Volume Title: The Analysis of Firms and Employees: Quantitative and Qualitative Approaches

Volume Author/Editor: Stefan Bender, Julia Lane, Kathryn Shaw, Fredrik Andersson, and Till von Wachter, editors

Volume Publisher: University of Chicago Press

Volume ISBN: 978-0-226-04287-9; 0-226-04287-1

Volume URL: http://www.nber.org/books/bend08-1

Conference Date: September 29-30, 2006

Publication Date: October 2008

Chapter Title: Wage and Productivity Premiums in Sub-Saharan Africa

Chapter Author: Johannes Van Biesebroeck

Chapter URL: http://www.nber.org/chapters/c9121

Chapter pages in book: (345 - 371)

11

Wage and Productivity Premiums in Sub-Saharan Africa

Johannes Van Biesebroeck

11.1 Introduction

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

A well-functioning labor market should perform at least two tasks: matching workers with firms and setting wages. The ability of the labor market to allocate workers to firms or industries with the highest productivity or the best future prospects is of particular importance for the likely effect of trade reforms, and this has been studied extensively—see Pavcnik (2002), Eslava et al. (2004), and Filhoz and Muendler (2006) for studies on

Johannes Van Biesebroeck is an associate professor of economics at the University of Toronto, and a faculty research fellow of the National Bureau of Economic Research.

This paper was presented at the Conference on Firm and Employees (CAFE) held September 29–30, 2006, in Nuremberg, Germany. We gratefully acknowledge the financial support provided by the Institute for Employment Research (IAB), the Data Access Center (FDZ-BA/IAB), The Deutsche Forschungsgemeinschaft (German Research Foundation), their Research Network "Flexibility in Heterogeneous Labour Markets," the Alfred P. Sloan Foundation, and the National Science Foundation. Seminar participants at the University of Illinois, Kellogg School of Management, Catholic University of Louvain, the NBER Productivity meetings, and the CAFE conference provided useful suggestions.

Latin American countries. Van Biesebroeck (2005) investigates the effectiveness of labor markets in several African countries, including the three countries studied here, in performing this task, and finds that the reallocation mechanism is less effective than in the United States.

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

The contribution of this chapter is foremost to provide evidence for three sub-Saharan countries on the extent to which observed wage premiums for a number of worker characteristics are equal to the productivity premiums associated with those same characteristics. Initially, the methodology in Hellerstein, Neumark, and Troske (1999) is followed and the two premiums are compared at the firm level. Here, the nature of the comparison is implicitly between the wage bills and output levels of two firms that are identical, except that one firm has a workforce with, on average, one more year of schooling, or a higher fraction of male workers, and so on. We consider five characteristics: gender, labor market experience, eduction, tenure with the current employer, and whether a worker has followed a formal training program. As some of the human capital characteristics are influenced by the workers, such as tenure or training, providing workers with the correct investment incentives is crucial.

Labor market frictions are likely to be at least as important in developing countries as in the more developed countries where most previous studies were conducted. As stressed by Fafchamps (1997) in the introduction to a symposium on "Markets in Sub-Saharan Africa," one should be careful not to assume outright that markets are efficient, regardless of the institutions required to perform their function. The model is estimated using data for Tanzania, Kenya, and Zimbabwe. While all three countries are relatively poor, GDP per capita for Zimbabwe exceeded that for Tanzania by a factor of five (during the sample period), while Kenya was intermediately developed.

A second contribution of the chapter is to estimate the firm-level production function jointly with the individual-level wage equation. Using the additional information of individual workers leads to more precise estimates, especially of the wage premiums, and to a more accurate test. We show how to test for equality between wage and productivity premiums in this context and implement a feasible GLS estimator. While still allowing for correlation between the error terms in the wage equation and production function, we additionally introduce a random effect in the wage equation that is shared by all workers with a common employer.

The main empirical finding is that in Tanzania, the poorest country we consider, the wage premiums deviate substantially from the corresponding productivity premiums. The gaps between wage and productivity premiums are much smaller, and all are insignificant, in Zimbabwe. Results for Kenya, an intermediate country in terms of level of development, are intermediate: equal remuneration can be rejected for some characteristics (e.g., experience), but not for others (e.g., schooling). A test for equality of all wage and productivity premiums on the firm-level estimates yields a *p*-value of 1 percent in Tanzania, 18 percent in Kenya, and 64 percent in Zimbabwe. Using the individual-level estimates, the corresponding *p*-values are 0 percent, 1 percent, and 38 percent.

Moreover, the breakdown in correct remuneration in the two least developed countries follows a distinct pattern. On the one hand, wage premiums exceed productivity premiums for general human capital characteristics (experience and schooling). On the other hand, salaries hardly increase for more firm-specific human capital characteristics (tenure and training), even though these have a clear productivity effect. Equality of the returns fails most pronouncedly for the two indicators that capture how a worker's salary rises over his or her career. Even though productivity rises more with tenure than with experience,[1] salaries rise only with experience in Tanzania and much more with experience than with tenure in Kenya. In contrast, in Zimbabwe, workers are predominantly rewarded for tenure, consistent with the estimated productivity effects.

Finally, we estimate the gaps between wage and productivity premiums separately for firms that report facing international competition and those that do not. While the results are somewhat noisy, equality of the two returns is always less likely to be rejected for firms facing international competition. The difference is most pronounced for labor market experience: excessive salary increases over workers' careers, compared to productivity growth, are more moderate. It points to an additional channel through which international trade can improve resource allocation.

