 151st or (22nd last) place with 0.440, putting it in the "low development" category. Kenya and Zimbabwe rank rather closely at places 134 and 128, with a score of 0.513 and 0.551, near the bottom of the "medium development" group.[2]

[Table 1]

The different development levels of the countries is also reflected in the share of workers employed in industry.[3] Only 4.7% of all employment in Tanzania is in industry, while it is almost double in Zimbabwe at 8.6% and intermediate in Kenya at 7.3%. The patterns of employment shares in agriculture are the reverse. In Tanzania, almost half of all workers were still employed in agriculture at the end of the 1990s and this share is declining fast (it stood at 60% a decade earlier). In Kenya, the employment share of agriculture is much lower, at 27.5%, but the transformation from agriculture to industry, and especially to services is still in full swing. Two decades ago 42% of the working population worked on the land. Zimbabwe, on the other hand, has seen a stable 18.5% of its workforce employed in agriculture for the last 25 years.

[2] Norway tops the ranking with a score of 0.942.

[3] Manufacturing employment that matched manufacturing value added was not available for Tanzania in 1991.

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

Infrastructure statistics 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 enrollments, infant mortality, etc.[5]

Tanzania and Kenya each counted approximately 25 million inhabitants, while Zimbabwe only had 10 million in 1991. The manufacturing sector, which I will focus on, is more evenly sized because of the much higher importance in Zimbabwe. All countries count between 126,000 and 188,000 manufacturing workers. A stratified sample of manufacturing plants in three consecutive years, provides the micro data used in the analysis.[6] Approximately 200 plants were surveyed each year in each country, covering four broadly defined manufacturing sectors: food, textile and clothing, wood and furniture, metal and equipment. A maximum

[4]Export diversification is another important benefit of developing a strong manufacturing sector. Coffee and tea bring in 52% of foreign exchange in Tanzania and 54% in Kenya. It makes these countries very vulnerable to price volatility on only two world markets, especially because they spend respectively 53% and 38% of all foreign exchange on investment. For more details, see **?**).

[5]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.

[6]The data was collected between 1991 and 1995 by three different research teams, coordinated by the Regional Program of Enterprise Development at the World Bank. Sampling was stratified by size to give (the plant of) each manufacturing worker equal probability to be included in the sample.

of 10 employees per plant were interviewed each year.[7] While plants could be linked over time as a panel, this was not possible for the workers.

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

For the plants in the sample, the differences between the countries are equally pronounced. The median plant in Tanzania achieves only 38% of the labor productivity of the median plant in Kenya, while labor productivity in Zimbabwe is 42% higher than in Kenya. Total factor productivity numbers, taken from Van Biesebroeck (2005), show similar differences when capital intensity is taken into account. The median plant in Kenya is twice as productive as in Tanzania, but achieves only two thirds of the productivity level of the median plant 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 median labor productivity at their employers stands at 26.8%. Salaries in Kenya, on average $120, are slightly lower than 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 remainder of Table 1 provides averages and standard errors for the variables used in the analysis. Workers in Zimbabwe work on average in larger plants, 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 even more dominated by males and unions are less popular than in the other countries. In Tanzania, workers receive

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

the lowest salaries, but paradoxically they have the highest years of schooling. How these characteristics are rewarded is analyzed in the next section.

3 The wage premium for different characteristics

Because information on productivity is only available at the plant-level, individual wages have to be aggregated to carry out the comparison. To make sure that the aggregation does not obscure how an individual's characteristics are rewarded at the most detailed level, I first estimate a wage equation at the individual level. Different specifications of a log-linear wage regression, motivated by a model of human capital as in Mincer (1974), are estimated. The first column for each country in Table 2 contains the baseline specification with gender, years of experience on the job market, and years of formal education as explanatory variables. I do not include a dummy for marital status as is usually done because this question was not asked in Kenya in one of the years and almost a fifth of Tanzanian workers did not answer it. Relative to the usual specification for the U.S., I also omit information on race. This was deemed a sensitive question and was only included in select years. In some countries, especially Tanzania, there are so many ethnicities that it would be impossible to control for all groups. The only specification that produced meaningful results, was the inclusion of a dummy for non-African workers. In most cases, foreigners are owners or higher management and their wage premiums range from 70% to 120%. Because this effect is unrelated to the reason race dummies are included in regressions for developed countries—potential discrimination—I omit the race variable. In every regression, I include hours worked and dummies to control for time, sector, and location.

The gender premium for males is relatively small in Tanzania and Zimbabwe and nonexistent in Kenya. Moreover, it is estimated very imprecisely. The returns to experience and schooling, on the other hand, are estimated very precisely. They decline with the level of development in the country. While in Tanzania an extra year of experience brings 2.3% higher salary and a year of education 6.8%, the rewards drop to 1% and 4.9% in Zimbabwe. The Tanzanian results are most alike results for manufacturing workers in the United States. The estimated returns include the reward to effort and ability insofar as they are observable to the employer and correlated with schooling or experience. Self-selection into the salaried labor market and into the manufacturing sector, which is likely to be nonnegligible in Africa, also influences the coefficient estimates if it is correlated with one of the explanatory variables.[8] Note that the explanatory power of the regressions declines in line with the estimated returns to schooling and experience. The results are not directly comparable with those in Bigsten et al. (2000) due to different specifications (especially the quadratic terms and inclusion of tenure), but many effects correspond well.[9]

[Table 2]

The second specifications in Table 2 have additional occupation dummies as controls, and the third columns control for firm-size dummies instead. These extra controls are intended to help interpreting the previous coefficient estimates and put the magnitudes of the effects in context. Results for the United States in Groschen (1991) show that male and female workers doing the same job in the same establishment earn very similar wages. There is substantial segmentation in the labor market. Women are disproportionately employed in lower paying establishments and occupations, each of which explains approximately half of the 11% gross salary differential by gender in manufacturing plants.

In Africa, the results are reversed. Controlling for occupation increases the gender pay differential in each country. More careful inspection of the data reveals that women are more likely to be employed in nonproduction occupations, such as office support or sales, that pay on average higher wages. Controlling for occupation raises the gender gap to 8.5% in Tanzania, 13.5% and 18.5% in Zimbabwe. The changes in the gender wage gap are mixed when controls for firm-size are introduced. In Tanzania, the difference increases, indicating that women are more likely to work for larger employers. Almost 50% of all women, against only 34% of men, work in plants that employ at least 50 workers. In Kenya, there is no gender segmentation by plant-size and in Zimbabwe the effects works in the opposite

[8]Most of the results discussed in Schultz (1988) refer to average returns in the population at large and are incomparable with my results. The result for Ghana in Schultz (1999) match the returns to schooling I estimate for Zimbabwe.

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

direction. Women are less likely to work for large plants that pay more on average, which explains almost two thirds of the gross wage gap. Given that the gender effects are most sensitive to the exact set of controls and not comparable to developed countries' results, they will not figure prominently in the wage-productivity comparison. The relative labor market experience in Africa for the sexes is markedly different from developed countries and a more nuanced discussion of the pay differentials by sex is beyond the scope of this paper.