There are a number of important debates in development economics that would benefit from a better understanding of the relationship between wages and productivity. First, it is often argued that more education is a prerequisite for economic growth—see, for example, Knight and Sabot (1987). However, the Tanzanian firms in this sample have, on average, a more educated workforce, but the productivity effects of schooling fall far short of the wage effects. At the very least, higher education does not trans-

1. In some cases, productivity declines less with tenure than with experience, or productivity declines with experience, but rises with tenure. Crucial is that, in relative terms, tenure has a more positive effect on productivity than experience, in all three countries.

late automatically into higher output. Second, the measurement of productivity growth relies explicitly on the equality of relative wages and relative productivity. When labor growth is subtracted from output growth, categories of workers are weighed by their wage shares—see, for example, Jorgenson and Griliches (1967). If the equality between wages and productivity fails to hold systematically in developing countries, productivity growth measures will be biased.

The remainder of the chapter is organized as follows. The measurement framework to compare the wage and productivity premiums associated with worker characteristics is introduced first, in section 11.2, followed by a discussion of the evidence for other regions in section 11.3. The employer-employee data and the countries included in the analysis are discussed next, in section 11.4. Results at the firm and individual level are presented with some robustness checks in section 11.5, and section 11.6 concludes.

11.2 A Measurement Framework

11.2.1 Wage and Productivity Premiums

The methodology we use to compare wage and productivity premiums 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 can be identified by jointly estimating a wage equation and production function, which characterize how wages and output depend on worker characteristics.

As an example, assume that the productivity of male workers exceeds the average productivity of female workers by ϕ_M percent. The production function can be written as a function of capital and both types of labor (men and women), which are assumed to be perfect substitutes:[2]

$$Q = Af[K, L_F + (1 + \phi_M) L_M].$$

The first-order conditions for cost minimization by the firm dictate that the composition of the firm's labor force is adjusted such that the relative wage for both types of workers is equalized to the relative productivity ratio:

$$\frac{w_M}{w_F} = \frac{MP_M}{MP_F},$$

2. Given sufficiently detailed information on the labor force composition, this assumption can be relaxed. In the robustness checks at the end, we allowed for imperfect substitutability between experienced and inexperienced workers.

or equivalently,

$$\lambda_M \equiv \frac{w_M - w_F}{w_F} = \frac{MP_M - MP_F}{MP_F} \equiv \phi_M. \tag{1}$$

11.2.2 Firm-Level Estimation

The identification of the productivity premium (ϕ) is necessarily done at the plant or firm level. The wage premiums associated with worker characteristics (λ) can be estimated using a standard wage equation derived from the Mincer (1974) model of human capital. The most straightforward estimation strategy is to aggregate the wage equation to the firm level and estimate it jointly with the production function—see, for example, Hellerstein, Neumark, and Troske (1999).

Labor researchers have been concerned with a potential bias introduced by unobserved worker ability in the wage equation. Productivity researchers have estimated production functions controlling explicitly for unobserved productivity differences. Joint estimation should to a large extent alleviate such concerns, as the bias works in the same direction in both equations. A large component of the unobservables in both equations are expected to represent the same factors.[3] Results in Hellerstein and Neumark (2004) demonstrate that the results tend to be relatively unaffected if more sophisticated estimation strategies are employed.

Sticking with the earlier example, we now show how one can aggregate an individual wage equation to identify the left-hand side premium in equation (1). 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 a dummy that takes a value of 1 if individual i is a woman—and w_M to men. Summing over all workers of the firm gives

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

Taking logarithms and adding an additive error term, representing measurement error in the wage and unobservable worker characteristics, gives

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

$$\ln \frac{W}{L} = \ln w_F + \ln\left(1 + \lambda_M \frac{L_M}{L}\right) + \eta. \tag{2}$$

Nonlinear least squares estimation of the firm-level equation (2) produces an estimate of the average baseline wage (w_F) and of the gender wage premium (λ_M). The only information needed is the average wage and the proportion of male workers by firm.

Assuming the Cobb-Douglas functional form for the production function, it can be written in logarithms as[4]

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

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 $1 + \phi_M$):

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

The total labor force is $L = L_F + L_M$. 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 that takes more worker characteristics into account is limited by the data. For example, differentiating workers by gender (*M* or *F*), experience (*Y* or *X*—young versus high experience), and schooling (*U* or *S*—uneducated versus highly educated), creates eight categories of workers: inexperienced, educated males, and so forth. Given that we observe a maximum of ten workers in each firm, the proportion of each category in the firm's workforce would be estimated extremely inaccurately. Furthermore, it would be entirely impossible to look at any further characteristics or at characteristics that divide the workforce more finely.

Making three assumptions for each characteristic—or rather, three sets of assumptions—avoids this type of dimensional problem. For example, if we assume that the relative number of male to female workers, the relative productivity, and the relative wage by gender are all invariant to changes in other characteristics, we can use the full workforce to estimate the gender premiums. 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. In the previous example with three characteristics, this boils down to:

4. It is straightforward to generalize the methodology to other functional forms. Hellerstein and Neumark (2004) demonstrate that the qualitative results are very robust to alternative specifications of the production function.

$$(4) \qquad \text{Equal proportions:} \quad \frac{L_{\mathbf{M}YS}}{L_{\mathbf{F}YS}} = \frac{L_{\mathbf{M}XS}}{L_{\mathbf{F}XS}} = \frac{L_{\mathbf{M}YU}}{L_{\mathbf{F}YU}} = \frac{L_{\mathbf{M}XU}}{L_{\mathbf{F}XU}},$$

$$\text{Equal productivity:} \quad \frac{\phi_{\mathbf{M}YS}}{\phi_{\mathbf{F}YS}} = \frac{\phi_{\mathbf{M}XS}}{\phi_{\mathbf{F}XS}} = \frac{\phi_{\mathbf{M}YU}}{\phi_{\mathbf{F}YU}} = \frac{\phi_{\mathbf{M}XU}}{\phi_{\mathbf{F}XU}},$$

$$\text{Equal wage premium:} \quad \frac{\lambda_{\mathbf{M}YS}}{\lambda_{\mathbf{F}YS}} = \frac{\lambda_{\mathbf{M}XS}}{\lambda_{\mathbf{F}XS}} = \frac{\lambda_{\mathbf{M}YU}}{\lambda_{\mathbf{F}YU}} = \frac{\lambda_{\mathbf{M}XU}}{\lambda_{\mathbf{F}XU}},$$

and similarly for young versus experienced workers and for uneducated versus highly educated workers. 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:

$$(5) \qquad \tilde{L} = L_{FYS} + (1 + \phi_{FXS})L_{FXS} + (1 + \phi_{MYS})L_{MYS} + \ldots + (1 + \phi_{MXU})L_{MXU}$$
$$= L\left(1 + \phi_M \frac{L_M}{L}\right)\left(1 + \phi_X \frac{L_X}{L}\right)\left(1 + \phi_S \frac{L_S}{L}\right),$$

and similarly in the wage equation. One can proceed in the same fashion to add further characteristics to (5). These assumptions cannot be tested, or they would not have been necessary. 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 few employees are sampled.

The baseline model constructed so far is

$$(6) \qquad \ln \frac{W}{L} = \lambda 0 + \sum_{k=1}^{K} \ln\left(1 + \lambda k \frac{L_k}{L}\right) + \eta$$

$$(7) \qquad \ln Q = \alpha_0 + \alpha_K \ln K + \alpha_L\left[\ln L + \sum_{k=1}^{K} \ln\left(1 + \phi_k \frac{L_k}{L}\right)\right] + \varepsilon$$

where λ_0 is the base salary (in the previous example, for a female, inexperienced, uneducated worker), λ_k is the wage premium and ϕ_k the productivity premium associated with characteristic k ($k \in K$). Equations (6) and (7) are estimated jointly with Zellner's seemingly unrelated regression estimator, allowing for correlation between the two error terms.[5]

5. As the fraction of workers with characteristics k enters equations (6) and (7) nonlinearly, the point estimates of λ_k and ϕ_k will depend on the normalization (thanks to an anonymous referee for pointing this out). However, the effect is only noticeable for fractions that are far away from 0.5, especially 'male' and to a lesser extent 'training'. Because the correlations between fraction of male or fraction of female workers and all other variables are identical in absolute value, the effect of the normalization does not spill over to the estimates for returns on other characteristics.

11.2.3 Individual-Level Estimation

While the previous approach allows identification of the wage and productivity premiums, it does not use all available information on the wage side. We do observe salaries and characteristics for a sample of individual workers at each firm. Rather than aggregating the wage equation to the firm level, we can also estimate a Mincer wage equation jointly with the production function. Estimating with a much larger number of observations—for example, for Tanzania with 520 individuals instead of 113 firms, is likely to yield more precise estimates of the wage premiums.

As productivity can only be estimated at the firm level and the productivity premiums associated with each characteristic are still restricted as in (4), we still use the same set of worker characteristics as before. The Mincer wage regression assumes additive separability of the returns to different characteristics, which is very similar to the equal wage premium assumptions in (4). We follow the usual practice and estimate the wage equation in logarithms:

$$\ln W_i = \omega_0 + \sum_{k=1}^{K} \omega_k X_i^k + \eta_i.$$

The i subscript indexes individuals and the variable X_i^k is a dummy for characteristic k ($k \in K$)—for example, the gender dummy M_i. This specification assumes that if a female worker has a salary of w_F, the salary for a male worker with otherwise equivalent characteristics would be w_F $\exp(w_M)$. Expressed differently, the baseline salary for a worker with all characteristics dummies equal to zero is $\exp(w_0)$, while a worker with characteristic X^k switched from zero to 1 has a salary equal to $\exp(w_0 + w_k)$.

The equality in percentage terms of the productivity and wage premiums associated with gender, as in equation (1), now boils down to

$$\exp(\omega_M) - 1 \equiv \frac{w_M - w_F}{w_F} = \frac{MP_M - MP_F}{MP_F} \equiv \phi_M.$$

Expressed differently, for each of the characteristics k, we want to test whether

$$\omega_k = \ln(1 + \phi_k).$$

The individual wage equation is now estimated jointly with the firm-level production function. As in the previous set-up, we still allow the errors in the two equations to be correlated. In addition, we allow for a random effect in the wage equation to take into account that errors for employees at the same firm are likely to be correlated. We implement the feasible generalized least squares (GLS) transformation as in Wooldridge (2000, 450) and jointly estimate the transformed wage equation with the production function. Because not all firms have the same number of employees sampled, we have to correct for the unbalancedness of our panel. As long as we assume that the reason for unbalancedness is random—not too unlikely for our application—the adjustments are straightforward. All variables in the wage equation are transformed according to

$$x^*_{ij} = x_{ij} - \lambda_j \bar{x}_j \qquad \text{with } \lambda_j = 1 - \sqrt{\frac{s_e^2}{s_e^2 + N_j s_f^2}},$$

with i indexing individuals and j firms. The estimate of the standard error of the full residual combining individual errors and the random firm effect is s_e^2, which itself has an estimated standard error of s_f^2. The number of employees sampled at firm j is N_j.[6]

11.3 Evidence from Other Regions

Matched employer-employee data sets contain the necessary information to compare wage and productivity premiums, but their limited availability has lead to only a small number of previous studies.[7] From the observed employees, one can estimate average values of worker characteristics for each employer. Hellerstein et al. (1999) pioneered the approach, jointly estimating a plant-level wage equation with a production function using U.S. administrative record information. They test for equality of the wage and productivity premiums associated with a number of characteristics and only find a statistically significant discrepancy for the gender dummy: women are only 16 percent less productive than their male coworkers, but paid 45 percent less.