Changes in the returns to education and experience after controlling for occupation or plant-size are uniform across countries. Segmentation of more experienced and more highly educated workers by firm-size, in the third column, accounts for 5% to 15% of the rewards to experience and education. Running the regressions separately by firm size-class reveals that the effect on wages comes mostly through the intercept and less through the slope of the earnings function. More educated and experienced workers are found in larger plants that pay higher salaries, especially in Zimbabwe, while firms of different sizes pay similar premiums for schooling and experience.

Segmentation by occupation, in the middle columns of Table 2, is even more important and equally uniform across countries. In Kenya and Zimbabwe, at least half of the benefit of schooling comes from having access to a better paid occupation, even when the job classification is relatively coarse (I observe only 11 categories). In Tanzania a third of the schooling premium accrues in terms of getting a better paid occupation. Experience also gets a large part of its value, between 33% and 43%, from the extent it allows workers to move up the occupational ladder. Adding the 11 occupation dummies to the regression raises the explanatory power of the regression substantially, especially in Zimbabwe.

An obvious shortcoming of the specification in Table 2 is the limitation to linear effects. Intuitively, we expect the returns to experience and schooling to taper off and they are likely to be substitutes. Estimating individual wage regressions with quadratic and interaction effects yield some counterintuitive results: returns to schooling are convex in Tanzania and Kenya and experience and schooling are complements in Tanzania. For Zimbabwe all results are in line with U.S. findings. The short sample in the plant-level analysis limits our ability to include quadratic and interaction effects. A sensitivity check is performed in Section 7.4.

Finally, in the first column of Table 3, I add more explanatory variables to the wage regressions and still estimate with least squares. Few of the original variables change noticeably. Only in Zimbabwe, the male wage premium disappears largely and the return the schooling drops by 1%. It is also the country with the highest return to formal training, so it is not implausible to see the largest decline in the return to pre-employment education. The wage premium for workers that received formal training (excluding on-the-job training) is positive in all countries and especially large in Zimbabwe, exceeding 30%. Training is more valuable relative to education if the country is more developed. Relative to schooling, training can be interpreted as a proxy for more firm-specific skills. Similarly as schooling, it is likely to include a return to unobserved ability or effort as selection for a training program is at the discretion of the employer and finishing a training program is likely to require extra effort on behalf of the employee.

[**Table 3**]

Introducing a tenure variable, measuring the number of years an employee has spent with his current employer, hardly changes the return to experience or schooling. Rewards to tenure are estimated to be negative for Tanzania, but positive and slightly higher than half of the return to experience in the two more developed countries. Relative to experience, tenure can be interpreted as a proxy for the accumulation of firm-specific skills. Alternatively, it can capture a reward for loyalty to the current employer, a type of efficiency wage. I also find that union workers are paid less than nonunion workers and members of the owner's family are paid below average in Zimbabwe, but they receive a higher salary in the two less developed countries. Closer inspection of the data reveals that within occupation categories, salary is often positively correlated with union status.

All of the coefficients estimated by least squares in Tables 2 and the first column of Table 3, capture both a within and between firm effect. 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. The second and third columns in Table 3 separately identify the magnitude of both effects. In most cases they work in the same direction. For example, more experienced or more highly educated workers are paid more than their coworkers *and* they tend to work for plants that pay all employees more on average. In the case of experience, both effects are approximately equal in size, while the between firm effect substantially exceeds the within effect for the return to schooling.

The comparison between wages and productivity, in Section 6, is carried out at the plant-level, identifying the returns to characteristics by variation across plants. When both the within and between effect work in the same direction, the interpretation is straightforward. When both effects have opposite sign, caution is warranted. The interpretation of the wage differential by gender is thus complicated. 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 plants. The pay differential is reduced by sorting of men towards low-paying employers. Comparing average earnings across plants will show a negative wage premium for men, because plants that employ a high proportion of men pay lower salaries on average, even though men employed in those plants still earn more than their female coworkers. This complicates further the interpretation of the gender dummy.

Similar caution should be exerted in interpreting the coefficient for family members in Kenya and Zimbabwe. Within each plant family members are paid higher salaries than other employees, but they tend to work for plants that pay lower average salaries. In Zimbabwe the between effects dominates, resulting in lower pay in total, while in Kenya the within effect leads to higher pay for family members. Tanzania is the only country where firms that offer high salaries are also more likely to employ family members and both effects work in the same direction. Perhaps not surprisingly, the coefficient on the share of workers that are related to the owner as an explanatory variable in the production function turns out to be significantly negative in each of the three countries. It is interesting to note that most of the lower pay for union workers is a within plant effect, while segregation of employees reduces the differential. Unionized workers are employed at plants that pay higher wages. In the production function a unionization share yields a positive coefficient in each country. Union members either choose to work in very productive firms or that they raise the productivity level of their employers. The higher salary for workers that received training is largely a between effect, while the within effect is constant across countries.

The positive coefficient on tenure could 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 Kenya and, especially, in Zimbabwe, workers stay longer with well-paying employers and this explains the positive wage premium for tenure entirely. In contrast, workers with high tenure in Tanzania are more likely to be employed at low-paying employers. To sustain such a pattern there have to be switching costs in the labor market.

The results in Tables 2-3 sketch a fairly comprehensive picture of the returns to different characteristics and how they differ across countries by level of development. The next task is to line up the wage premiums for different characteristics with their productivity impact. The results of that analysis are in Section 6. First, I introduce a framework to carry out the comparison in the following Section.

4 A measurement framework

The methodology owes a great deal to Hellerstein, Neumark, and Troske (1999). If labor markets are efficient, operate as a spot market, and firms minimize costs the wage premium of a worker should equal its productivity premium. Barring imperfect information, any difference will be arbitraged away. Both premiums will be identified by jointly estimating a wage equation and production function at the plant-level. As an example, assume that the productivity of male workers exceeds the average productivity of female workers by ϕ_M percentage. The production function can be written as a function of capital and both types of labor (men and women),

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

Note that men and women are assumed to be perfect substitutes. This assumption is investigates later (see Section 7.2). In this case, the first order conditions of the firm entail that in an efficient labor market the relative wage for both types of workers should equal their relative productivity:

$$
\begin{aligned}
\frac{w_M}{w_F} &= \frac{MP_M}{MP_F} \equiv 1 + \phi_M \\
\lambda_M \equiv \frac{w_M - w_F}{w_F} &= \frac{MP_M - MP_F}{MP_F} \equiv \phi_M. \qquad (1)
\end{aligned}
$$

Jointly estimating the wage (λ_M) and productivity (ϕ_M) premiums associated with each characteristic allows me to test for 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 largely alleviate such concerns as the bias works in the same direction for both equations. The unobservables are to a large extent two sides of the same coin.[10] I am only interested in the relative magnitudes of the coefficients in each equation, which should be less affected.

Because both equations are estimated at the plant-level, identification of the wage and productivity effects comes from correlation across plants of the composition of the workforce with average salaries and output. The discussion of the between and within estimates in Table 3 showed that, in general, the magnitude and sign of the coefficients estimated from the variation across plants corresponded well to the gross wage-effect of the characteristics estimated at the individual-level.

For joint estimation, I have to derive a plant-level wage equation consistent with the Mincer (1974) model of human capital. Sticking with the earlier example, define a wage equation for the individual 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 the value of one if individual i is a women—and w_M to men. Aggregating the wage equation to the plant-level

[10]See for example Frazer (2001) where this assumption is exploited to control for unobserved ability in the wage equation.

gives

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

which I will estimate in logarithms

$$\ln \frac{W}{L} = \ln w_F + \ln[1 + \lambda_M \frac{L_M}{L}]. \tag{2}$$

Nonlinear least squares estimation produces 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 by plant.