The bulk of the evidence for developed countries points toward equal wage and productivity returns for various worker characteristics. Using more recent 1990 U.S. data, Hellerstein and Neumark (2004) confirm that the wage gap between males and females exceeds the productivity gap. In contrast, the lower wages for blacks is in line with productivity estimates, and even though attaining "some college" education only attracts a 43 percent wage premium while productivity is 67 percent higher, the difference is not statistically significant. Similar work for France in Pérez-Duarte, Crepon, and Deniau (2001) and for Israel in Hellerstein and Neumark (1999) finds no gender discrimination. In a study for Norway, Haegeland and Klette (1999) also finds that wage premiums for gender and eduction are in line with productivity premiums.

The only characteristic in those studies for which the wage premium differs significantly from the productivity premium is age in France—older

6. How to estimate the different standard errors is discussed in Wooldridge (1999, 260–261).

7. A conference symposium in the *Monthly Labor Review* (July 1998) provides an overview of sources; see also Haltiwanger et al. (1999).

workers are overpaid—while engineers are underpaid in Israel. For Norwegian workers with eight to fifteen years of experience, the productivity premium exceeds the wage premium, while the opposite is true for workers with more than fifteen years of experience.

Dearden, Reed, and Van Reenen (2006) focus on the effects of training using an industry-level data set covering the U.K. manufacturing sector. They separately estimate wage equations and production functions and find that the productivity effect of training substantially exceeds the wage effect, but no formal test is presented. They conclude that the usual approach in the literature of quantifying the benefits of training by looking at wages underestimates the impact. Another finding is that aggregation to the industry magnifies the effect of training, potentially due to externalities.

The only similar study in a developing country, Jones (2001) estimates a firm-level production function jointly with an individual-level wage equation for Ghana. However, no details are given regarding the assumptions on the variance-covariance matrix when the individual- and firm-level data is combined.[8] She finds that women are 42 percent to 62 percent less productive, depending on the specification, and paid 12 percent to 15 percent less. No formal test is reported, but the standard errors are fairly large. Her focus is on the premiums associated with an extra year of schooling, which are estimated similarly in the production function and the wage equation: both are around 7 percent. When discrete levels of education attainment are used, the results are ambiguous. The differences in point estimates are large, but the education coefficients in the production function are estimated imprecisely and none of the formal tests finds a statistically significant difference.[9]

Bigsten et al. (2000) gauge the link between wages and productivity indirectly, similar to the U.K. analysis. First, they estimate the returns to education in five sub-Saharan countries using a wage equation. Then, they separately estimate the production function, including lagged levels of education as a proxy for human capital. They find that the implied rate of return to human capital is very low—in particular, it is only a fraction of the return to physical capital.

11.4 Data

11.4.1 Countries

The three countries included in the sample are middle-sized former British colonies in East Africa that obtained independence in the early

8. We contacted the author to obtain further information, but did not receive a response.
9. Many differences are large in absolute value—five of the eight estimated differentials exceed 20 percent—but the direction of the difference varies by schooling level.

1960s.[10] The World Bank classifies all three as low income, even though they differ substantially by level of development. One way to see this is from GDP per capita, which stood at $477 (in purchasing power parity [PPP]) in Tanzania, less than half of the $1,092 attained in Kenya, and only slightly more than one fifth of the GDP per capita of Zimbabwe—all figures are for 1991 and reported in table 11.1. The differences are smaller on the United Nations' human development index, which also takes education and life expectancy into account, but the order is the same. 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, respectively, near the bottom of the "medium development" group.[11]

The different development levels of the countries are also reflected in the share of workers employed in industry.[12] Only 4.7 percent of all employment in Tanzania is in industry, while it is almost twice as high in Zimbabwe (8.6 percent) and intermediate in Kenya (7.3 percent). In Tanzania, the transition from agriculture to other sectors had only just begun: agriculture comprised almost half the workforce at the end of the 1990s. In Kenya, the transformation was in full swing: the employment share of agriculture declined from 42 percent in 1975 to 27.5 percent by the sample period. Zimbabwe, on the other hand, has seen a stable 18.5 percent of its workforce employed in agriculture for the last twenty-five years.

Given that Zimbabwe is much more advanced in its industrial transformation, it is not surprising that it far surpasses the other two countries in GDP per capita. The difference in labor productivity in industry is even more stark. While industry workers in Kenya produce twice as much as Tanzanian workers, Zimbabwe's output per worker outstrips Tanzania by a factor of seven and Kenya by a factor of four. It underscores the importance of developing a strong manufacturing sector. World Bank (2000) statistics also 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.

Infrastructure statistics confirm the different levels of development of the three countries. Zimbabwe had 22km of paved highways per 1000 km^2

10. Unfortunately, only three countries could be included in the analysis due to data constraints. A partial analysis was possible with data from Cameroon (almost as developed as Zimbabwe) and Burundi (even less developed than Tanzania), but the sample size is smaller, some variables (e.g. capital) are measured less accurately, and other variables (e.g. training in Burundi) are missing. Results for these countries are in between the extremes of Tanzania and Zimbabwe. The failure of the equality between wage and productivity premiums to hold is much more pronounced in Burundi than in Cameroon: the *p*-values for the joint test, corresponding to the first joint test in table 11.3, were, respectively, 0.03 and 0.22.

11. Norway tops the human development ranking with a score of 0.942.

12. Manufacturing employment that corresponds to manufacturing value added was not available for Tanzania in 1991.

Table 11.1 Summary statistics

	Tanzania		Kenya		Zimbabwe	
Population	26.3m		24.3m		10.0m	
Percent employed in industry	4.9		7.3		8.6	
Manufacturing workers[a]	126312		177738		187937	
GDP / capita (PPP)	477		1092		2201	
VA / employee in industry (USD)[b]	983		1705		7049	
Median LP in sample[c]	38		100		142	
Median TFP in sample[c]	54		100		143	
Monthly wage in sample (USD)	55.9	(58.6)	117.0	(322.2)	203.3	(261.3)
Exports as % of domestic prod.[d]	8.8		23.5		23.6	
Imports as % of domestic cons.	76.9		73.3		50.3	
Manufacturing exports as % of total	6.1		20.9		40.5	
Export participation in the sample (%)	9		22		49	
Share of manuf. GDP covered	0.31		0.17		0.26	
Share of manuf. labor force covered	0.15		0.12		0.31	
Number of firms	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)

Source: World Bank (2000) and own calculations for the sample statistics.

Notes: Data is for 1991 for aggregate statistics and for first year of interviews for sample statistics. Standard errors in parentheses.

[a]UNIDO.

[b]Using exchange rates.

[c]Relative to Kenya, see Van Biesebroeck (2005).

[d]Trade statistics are for 1993. The trade share is for manufacturing only, and manufacturing sales is assumed to be double of value added.

of land, while the corresponding numbers for Kenya and Tanzania were 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, and so forth.[13]

The three countries also differ substantially in their exposure to interna-

13. 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.

tional trade. Manufacturing exports as a fraction of domestic production is almost three times higher in Zimbabwe than in Tanzania, 23.6 percent versus 8.8 percent, but almost as high in Kenya. On the import side, we see that only in Zimbabwe domestic production accounts for half of the total domestic consumption. In the other two countries, approximately three-quarters of all manufactures consumed are imported. This aggregate trade exposure is reflected in the export participation rate for the firms in the sample. The differences are even more pronounced, with firms in Zimbabwe more than five times as likely to export than Tanzanian firms. The importance of the manufacturing sector in the three countries is well illustrated by the share of total export earnings accounted for by the manufacturing sector. This rises from a mere 6.1 percent in Tanzania, to 20.9 percent in Kenya, and a full 40.5 percent in Zimbabwe.

11.4.2 Firms and Workers

In 1991, Tanzania and Kenya each counted approximately twenty-five million inhabitants, while Zimbabwe only had ten million. The manufacturing sector, which we focus on, is more evenly sized because of its greater importance in Zimbabwe. All countries count between 126,000 and 188,000 manufacturing workers. A stratified sample of manufacturing firms in three consecutive years provides the micro data used in the analysis.[14] Approximately 200 firms were surveyed each year in each country, covering four broadly defined manufacturing sectors: food, textile and clothing, wood and furniture, and metal and equipment. A maximum of ten employees per firm were interviewed each year. While firms could be linked over time as a panel, this was not possible for the workers. Because questions on training were not asked in the third year, we only use the first two years in the analysis.

The resulting sample is an unbalanced panel of firms with, on average, 110 to 183 observations per year in each country. In the first year, the firms employed 19,383 to 58,108 workers and 619 to 1,206 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 percent of manufacturing GDP in Tanzania, 17 percent in Kenya, and 26 percent in Zimbabwe. The share of all manufacturing workers who are employed by firms included in the sample is substantially lower in the first two countries, a result of the higher productivity levels achieved by larger firms.

The differences between the countries described earlier are equally apparent when we compare the firms in the sample. The median firm in Tanzania achieves only 38 percent of the labor productivity level of the median firm in Kenya, while labor productivity in Zimbabwe is 42 percent

14. 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. Firms were sampled to give (the firm of) each manufacturing worker equal probability to be included in the sample—an implicit stratification by employment size.

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 firm in Kenya is twice as productive as in Tanzania, but achieves only two-thirds of the productivity level of the median firm in Zimbabwe. The salary differences between the countries match the labor productivity differences rather well. Workers in Tanzania earn 27.4 percent of the average salary in Zimbabwe, while the median labor productivity of their employers stands at 26.8 percent. Salaries in Kenya, on average $120 (in 1991 USD), 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 11.1 provides averages and standard errors for the variables used in the analysis. Workers in Zimbabwe work, on average, in larger firms, are slightly older, stay longer with the same firm and are more likely to receive (or choose to enroll in) formal training once they are employed. The sample of workers in Kenya is even more dominated by males than in the other countries. In Tanzania, workers receive the lowest salaries, but paradoxically they have the highest years of schooling. How these characteristics are rewarded is analyzed in the next section.

11.5 Results

The discussion of the estimation results is organized in the same three subsections as the earlier discussion of the measurement framework. This is followed by a discussion of some robustness checks and an analysis of the importance of trade exposure.

11.5.1 Wage and Productivity Premiums

Information on productivity is only available at the firm level and, hence, the identification of the productivity premiums necessarily exploits between-firm variation. For wages, we have the option to exploit only between-firm variation as well, in which case individual wages have to be aggregated to the firm level. Alternatively we can incorporate the information contained in the individual wages in the estimation. We will employ both strategies, but first we look at the wage equation in isolation to verify whether the estimated wage premiums for worker characteristics differ in important ways when we limit identification to between-firm or within-firm variation.[15]

15. The working paper version, Van Biesebroeck (2003), shows additional results for the individual level wage equation. A full survey of the returns to education estimated from Mincer wage regressions in sub-Saharan Africa is in Appleton, Hoddinott, and Mackinnon (1996).

Individual wage regressions with least squares capture both variation within and between firms; results for the three countries are in the columns labeled "total" in table 11.2. For example, the positive salary premium for male workers can be the result of men receiving, 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. In the columns labeled "within" and "between," we separate the two effects. Within estimates are obtained using the standard fixed-effects estimator (including firm-year fixed effects) and between estimates are obtain by averaging all variables by firm-year and estimating with least squares.