Assuming the Cobb-Douglas functional form and perfect substitutability between male and female workers, the production function can be written in logarithms as[11]

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

Male and female workers are aggregated in $\tilde{L}$, where each type of employee (L_F and L_M) is multiplied by its relative productivity level (1 or 1+ϕ_M),

$$\begin{aligned} \tilde{L} &= L_F + (1 + \phi_M)L_M \\ &= L[1 + \phi_M \frac{L_M}{L}]. \end{aligned} \tag{3}$$

L is the total labor force ($L_F + L_M$). Substituting (3) 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.

Generalizing this approach to construct a wage and production equation with more dimen-

[11]It is straightforward to generalize the methodology to other functional forms. Hellerstein and Neumark (2004) demonstrate in a similar application that the qualitative results are very robust to alternative specifications of the production function.

sions on which workers differ is limited by the data. At the very least, I 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.). Because I observe a maximum of ten workers in each plant, the proportion of each group in each plant's workforce will be estimated extremely inaccurate. Making three assumptions for each characteristic, or rather three sets of assumptions, lets me avoid this type of dimensional problem.

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). I assume, for example, that the relative number of workers, the relative productivity, and the relative wages by gender are constant in each experience-schooling category. 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.

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

and similarly for other characteristics. This allows the simplification of the labor aggregate in the production function from eight terms, one for each worker category, to three multiplicative factors, one for each characteristic:

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

and similarly in the wage equation. If the number of characteristics increases, one can proceed in the same fashion, adding factors to (5). With more characteristics included, it becomes even more indispensable to make the assumptions that all ratios are equal conditional on the other characteristics, as in (4). 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.[12] The assumption of perfect substitutability between workers with different characteristics is investigated in Section 7.2.

The baseline model constructed so far is

$$
\begin{aligned}
\ln \frac{W}{L} &= \lambda_0 + \ln(1+\lambda_M \frac{L_M}{L}) + \ln(1+\lambda_X \frac{L_X}{L}) + (1+\lambda_S \frac{L_S}{L}) + \eta && (6)\\
\ln Q &= \alpha_0 + \alpha_K \ln K \\
&+ \alpha_L[\ln L + \ln(1+\phi_M \frac{L_M}{L}) + \ln(1+\phi_X \frac{L_X}{L}) + \ln(1+\phi_S \frac{L_S}{L})] + \epsilon && (7)
\end{aligned}
$$

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 (high versus low). Equations (6) and (7) are estimated jointly with Zellner's seemingly unrelated regression estimator, allowing for correlation between the two error terms.

When characteristics vary continuously, such as schooling or experience, the derivation of both 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 of all workers L_j with each type of worker j multiplied by its human capital component. The adjustment takes the form of $e^{\phi_0+\phi_S S_j+\phi_X X_j}$, if types differ by schooling and experience. A first order Taylor approximation of the production

[12] For some plants, enough workers are observed that the assumptions in (4) can be rejected. To rationalize such observations, I have to invoke some measurement error. If enough employees are observed per plant, some of the assumptions underlying the construction of the labor aggregate in (5) can be relaxed. For example, if we have enough observations to calculate the number of employees with high experience and schooling separately by gender, we do not have the impose equal productivity and wage differentials by gender in each sub-group (high and low schooling or experience). Instead, we can separately calculate high and low educated workers by gender. We will still have to assume that the average experience is similar across each of the four groups defined by education and gender. If the outside category is female, inexperienced, uneducated workers (FYU) the labor aggregate in the production function ($\tilde{L}$) can be written as

$$
\begin{aligned}
\tilde{L} &= L\,[1+\phi_{FX}\frac{L_{FX}}{L} + \phi_{MY}\frac{L_{MY}}{L} + \phi_{MX}\frac{L_{MX}}{L}] \\
&\quad \times [1+\phi_{FS}\frac{L_{FS}}{L} + \phi_{MU}\frac{L_{MU}}{L} + \phi_{MS}\frac{L_{MS}}{L}]
\end{aligned}
$$

and similarly for the wage equation. Categorical variables that take on more than two variables can be accounted for similarly.

function with the nonlinear human capital factors produces a log-linear equation.[13] 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 plant:

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

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, by replacing $\tilde{L}$ in (7′) by $L\ (1 + \phi_M \dfrac{L_M}{L})$. The limited model allowing for continuous characteristics that I take to the data is

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

$$\ln Q \;=\; \alpha_0 + \alpha_K \ln K + \alpha_L [\ln L + \ln(1 + \phi_M \frac{L_M}{L}) + \phi_X \overline{X} + \phi_S \overline{S}] + \epsilon, \qquad (9)$$

and similarly for the wage equation. The full models adds continuous terms for years of tenure $(\phi_T \overline{T})$ and discrete terms for the share of workers that received training $(\ln(1 + \phi_{TR} \frac{L_{TR}}{L}))$.

5 Related literature

Even though the question whether wages equal productivity is acknowledged as an interesting and important one, data limitations have hampered empirical testing. Variations of the approach I outlined—limited to discrete characteristics—have been applied to a number of countries. What is needed to estimate the model is input, output, and average wage data at the plant-level, which are widely available. In addition, one needs to observe the average values for a number of worker characteristics or the ratio of workers that display a certain

[13] 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 plant in the equations. Because of the limited number of workers I have available per plant in my sample (a maximum of 10), I refrain from doing so. When the returns for characteristics are modeled as quadratic instead of linear, see Section 7.4, I will be forced to introduce a second order approximation.

characteristic. Because such questions are rarely posed directly in plant-surveys, researchers have relied on employer-employee data sets to estimate average values for each plant from the fraction of employees that are observed.[14]

In the United States Hellerstein et al. (1999) find that women are 16% less productive, but paid 45% less than their male coworkers. The bulk of the gender wage gap cannot be explained by differential productivity. More recent work using a different data set, see Hellerstein and Neumark (2004), confirms that in the United States the wage gap between males and females exceeds the productivity gap. The lower wages for blacks is in line with productivity estimates. College graduates, on the other hand, are 67% more productive on average and only paid 43% more. In a sense, they are also discriminated against in the U.S. labor market, although the difference is not statistically significant. Similar work for France in Prez-Duarte et al. (2001) and for Israel in Hellerstein and Neumark (1999) finds no gender discrimination. In each country, the remuneration for only a single characteristic differed significantly from the productivity effect associated with it. In France, older workers are significantly overpaid relative to their productivity level, while engineers are significantly underpaid in Israel.

Using RPED data for Ghana, Jones (2001) estimates a plant-level production function jointly with an individual-level wage equations. Unfortunately, no information is provided on the estimation method. When combining individual and plant-level data in one joint estimation, it is not immediately obvious what the most plausible assumptions are on the variance-covariance matrix. 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. The reward for an extra year of schooling equals the productivity gain associated with it, both are 7%. When different discrete levels of education attainment are used, the results are ambiguous. Sometimes the wage premium exceeds the productivity contribution, for example, for primary education the difference is almost fourfold. For other education categories the productivity effect dominates, e.g. for vocational, polytechnic, and university education. Even though many differences are large in absolute value—five of the eight estimated differ-

[14]I perform two types of Monte Carlo analysis to verify to what extent the results are sensitive to sampling error in the first estimation stage.

entials exceed 20%—none of the formal tests finds a statistically significant difference. The education coefficients in the production function are estimated especially imprecisely.[15]

One of the goals in Bigsten et al. (2000) is to calculate returns to education, also using RPED data for five sub-Saharan countries (including Ghana, Kenya, and Zimbabwe). Looking only at the wage equation in isolation, they find the highest education-induced salary increase in Zimbabwe, the most developed economy, and the lowest increase in Ghana, the country with the least developed manufacturing sector in their sample. Separate estimates of the production function with ad-hoc measures for human capital (such as lagged education) produces highly significant and positive impact of human capital on output, but low implied rates of return. In particular, the return to human capital is only a fraction of the return to physical capital.

Another related study is by Benjamin (1995). He 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. In theory, higher output per worker on smaller farms is consistent with higher unobserved land quality at those farms. Using instrumental variable techniques, he shows that accounting for such unobservable land quality completely eliminates the inverse productivity-size relationship. In Section 7, I perform several robustness checks to investigate alternative explanations—other than market imperfections—for the gap between measured wage and productivity returns. For an unobservable input in the production function to have the same equalizing effect in this paper, it should be most strongly correlated with average experience of workers across plants; the variable for which equality of wage and productivity returns fails most markedly.

Finally, Velenchik (1997) investigates urban labor markets in Zimbabwe, using some of the same RPED data that I use in this study. She mainly looks at the worker data, ignoring much of the information on productivity differentials between firms, contained in the plant-level data. One of her principal findings is that profit growth of the employer has a positive

[15]Another problem with her analysis is the inclusion of experience squared in the plant-level production function. In Section 7.4 quadratic terms are introduced into the return to education and experience. When such returns are aggregated up to the plant level, one needs to include the variance for each characteristic by plant in the regression. Another puzzling finding is the decreasing returns to scale technology, which conflicts with most production function estimations for Ghana that usually find increasing returns.

coefficient in a wage growth regression. She interprets this as an indication of rent sharing between workers and employers and as evidence against efficiency wages. This finding is not inconsistent with our approach in this paper, as productivity is likely to have an impact on wages as well as firm profitability. The stylized fact is that workers with high wage growth work for plants with high rates of profit growth. This is fully consistent with an efficient labor market—if more able workers make the firm more profitable and receive higher salaries in return—and only indicative of rent sharing if rising profitability causes or precedes the wage growth.

6 Results

The estimation results by country for equations (8) and (9), with continuously measured experience and schooling, are in Table 4.[16]. As with the individual data, the gender wage gaps are estimated imprecisely with varying size and magnitudes. Plants that employ a high proportion of men are invariable more productive, but as mentioned earlier, it might be because men are more productive or because they tend to work for more productive firms. Regardless of the cause, the results indicate that differences in pay by gender do not correspond well to productivity differences. Perhaps surprisingly for Africa, the results tend to suggest that men are underpaid, although the differences are not statistically significant.

[Table 4]

The wage returns to experience and schooling, on the other hand, are precisely estimated and correspond well to the previous results. Salaries rise substantially with experience in Tanzania and Kenya, but not in Zimbabwe, where education is rewarded higher than in the two other countries. The effect of experience and education in the production function follow a consistent pattern. Both effects rise with the degree of development. In Tanzania, experience contributes negatively to productivity, while higher education contributes nothing.

[16]In each specification, hours worked and time, industry, and location dummies are added as controls to both the wage equation and production function.

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 plant return—higher output—associated with experience and schooling match almost perfectly.

The gaps in the salary and productivity premium for experience and schooling are highest in Tanzania, at respectively 4.8% and 6.0% and they are still sizeable in Kenya, at 2.8% and 3.3%. In Zimbabwe, the gaps are 0.3% and 1.2% and equality of the returns cannot be rejected at all with a formal statistical tests. The p-values are 0.81 and 0.75. 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 conclusions cannot simply be attributed to less precise coefficient estimates 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 are statistically significant, and the same is true for the joint test.

The largest discrepancy between wage and productivity premium is for experience. In the two least developed countries, workers get substantial pay increases over their career, which are not matched by any discernible productivity effect. The return to 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 6% even though there is no productivity effect to speak of. In Kenya, the return to schooling is much larger, 9.1%, which still exceeds the productivity it brings the employer by more than half. In Zimbabwe, the excess return to schooling is kept to a moderate 1.2% per year, which is only 10% of the productivity gain a year of schooling brings on average.

Qualitatively the same and quantitatively very similar results are obtained when experience and schooling are included as dummy variables—high versus low—, see Table A.1 in the Appendix. 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 input coefficients in the production function are estimated precisely and the point estimates are plausible. Returns to scale are estimated to be slightly increasing, but only in Kenya do they significantly exceed one (at a 5% significance level). The relative importance of capital and the labor aggregate is rather similar for each country.

Including more explanatory variables in the wage equation and production function, results are in Table 5, identifies more characteristics that are rewarded differently from their productivity effect.[17] The gender coefficients vary somewhat, but are still measured inaccurately. Experience is still rewarded with higher salary increases than the productivity effect warrants, especially in Tanzania, to some extent in Kenya, and 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 estimates similar, as before.

[**Table 5**]

Inclusion of a variable measuring the tenure of an employee at his current employer, conditional on experience, indicates that tenure is particularly well rewarded in Zimbabwe, where it matches the 1.7% increase in production that is associated with an average year of tenure. The gap between the individual and plant return is, again, largest in Tanzania and intermediate in Kenya. The same is true for formal training. In the two least developed countries, workers that receive 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. Together with the 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

[17] The results in Table 5 rely on continuous measures for schooling, experience, and tenure. The corresponding results in Table A.2 in the Appendix measure those variables discretely. The results are, again, very similar.

between training and tenure at the individual-level. Controlling for experience, workers with a longer tenure are more likely to have completed a training program. On average, workers that have completed training were employed for half a year longer at their last employer, which is significantly positive. The relationship is particularly strong in Zimbabwe, but hardly noticeable in Kenya.

It is illuminating to compare the size and composition of the salary and productivity increases over a worker's career across countries. A Tanzanian employee that remains with the same employer will see his salary grow by 0.6% on average, while the salary increase would be higher if he changed employers. The productivity of workers declines by almost 3% per year and this is not 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 changes employers, none otherwise. In Zimbabwe, the wage and productivity increases match remarkably well and they mostly accrue with tenure, not general experience. Controlling for tenure, as a proxy for firm-specific skills, and education and training, as a proxy for general skills, lowers the return to experience almost to zero.

A joint test for the hypothesis that for the four variables that determine the human capital component in a plant—experience, schooling, tenure, training—wage premiums equal productivity premiums 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. The tests follow the same pattern as the joint test with the restricted set of variables and it emerges even more strongly from the results with discrete variables in Table A.2 in the Appendix: the probability of rejection decreases with the level of development.

Relative to the productivity effects, experience and schooling are over-rewarded in the two poorest countries, while the reverse is true for training and tenure. Workers can 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 effects warrants. 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.