All five characteristics are measured as dummy variables. Experience is coded as 1 if a worker attained more labor market experience than the median (interviewed) worker for the country, and tenure is defined similarly. The schooling dummy takes on a value of 1 if the worker has at least attended secondary school, but not necessarily finished it. The training dummy is switched on for workers who completed a formal training program (excluding on-the-job training) after they finished their formal education or apprenticeship.

The main message from table 11.2 is that in all but two cases the between estimates are of the same sign as the total estimates and in most cases even the magnitudes are very similar. The only two instances where the signs do not correspond—tenure in Tanzania and gender in Zimbabwe—the between coefficient is estimated extremely imprecisely and not significantly different from zero (the t-statistics are 0.46 and 0.78). One pattern to note is that for Zimbabwe four of the five between estimates exceed the total estimates, with the reverse being true for the within estimates. At least for Zimbabwe, identifying wage premiums from between-firm variation tends to overestimate the unconditional premiums in a sample of workers.

The magnitudes of the wage premiums for different characteristics seem reasonable. Male workers earn substantially more, but a gender wage premium of 10.5 percent to 28.6 percent is not unreasonably large. In the first two countries, the pay differential by gender is larger between firms than within, while in Zimbabwe the between estimate surprisingly turns negative. Only in Zimbabwe are female workers concentrated in higher-paying, larger firms. Experience and schooling premiums are estimated surprisingly similar in the three countries, especially the wage gradient within firms. Differences are more pronounced for tenure and training: for both variables, workers in Zimbabwe are rewarded more generously than in the other two countries. The tenure premium in Zimbabwe is exclusively driven by the between effect, indicating that salaries do not really increase with tenure, but firms that pay higher salaries have lower worker attrition.

While we could have included occupation controls, we follow the convention in the literature not to do so. A substantial fraction of the return

Table 11.2 **Mincer wage regressions at the individual level with discrete characteristics**

	Tanzania			Kenya			Zimbabwe		
	Total	Within	Between	Total	Within	Between	Total	Within	Between
Male	0.286	0.302	0.328	0.105	0.089	0.294	0.109	0.108	–0.153
	(0.044)	(0.038)	(0.120)	(0.043)	(0.042)	(0.103)	(0.063)	(0.061)	(0.196)
Experience	0.212	0.202	0.309	0.245	0.247	0.196	0.224	0.242	0.206
	(0.040)	(0.034)	(0.110)	(0.033)	(0.032)	(0.084)	(0.054)	(0.051)	(0.189)
Schooling	0.412	0.417	0.583	0.405	0.390	0.317	0.450	0.389	0.879
	(0.039)	(0.035)	(0.101)	(0.030)	(0.030)	(0.070)	(0.051)	(0.048)	(0.178)
Tenure	0.082	0.102	–0.047	0.061	0.093	0.059	0.073	0.002	0.406
	(0.040)	(0.036)	(0.107)	(0.033)	(0.033)	(0.084)	(0.052)	(0.051)	(0.157)
Training	0.042	–0.007	0.047	0.095	0.099	0.096	0.173	0.175	0.270
	(0.061)	(0.056)	(0.141)	(0.044)	(0.043)	(0.095)	(0.057)	(0.060)	(0.137)
Obs.	1215	1215	266	2180	2180	375	1162	1162	213
R^2	0.210	0.206	0.274	0.272	0.099	0.467	0.246	0.062	0.441

Notes: The dependent variable is the logarithm of the individual hourly wage rate. All characteristics are dummy variables. Male and training are coded as 1 for yes and zero for no. The other variables are 1 if the value is higher than the median for the country and zero otherwise. Total: OLS regression, controls include hours worked, firm size (log-employment), and year, sector, and location dummies. Within: Fixed-effects estimator controlling for hours worked and firm-year dummies. Between: OLS regression with variables averaged by firm (by year if applicable); same controls as in "Total."

to human capital characteristics will materialize through occupation changes—for example, promotions, which are surely endogenous.[16]

11.5.2 Firm-Level Estimation

The SUR estimation results for equations (6) and (7) by country, with discretely measured worker characteristics, are in table 11.3. In this and all following specifications, hours worked and time, industry, and location dummies are added as controls in both the wage equation and production function. The production function always has to be estimated at the firm level, and here we aggregate the wage equation to the same level. Results in the following section are for the individual wage equation jointly estimated with the firm production function, which severely complicates the estimation.

Larger firms tend to pay higher salaries, in line with evidence for many African countries in Mazumdar and Mazaheri (2002), although the effect is small in Tanzania. The capital and labor elasticities in the Cobb-Douglas production function are estimated similarly in the three countries, with labor somewhat more important in Zimbabwe and the capital coefficient highest in Kenya. Returns to scale are moderately increasing in each country. The sum of the two input coefficients ranges from 1.041 to 1.141, in line with results for the manufacturing sector in other developing countries, as surveyed in Tybout (2000).

Consistent with the results for the individual wage data in table 11.2, we find the highest wage premium for males in Tanzania and the estimate in Kenya is approximately 10 percent lower. However, these salary gaps fall far short of the higher productivity realized by firms that employ a high percentage of male workers. The extremely high point estimates on the male dummy in the production function imply that raising the fraction of males by one standard deviation would raise output by 32 percent in Tanzania, by 40 percent in Kenya, but only by 2 percent in Zimbabwe. Given that wage premiums for males are below the corresponding productivity premiums, it suggests that men are underpaid, although none of the differences is statistically significant. These estimates are somewhat misleading though, because the majority of firms in the sample employ only male workers. The choice not to employ any female workers is undoubtedly related to the line of work a firm carries out. The productivity premium by gender is also estimated extremely imprecisely, and in the following we will mostly disregard the gender variable.