Performing separate tests for the firm-specific aspects of human capital—tenure and training—and general human capital—experience and schooling—points to the general characteristics as the drivers for the correlation between equality of returns and development level of the country. Firms in each country seem to reward firm-specific characteristics in relation to their productivity, all p-values are high, although it should be noted that the effects of training are estimated especially imprecisely for Tanzania and Kenya. The differences between countries are especially stark for 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 (4.7%), intermediate for Kenya (2.7%), and almost perfect equality for Zimbabwe (0.1%). The underlying phenomenon is that over time salaries increase with experience in Tanzania and Kenya and with tenure in Zimbabwe, while productivity is more closely related to tenure than experience in each country.

It is interesting to note that including two more variables from Table 3 in the joint estimation—dummies for a relationship with the owner and belonging to a labor union—would yield markedly different results.[18] For the variables that have a less direct bearing on human capital—gender, family member of owner, union—the pattern identified earlier breaks down. It is in Tanzania that labor markets are most successful at lining up the salary rewards with productivity effects. Unfortunately, this seems to be less important in developing a strong manufacturing sector. Gender and relation to the owner, for example, cannot be changed by employees, so there is no need for correct incentives to obtain optimal levels of investment or adoption.

[18] Results available upon request.

If firms are cost-minimizing and labor markets work efficiently, differences between wage and productivity effects should be arbitraged away. Before jumping to conclusions, I investigate a number of alternative explanations for the disparities in returns. These can be interpreted as robustness checks for the pattern that the extent to which characteristics are rewarded in line with their productivity contribution is correlated with the level of development of the country.

7 Potential explanations

7.1 Localized labor markets

One feature of labor markets in developing countries that might explain the failure of wage effects to match productivity effects is the segregation of economic activities by geographic area. If workers rarely migrate between different cities and daily commuting is impossible because of poor transportation infrastructure, pooling firms that operate in different cities will produce misleading results. Reardon (1997) surveys some evidence that suggests localized labor markets are likely to be important in Africa. Reviewing studies of household income surveys in several sub-Saharan countries, he concludes that the poor distribution of nonfarm earnings implies market segmentation.

The small sample size makes it impossible to carry out the analysis separately by city. Location dummies are included in all previous regressions, but this might not be enough to control for local effects. If unobserved productivity differs by area of the country and is correlated with the composition of the labor force, the estimates of the coefficients on characteristics will pick up some of the location effect. If the relative wage rate for workers with high and low education varies by region the wage differentials will only match productivity differences if plants are equally representative in all areas. Given the concentration of the bulk of manufacturing activities in a couple of 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 limiting firms to those 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, which is close to the border with Kenya, rather than the capital, Dar es Salaam. 41% of all plants in the sample are located there. In Zimbabwe, manufacturing activity is less concentrated than in the other countries. Still, 42% of the plants in the RPED sample are located in the capital, Harare.

[**Table 6**]

The results for the limited sample are in Table 6. For 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 remains for the joint test. Local labor markets do not seem to be an explanation for the excess wage return to the different characteristics.[19]

The results for Kenya indicate that for experience the gap is cut in half, from 2.8% to 1.4%. For schooling and gender, all point estimates change very little. As 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, Nairobi is a lot more developed than the rest of the country. No detailed local statistics are available, but one could argue that Nairobi more closely resembles cities in Zimbabwe than other cities in Kenya.

For Zimbabwe, equality can never be rejected, even thought 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 as before: rejection is negatively correlated with the level of development in the country.

[19] The same conclusion is obtained for the estimation that includes tenure and training, as in Table 5.

7.2 Imperfect substitutability

A crucial assumption underlying the estimation strategy is perfect substitutability between all types of workers. In that case, cost minimizing firms are expected to arbitrage away wage differences that do not correspond to productivity differences. With imperfect substitutability, the marginal product of a male worker, for example, will depend on the share of male workers already employed and on the other characteristics of the workforce. The average productivity differences between male and female workers across plants, will not necessarily match the average wage gap anymore.

In this Section, I will allow imperfect substitutability between workers with different levels of experience. This was the characteristic with the greatest gap between wage and productivity returns in all previous tables. The most straightforward approach would be to introduce two labor aggregates, one for each experience category, in the Cobb-Douglas production function:

$$\ln Q = \alpha_0 + \alpha_K \ln K + \alpha_{LX} \ln \tilde{L}_X + \alpha_{LY} \ln \tilde{L}_Y + \epsilon \tag{10}$$

$$\ln \tilde{L}_x = \ln L_x + \ln(1 + \phi_{xM} \frac{L_{xM}}{L_x}) + \ln(1 + \phi_{xS} \frac{L_{xS}}{L_x}) \qquad x = X,\ Y \tag{11}$$

if schooling is modeled as a discrete variable—high versus low—or

$$\ln \tilde{L}_x = \ln L_x + \ln(1 + \phi_{xM} \frac{L_{xM}}{L_x}) + \phi_{xS} \overline{S}_x \qquad x = X,\ Y, \tag{12}$$

if schooling is measured continuously. In either case, one can assume that the fraction of male workers is equal for each experience category maintaining the assumptions in (4), e.g. $\frac{L_{XM}}{L_X} = \frac{L_{YM}}{L_Y} = \frac{L_M}{L}$, or calculate two different fractions. Similarly, the fraction of highly educated workers or the average schooling attainment can be assumed constant across experience categories or calculated separately. The elasticity of substitution between each type of workers and between both types of workers and capital would be unity. The output elasticities of each input, α_K, α_{LX}, and α_{LY}, capture the relative importance of each in the production function.

An even more general approach is to aggregate the two labor aggregates using the C.E.S.

functional form. While capital and (aggregate) labor have unitary elasticity of substitution, the elasticity of substitution between the different labor components can be estimated freely. The production function becomes

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

with the experience specific labor aggregates taking the form of (11) or (12). The constant elasticity of substitution between the two labor types is $\sigma = \frac{1}{1+\rho}$. Enforcing that the weights of the two experience categories sum to one, keeps returns to scale equal to $\alpha_K + \alpha_L$. In principle, it is straightforward to generalize this and include more than two levels of experience. In practice, it will be impossible to calculate average schooling and fraction of males separately for more finely defined experience levels and the greater detail will not yield a richer model.

The results for equal schooling and gender compositions for each experience category and schooling measured continuously are in Table 7.[20] It is important to note that the test for equality of returns to experience now has a different interpretation 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 plants, depending on the relative share of each group. The reported p-value is for the test evaluated at the mean ratio for each experience class.

[Table 7]

The results close mimic the results from Table 4. The joint test is significantly more likely to reject equality of returns in Tanzania and Kenya than in Zimbabwe. The principal source of rejection is still the return to experience. In Tanzania, the returns for gender and schooling are estimated marginally closer, but in Kenya the reverse is true.

One of the principal reasons is that the two types of labor are estimated to be close substitutes, in Zimbabwe, even perfect substitutes. It is interesting to note that the weight of the more experienced workers in the production function increases with the development

[20]The corresponding results with discrete schooling attainment are very similar and available upon request.

level of the country, which one would expect if the technology is more advanced in richer countries. Given that experienced workers are perfect substitutes for young workers, in Zimbabwe, 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 plants 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. Because both types of workers are estimated to be rather close substitutes, a much higher ratio than observed would be required to rationalize the estimated wage effects. In sum, imperfect substitutability failed as an explanation for the rejection of equal wage and productivity returns.

7.3 Sampling error

Up till now I have treated the average employee-characteristics per plant as known, even though they were estimated from a subsample of workers. How sensitive are the results to sampling of workers?[21] Would the conclusions still hold if we had drawn a different sample of workers from each firm to calculate the average characteristics? I check the robustness of the results using two different approaches.

The first method extends the approach in Hellerstein, Neumark, and Troske (1999) to continuous variables. I draw different samples of workers 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, I sample without replacement from the empirical distribution of the observed

[21] For 8% of the plants I observe all employees and sampling is not an issue. On average, 30% of a plant's employees are interviewed, but the distribution is right skewed. For half of all plants, I observe less than 18% of its workers and for one out of ten plants, I observe less than 2% of its workforce.

sample of employees, which is scaled up to the total number of employees.

The samples are generated independently for all characteristics and plants, drawing for each plant a hundred times the same number of workers as found in the original sample. For plants where all employees are observed, I use the observed averages in each simulation. Using each of the hundred simulated samples, the wage and production equation are estimated with the limited number of characteristics as in Table 4. The top panel of Table 8 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 8**]

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 results confirm the previous conclusions, but in a sense, this is not really the exercise one would like to perform. What I verified was, assuming that the estimated averages were the true underlying means, how robust the results are to different possible samples of workers. What one would like to know is what the results would be 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 as likely given that we observe one estimate of the mean. For any randomly generated number between 0 and 1, it is possible using Bayes' law to calculate what the probability is that it represents the true underlying proportion of male workers in the plant, given that we observe one estimate of the average proportion from one particular sample.

The law of large numbers tells us that the mean of any i.i.d. random variable is normally distributed and the observed mean and standard deviation are consistent estimates of the true mean and variance of the underlying random variable. 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 the exact probability for any difference. For continuous variables, the probability of any number is zero and I calculate the probability the true average lies in an interval, given the observed average. As an approximation, I draw random intervals of constant width for each characteristic.[22] Assuming that the estimator for the true average is normally distributed with the observed average as mean and the estimated standard error over the square root of the number of workers interviewed as standard deviation, I calculate the probability for any given interval that it contains the true mean.

The product of the probability for each of the three characteristics is then used as weight on the firm in the SUR estimation. Plants for which I observe all employees, 8% of the sample, get a constant weight of one. As before, I draw 100 samples and the average estimation results are in the bottom panel of Table 8.

The results largely mimic those in Table 4, also for this analysis. Rejection of the joint hypothesis is still unanimous for Tanzania. Kenya and Zimbabwe are found to differ less than 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 Monte Carlo simulations, the standard deviations of the estimated coefficients are higher.

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

7.4 Nonlinear returns

Another shortcoming of the previous analysis that was noted before its the limitation to linear effects. The small sample makes it hard to identify nonlinearities precisely, but one certainly expects the returns to schooling and experience to be concave. An extra difficulty is that in the aggregation from the individual to the plant-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—evolves according to

$$\ln W_i = \lambda_0 + \lambda_M M_i + \lambda_X X_i + \lambda_S S_i + \tfrac{1}{2}\lambda_{XX} X_i^2 + \tfrac{1}{2}\lambda_{SS} S_i^2 + \lambda_{XS} X_i S_i + \eta \tag{13}$$

The derivation of the second order approximation to the production function—or the plant-level wage bill—consistent with a Mincer model of human capital as in (13) is in Appendix B. Estimation results are in Table 9. For comparison, the first panel contains the estimation results for the linear human capital model—$\lambda_{SS} = \lambda_{SS} = \lambda_{SS} = 0$—with a second order approximation for the wage equation and production function. In the second panel, the full quadratic model is estimated.

Little changes relative to the benchmark results in Table 4. The R^2 for the regressions hardly increase when quadratic terms are included. The rejection of equality of wage and productivity effects is more likely for Tanzania and Kenya than for Zimbabwe. The p-values become a lot larger. Unfortunately, this is not because of closer estimates of wage and productivity effects, but simply because of less precise estimates. For example, the wage return of experience is concave, as expected. The productivity effect is still negative, but convexly decreasing. The schooling results are much closer for Tanzania, but for Kenya they are completely unrelated now. As before, the main source of difference between the countries is in the experience effects.

[Table 9]

It is impossible to attach any firm conclusions to such imprecise estimates. Nevertheless, it is striking how similar wage and productivity effects for experience are estimated for Zimbabwe. It is also the only country for which the sign on all coefficients, including the quadratic and interaction terms, are equal in the wage equation and production function. Evaluating the marginal returns to schooling and experience at the sample averages, gives results that are close to the linear estimations. The average productivity effect of a year of schooling in Zimbabwe is 8.4%, while the wage effect is 8.5%. In Tanzania, the two effects are -0.6% and +1.6%, while the corresponding effects for Kenya are -1.8% and +6.7%. Similar discrepancies apply to the average experience effects. Enforcing linearity of the effects does not seem to be the driving force behind the rejections in the poorer countries.

7.5 Other explanations

Unobservables

Even more than for empirical work in developed countries, one should be aware of data limitations. Unobservables like non-wage compensation or errors in measuring 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 is most important in the least developed countries, like Tanzania. Approximately 60% of the plants in the sample report the amounts of in kind payments (zero in some instances). Adding payments in kind to the dependent variable of the wage regression increases the premiums associated with schooling and experience in Tanzania, with little change for Kenya and Zimbabwe. This exacerbate the excess wage premium for Tanzania, relative to the productivity premium.[23]

A second variable prone to measurement error is the capital stock. In each of the production function estimates, 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 cap-

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

ital coefficient estimate for Tanzania, based on the expected resale value of the plant and equipment by the owner, is upward biased. If the human capital measures are positively correlated with physical capital, as in developed countries, such an upward bias will translate in a downward bias of the skill and schooling 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. Such restrictions can be rejected at the 5% significance level.

Long term contracts

One explanation for the difference between the wage and productivity returns of experience is long term contracts. In Tanzania, and to a lesser extent in Kenya, older workers earn more than their productivity warrants, while the reverse is true for younger workers. A similar pattern was found in France, see Prez-Duarte, Crepon, and Deniau (2001). If contracts in the economy are such that workers are paid less early in their career with higher earnings later on, at any given time wage effects might differ from productivity effects, if the effects are identified across firms. It remains puzzling why individual firms would stick with such contracts. It makes firms with an older than average workforce particularly uncompetitive. It would make more sense if these long term effects were tied to tenure, but paradoxically we find the reverse. Workers with high tenure are paid less than their productivity warrants. 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.

Matching

If the labor market does not operate as a perfect information spot market, one would also expect to find differences in wage and productivity effects. For example, if workers are matched with firms and bargain over the surplus over 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 (that might be 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 worker—young, uneducated women—are paid less than their productivity warrants and that more educated or older workers do not have higher productivity, but 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 $w_0 = \alpha_l \frac{Q}{L}$ or in logarithms $\lambda_0 = \ln \alpha_L + \ln \frac{Q}{L}$. For Tanzania we can reject equality at a 1% significance level, evaluated at the average or median plant, indicating that the outside 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 any necessary productivity effects.