The wage premiums associated with experience are not estimated very precisely either, except in Tanzania, but the point estimates again correspond well to the between results in table 11.2; only the return to experi-

16. Results in Van Biesebroeck (2003) illustrate that 28 percent to 55 percent of the return to schooling and education is associated with occupation changes.

Table 11.3 **A market efficiency test: Production function and wage equation at the firm level**

	Tanzania		Kenya		Zimbabwe	
Dependent variable:	Wage	Output	Wage	Output	Wage	Output
Labor	0.035	0.781	0.136	0.851	0.200	0.901
	(.025)	(.082)	(.020)	(.070)	(.035)	(.068)
Capital		0.260		0.290		0.228
		(.041)		(.039)		(.040)
Male	0.537	1.386	0.422	2.186	–0.137	0.062
	(.235)	(1.32)	(.211)	(1.59)	(.182)	(.313)
Experience	0.308	–0.404	0.193	–0.205	0.119	0.349
	(.147)	(.229)	(.126)	(.233)	(.221)	(.357)
Schooling	0.717	0.162	0.467	0.077	1.289	1.764
	(.175)	(.401)	(.133)	(.270)	(.463)	(.781)
Tenure	–0.075	–0.249	0.063	0.366	0.470	0.801
	(.104)	(.271)	(.115)	(.407)	(.246)	(.410)
Received training	–0.074	0.700	0.029	0.560	0.295	0.231
	(.157)	(.810)	(.125)	(.476)	(.195)	(.254)
*Test for equality of coefficients in both equations (*p*-values)*						
Joint test (all 5 characteristics)		0.01		0.18		0.64
Joint test—without male		0.01		0.23		0.73
Joint test—general HC		0.00		0.15		0.72
Joint test—firm-specific HC		0.55		0.42		0.73
Joint test—learning		0.29		0.28		0.42
Joint test—over time		0.00		0.21		0.79
Observations		266		375		213
R^2	0.27	0.71	0.41	0.80	0.45	0.87

Note: Controls added to both the wage equation and the production function are hours worked and year, industry, and location dummies. Estimation is with SUR. Experience and schooling are grouped as general human capital (HC) characteristics, with tenure and training grouped as firm-specific human capital. "Learning" combines schooling and training and "over time" combines experience and tenure.

ence in Zimbabwe is estimated rather low. Salaries rise substantially with experience in Tanzania and Kenya, but not in Zimbabwe, where education is rewarded higher than in the other two countries. The impact of experience in the production function follows a peculiar pattern: the relative size of the productivity premiums in the three countries is exactly the opposite of the wage premiums ranking. In the country where salaries are most responsive to experience, Tanzania, the productivity of firms drops with the experience/age of the workforce. The country that rewards experience the least, Zimbabwe, is the only one where experience is associated with a positive productivity effect. The gap between the wage and productivity premium associated with experience is more than 50 percent larger in Kenya than in Zimbabwe, and the gap in Tanzania is almost three times as large as in Zimbabwe. For Tanzania, we can reject equality between the two premiums at the 1 percent significance level and for Kenya at the 10 percent level.

For schooling, the size of the productivity premiums follows the same pattern between countries as the wage premiums: highest in Zimbabwe, lowest in Kenya, and intermediate in Tanzania. Still, in the two least-developed economies, educated workers are able to secure a wage premium that far outstrips the productivity contribution of education. In Zimbabwe, on the other hand, the difference goes the other way. Similarly as for experience, the gap between the wage and productivity premium associated with schooling is by far the largest in Tanzania and Kenya.

The tenure variable, which measures whether an employee has stayed more than the median number of years with his or her current employer, is associated with particularly large salary increases in Zimbabwe (47 percent). In the other two countries, salaries do not rise with tenure, only with experience. Strikingly, in each country the productivity effect of tenure largely exceeds that of experience. The same is true for the training dummy. In the two least-developed countries, workers who receive training are not paid a higher salary, even though training has a large (but imprecisely estimated) effect on productivity. In Zimbabwe, the wage premium for workers marginally exceeds the productivity effect.

Combined with the higher wage premium for tenure than for experience, the compensation pattern in Zimbabwe is likely to help reduce worker turnover, especially of those valuable employees that received training. This is borne out by a cursory look at the correlation between training and tenure at the individual level. Controlling for experience, workers with 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 current employer. The relationship is particularly strong in Zimbabwe, but hardly noticeable in Kenya.

A joint test for the hypothesis that for the four variables that determine the level of human capital in a firm (experience, schooling, tenure, and training) wage premiums equal productivity premiums is rejected for Tanzania at the 1 percent significance level. For Kenya, it can only be rejected if we are willing to tolerate a 23 percent significance level. The hypothesis can never be rejected for Zimbabwe, as the p-value is 73 percent. The tests follow the same pattern if we include the male dummy, with the p-value somewhat lower for Kenya and even higher for Zimbabwe.

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 driving the correlation between equality of returns and development level of the country. Firms in all three countries are rewarding firm-specific characteristics more closely in proportion to the productivity gains they bring. The p-values on these joint tests are always high, although it should be noted that the effects are estimated especially imprecisely for Tanzania and Kenya.

In contrast, the differences between countries are especially stark for general human capital characteristics. The *p*-value is 0.00 for Tanzania, 0.15 for Kenya, and 0.72 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 underlying tendency is for salaries to increase over time with experience in Tanzania and Kenya and with tenure in Zimbabwe, while productivity is more closely related to tenure than to experience in each country.