While, it remains a puzzle why the extent to which less skilled workers have less bargaining power is negatively correlated with the level of development of the country, at least it suggests an alternative explanation for the inequality of wage and productivity effects. It might still be the case that labor markets in the least developed countries are working less efficiently and fail to price worker characteristics properly. It might also be the case that firms in those countries are not maximizing profits or minimizing costs, because other considerations, such as having the right government connections or access to credit, are more important for survival. This analysis does not readily warrant such inefficiency interpretations.

8 Conclusions

A couple of conclusions can be drawn. First, the ability of countries to match wage premiums with productivity contributions for a number of characteristics is an increasing function of the level of economic development. Second, a lot of attention in the development literature is devoted to education. Rightfully so, because the returns in higher salary and output are important and I 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. On the other hand, it should be stressed 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 part in the remuneration of workers is the trade-off between paying workers for general experience versus firm-specific tenure. This mirrors a similar trade-off between pre-employment education and formal training. The poorer countries tend to reward the general skills (experience and schooling) relatively more than firm-specific skills (tenure and training). 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.

The analysis does not provide a causal interpretation for the correlation between the level of development and the extent to which wage differences reflect productivity differentials. Still, both directions of causation are interesting. One possible interpretation is that when labor markets work efficiently and characteristics are rewarded correctly at the margin, countries prosper. The reverse interpretation, that one important difference between countries that are developing successfully and those that are being left behind is the greater efficiency of their labor markets, is interesting as well. It is not necessarily the case that getting the match between wages and productivity right is a necessary condition for successful development of the manufacturing sector, but at the very least, it is a previously undocumented difference between more and less developed countries.

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Table 1: Summary statistics (1991)

	Tanzania		Kenya		Zimbabwe	
Population	26.3m		24.3m		10.0m	
% employed in industry	4.9%		7.3%		8.6%	
Manufacturing workers[a]	126312		177738		187937	
Workers in sample firms[b]	19383		21090		58108	
Workers in the sample[b]	1018		1206		619	
GDP/capita (PPP)	477		1092		2201	
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 plants	113		183		110	
Workers per firm	97.3		89.8		269.8	
Workers interviewed per firm	4.6		6.2		5.5	
Male (%)	0.79	(0.40)	0.87	(0.34)	0.84	(0.36)
Age (years)	35.3	(10.5)	34.1	(9.4)	37.0	(10.4)
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)
Received training (%)	0.09	(0.29)	0.12	(0.32)	0.21	(0.41)
Family (%)	0.13	(0.38)	0.06	(0.23)	0.06	(0.24)
Union worker (%)	0.47	(0.50)	0.35	(0.48)	0.54	(0.50)

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

Table 2: Simple Mincer wage regressions at the individual-level

	Tanzania			Kenya			Zimbabwe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Male	0.056	0.085	0.072	-0.017	0.135	-0.007	0.071	0.185	0.028
	(.042)	(.043)	(.042)	(.036)	(.032)	(.035)	(.067)	(.054)	(.064)
Exp.	0.023	0.015	0.022	0.018	0.013	0.015	0.010	0.005	0.009
	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)	(.002)	(.002)	(.002)
Sch.	0.068	0.044	0.062	0.060	0.032	0.051	0.049	0.022	0.042
	(.004)	(.004)	(.004)	(.004)	(.003)	(.004)	(.007)	(.006)	(.007)
Obs.	1254	1254	1254	3111	2997	3111	1157	1154	1157
R_a^2	0.33	0.43	0.34	0.21	0.43	0.26	0.12	0.45	0.19

(1) Hours worked and time, sector, and location dummies included as controls.
(2) Hours worked and time, sector, location, and occupation (11 categories) dummies.
(3) Hours worked and time, sector, location, and plant-size (4 categories) dummies.

Table 3: Mincer wage regressions at the individual-level with additional characteristics

	Tanzania			Kenya			Zimbabwe		
effects:	total	within	between	total	within	between	total	within	between
Male	0.060	0.133	-0.037	0.037	0.030	0.238	0.022	0.096	-0.265
	(.046)	(.043)	(.119)	(.042)	(.041)	(.101)	(.066)	(.062)	(.189)
Experience	0.025	0.019	0.041	0.019	0.017	0.024	0.011	0.011	-0.000
	(.002)	(.002)	(.006)	(.002)	(.002)	(.006)	(.003)	(.003)	(.010)
Schooling	0.068	0.045	0.089	0.058	0.042	0.079	0.039	0.019	0.083
	(.004)	(.004)	(.011)	(.004)	(.004)	(.011)	(.007)	(.006)	(.020)
Tenure (years)	-0.006	-0.000	-0.024	0.011	0.005	0.011	0.006	-0.003	0.026
	(.003)	(.003)	(.008)	(.003)	(.003)	(.008)	(.004)	(.004)	(.011)
Received training	0.123	0.107	0.203	0.136	0.075	0.144	0.305	0.103	0.492
	(.063)	(.060)	(.141)	(.042)	(.041)	(.102)	(.057)	(.054)	(.123)
Family member	0.435	0.496	0.347	0.310	0.686	-0.129	-0.251	0.398	-0.477
	(.061)	(.064)	(.114)	(.060)	(.064)	(.093)	(.099)	(.115)	(.164)
Union member	-0.064	-0.526	-0.047	-0.439	-0.521	-0.197	-0.361	-0.493	-0.079
	(.042)	(.059)	(.085)	(.030)	(.033)	(.079)	(.048)	(.047)	(.113)
Observations	1037	1037	237	2065	2065	357	1121	1121	208
R^2	0.29	0.19	0.34	0.31	0.19	0.36	0.20	0.07	0.38

total: Controls include hours worked and time, sector, and location dummies.
within: Fixed effects estimator controlling for hours worked and time and plant dummies.
between: Variables are averaged by individual across years; controls include hours worked, time, sector, and location dummies.

Table 4: A market efficiency test for limited characteristics

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Labor		0.8280		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	0.299
	(.135)	(.731)	(.123)	(1.11)	(.214)	(.456)
Experience	0.020	-0.024	0.026	-0.002	0.007	0.010
	(.004)	(.014)	(.004)	(.012)	(.008)	(.011)
Schooling	0.059	-0.002	0.091	0.056	0.117	0.104
	(.009)	(.034)	(.011)	(.030)	(.023)	(.036)
Test for equality of coefficients (p-value)						
Male ($\lambda_M - \phi_M$)	0.34		0.10		0.43	
Experience ($\lambda_A - \phi_A$)	0.00		0.02		0.81	
Schooling ($\lambda_S - \phi_S$)	0.07		0.31		0.75	
Joint test	0.01		0.05		0.72	
Observations	316		544		210	
R^2	0.30	0.69	0.32	0.81	0.37	0.88

Joint estimation (SUR) of the wage equation and production function at the plant-level. Controls in both equations include hours worked and time, industry, and location dummies.

Table 5: A market efficiency test for the full set of 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)
Test for equality of coefficients (p-values)						
Joint test		0.13		0.21		0.79
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
Observations		268		374		210
R^2	0.26	0.69	0.34	0.80	0.40	0.88

Estimation as in Table 4.

Table 6: A market efficiency test, limited to plants in the principal local market

	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)
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	
Observations	127		350		88	
R^2	0.18	0.73	0.20	0.84	0.30	0.87

Estimation as in Table 4, limited to the most prominent manufacturing city in the country.

Table 7: A market efficiency test, with imperfect substitution by experience

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Labor		0.804		0.782		0.812
		(.081)		(.058)		(.064)
Capital		0.240		0.293		0.221
		(.039)		(.032)		(.040)
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	0.108	0.098
	(.009)	(.031)	(.011)	(.030)	(.021)	(.034)
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		6.289		3.035		∞
		(11.2)		(1.46)		–
Test for equality of coefficients (p-values)						
Male ($\lambda_M - \phi_M$)	0.54		0.10		0.48	
Experience ($\lambda_A - \phi_A$)	0.00		0.00		0.63	
Schooling ($\lambda_S - \phi_S$)	0.15		0.25		0.77	
Joint test	0.00		0.00		0.68	
Observations	316		544		210	
R^2	0.28	0.68	0.31	0.81	0.37	0.88

Estimation as in Table 4, with high and low experienced workers imperfect substitutes, see text for details.

Table 8: Sensitivity analysis of the results using two Monte Carlo simulations

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
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	
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 7.3, for details on the simulations.

Table 9: A market efficiency test with nonlinear terms and second order approximations

	Tanzania		Kenya		Zimbabwe	
	wage	output	wage	output	wage	output
Only linear effects, second order approximations						
Male	-0.014	1.360	-0.067	2.323	0.027	0.221
	(.136)	(1.26)	(.123)	(1.61)	(.224)	(.431)
Experience	0.012	-0.047	0.013	-0.005	0.002	0.010
	(.003)	(.020)	(.002)	(.008)	(.003)	(.007)
Schooling	0.051	-0.013	0.080	0.060	0.118	0.064
	(.009)	(.032)	(.010)	(.034)	(.016)	(.030)
R^2	0.29	0.70	0.32	0.80	0.35	0.87
Test for equality of coefficients (p-values)						
Joint test	0.01		0.09		0.16	
Including quadratic and interaction effects, second order approximations						
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)
R^2	0.30	0.70	0.34	0.80	0.39	0.87
Observations	267		491		194	
Test for equality of coefficients (p-values)						
Joint test – linear terms	0.18		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 4, including variance, covariance, and squared terms, as derived in Appendix B.

Appendices

A Market efficiency test with discrete characteristics

The results in Table A.1 differ only from those in Table 4 by the treatment of experience and schooling. In Table 4 both variables are measured by the average number of years attained across all workers in the plant. In Table A.1 experience is measures as the proportion of workers in each plant that attain more experience than the median (interviewed) worker for the country. For schooling, I measure the proportion of workers in each plant that at least attended secondary school, but not necessarily finished it. The results in Table A.2 differ additionally from those in Table 5 by the same modification for the tenure variable as for experience. When discrete (dummy) variables are used for all characteristics, it is not necessary to rely on a Taylor approximation for the plant-level production function. Equation (7) can be estimated directly.

The main results go through, some become even stronger. Equality of wage and productivity premiums is strongly rejected in Tanzania, the least developed country in the sample. In Kenya, the rejection of equality is more strongly than using continuous variables and in Zimbabwe, equality can again not be rejected. Relative to the previous results, the premiums in the wage and production equations are still similar in Zimbabwe, but not nearly as alike as in Table 4. The inability to reject equality for Zimbabwe is partially the result of less precisely estimated coefficients. One conclusion that remains firm is that the rejection for the two poorest countries is largely driven by the estimates for experience and to a lesser degree by schooling.

The results in Table A.2 confirm both conclusions reached from the estimation results in Table 5. The p-value for a test for equality of all returns goes from 0.00 in Tanzania, to 0.06 in Kenya, and 0.38 in Zimbabwe. Higher standard errors in Zimbabwe are less of a factor explaining these results. The greater tendency to conclude in favor of equal returns with increasing level of development holds strongly for characteristics that have a clear human capital effect —experience, tenure, schooling, and training. The estimates for tenure and training are especially supportive to conclude that the labor market in Zimbabwe rewards workers' skills in proportion to the return they bring to their employer.

Table A.1: A market efficiency test for 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	0.298	0.698	0.453	2.524	0.292	0.788
	(.157)	(.690)	(.188)	(1.48)	(.300)	(.654)
Experience	0.267	-0.382	0.456	-0.234	0.108	0.385
	(.110)	(.156)	(.114)	(.174)	(.210)	(.362)
Schooling	0.654	0.160	1.011	0.452	1.260	1.904
	(.150)	(.379)	(.151)	(.339)	(.426)	(.846)
Test for equality of coefficients (p-value)						
Male ($\lambda_M - \phi_M$)	0.54		0.16		0.44	
Experience ($\lambda_A - \phi_A$)	0.00		0.00		0.44	
Schooling ($\lambda_S - \phi_S$)	0.21		0.11		0.44	
Joint test	0.00		0.01		0.67	
Observations	316		544		210	
R^2	0.28	0.69	0.34	0.81	0.36	0.89

Table A.2: A market efficiency test for the 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)
Test for equality of coefficients (p-values)						
Joint test		0.01		0.04		0.66
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
Observations		266		375		213
R^2	0.26	0.69	0.34	0.80	0.45	0.88

B Second order approximation of the production function

Following the derivation in Frazer (2001), the productivity adjusted labor aggregate for a plant with L workers can be written as

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

where the summation is over all workers in the plant. I 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.

$$\begin{aligned}
f(S_1,...,S_L,X_1,...,X_L,M_1,...,M_L) &= f(0,...,0) && (14)\\
&+ \sum_{i=1}^{L} S_i\Big(\frac{\partial f}{\partial S_i}|_{(0,...,0)}\Big) && (15)\\
&+ \sum_{i=1}^{L}\sum_{j\neq i}^{L} S_iS_j\Big(\frac{\partial^2 f}{\partial S_i\partial S_j}|_{(0,...,0)}\Big) && (16)\\
&+ \sum_{i=1}^{L} S_i^2\Big(\frac{\partial^2 f}{\partial S_i^2}|_{(0,...,0)}\Big) && (17)\\
&+ \sum_{i=1}^{L}\sum_{j\neq i}^{L} S_iX_j\Big(\frac{\partial^2 f}{\partial S_i\partial X_j}|_{(0,...,0)}\Big) && (18)\\
&+ \sum_{i=1}^{L} S_iX_i\Big(\frac{\partial^2 f}{\partial S_i\partial X_i}|_{(0,...,0)}\Big) && (19)\\
&+ \dots
\end{aligned}$$

Straightforward algebra yields the following results

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

$$
\begin{aligned}
(17) \quad &= \Big(-\frac{\phi_S^2}{L^2}+\frac{\phi_S^2}{L}+\frac{\phi_{SS}}{L}\Big)\sum_i S_i^2 \\
(18) \quad &= -\frac{\phi_S\phi_X}{L^2}\sum_i\sum_{j\neq i} S_iX_j \\
(19) \quad &= \Big(-\frac{\phi_S\phi_X}{L^2}+\frac{\phi_S\phi_X}{L}+\frac{\phi_{XS}}{L}\Big)\sum_i S_iX_i.
\end{aligned}
$$

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

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

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