Even at the firm level, coefficients on the worker characteristics are estimated more precisely in the wage equation than in the production function, although the R^2 tends to be higher in the latter. Comparing the different countries, standard errors are somewhat larger for Zimbabwe than for Kenya or Tanzania. However, the coefficient estimates also tend to be larger (in absolute value) for Zimbabwe, with the exception of the male and training dummies even uniformly so. While the average *t*-statistic in the wage equation is somewhat higher in Tanzania (1.93) and Kenya (1.56) than in Zimbabwe (1.48), the average *t*-statistic in the production function is higher in Zimbabwe (1.26) than in Tanzania (1.00) or Kenya (0.92). Only for the male dummy is the *t*-statistic in Zimbabwe below those in the other two countries. There is thus no evidence that the higher *p*-values for Zimbabwe are simply due to less-imprecisely estimated coefficients.

11.5.3 Individual-Level Estimation

While the joint tests at the bottom of table 11.3 for the results at the firm level showed a clear pattern, many of the wage and productivity premiums were estimated imprecisely. Incorporating the information on individual employees avoids aggregation of the wage equation and is likely to improve precision, especially for the wage premiums. The estimation results using the wage equation at the individual level with the methodology outlined previously are in table 11.4. The increase in precision is very large for all coefficients in the wage equation: on average, standard errors have decreased by a factor of three. The production function coefficients are estimated more precisely as well, especially in Tanzania. While all firms were treated identically in the firm level estimation, the current results implicitly weigh firms by the number of employees that are sampled, which partly explains the nonnegligible changes in the point estimates of both equations.

The labor and capital coefficients have changed the least; only the results for Tanzania are somewhat closer to those for Kenya and Zimbabwe. In the wage equation, all premiums are now estimated positively, in line with our priors. While most of the point estimates for Tanzania and Zimbabwe are slightly lower in absolute value than before, the estimates for Kenya are

Table 11.4 **A market efficiency test: Firm-level production function and individual wage equation**

	Tanzania		Kenya		Zimbabwe	
Dependent variable:	Wage	Output	Wage	Output	Wage	Output
Labor	0.057	0.864	0.074	0.701	0.208	0.850
	(.024)	(.035)	(.018)	(.029)	(.022)	(.028)
Capital		0.238		0.326		0.262
		(.047)		(.019)		(.017)
Male	0.340	0.878	0.089	0.117	0.115	0.217
	(.052)	(.431)	(.045)	(.267)	(.068)	(.178)
Experience	0.237	–0.639	0.283	–0.238	0.271	0.347
	(.047)	(.069)	(.039)	(.152)	(.064)	(.186)
Schooling	0.503	–0.289	0.470	0.268	0.567	1.109
	(.054)	(.121)	(.039)	(.194)	(.068)	(.313)
Tenure	0.080	0.099	0.104	0.067	0.203	0.592
	(.046)	(.174)	(.036)	(.214)	(.219)	(.193)
Received training	0.039	0.281	0.104	0.453	0.177	0.079
	(.069)	(.273)	(.048)	(.290)	(.069)	(.112)
*Test for equality of coefficients in both equations (*p-*values)*						
Joint test (all 5 characteristics)	_	0.00		0.01		0.67
Joint test—without male		0.00		0.01		0.59
Joint test—general HC		0.00		0.02		0.52
Joint test—firm-specific HC		0.63		0.40		0.41
Joint test—learning		0.00		0.19		0.36
Joint test—over time		0.00		0.00		0.48
Observations	1215	266	2180	375	1162	213
R^2	0.74	0.73	0.44	0.75	0.32	0.83

Note: Controls added to both the wage equation and the production function are as before: hours worked and year, industry, and location dummies. Estimation is with SUR. The production function is at the firm level, while the wage equation is at the individual level and has first been transformed to allow for a random firm effect. Groupings of characteristics for the joint tests are the same as in table 11.3.

slightly higher for most coefficients. With only a couple of exceptions, the returns to worker characteristics in the production function are estimated lower than before in absolute value. The relative position of the countries, however, is by and large unchanged.

The average size (in absolute value) of the gap between wage and productivity premiums in Tanzania went from 61.2 percent for the firm-level results to 49.3 percent for the individual results, from 67.6 percent to 22.7 percent in Kenya, and from 26.0 percent to 24.1 percent in Zimbabwe. Even though the absolute value of the differences declined, the standard errors declined even more, resulting in more of the gaps being significantly different from zero. The same joint tests as before yield almost uniformly lower p-values; see the results at the bottom of table 11.4.

The rejection of equality of the wage and productivity premiums for

Tanzania is as strong as before, but not solely due to experience anymore. The *t*-statistic associated with the "excess return" to experience is now 10.5, but the "excess return" to schooling now also yields a *t*-statistic of 6.1. Moreover, the direction of the differences is the same as before: experience and schooling are over-rewarded, while tenure and training are under-rewarded, although not significantly so. The same is true for Kenya, but less pronouncedly. Only one general human capital characteristics is clearly over-rewarded—experience—and only training receives a salary premium below the productivity effect, although the gap is not statistically significant.

Results for Zimbabwe are by and large similar as before, although the standard errors in the wage equation are somewhat higher than in the other two countries. The average size of the gap between wage and productivity premiums is still the lowest of the three countries, at least if we exclude gender, but the lower precision makes the tests less powerful in Zimbabwe. In contrast with the other two countries, the only two characteristics for which the gap is more than 10 percent are schooling and tenure, and both are rewarded below their contribution to productivity.

11.5.4 Robustness Checks

The working paper version of this chapter contains a number of sensitivity analyses that demonstrate the robustness of the results—see Van Biesebroeck (2003) for details. First, the findings are very similar using continuous measures (years) of experience, tenure, and schooling. In the two least-developed countries, workers are still estimated to secure substantial pay increases over their career that are not matched by any discernible productivity effect. The wage return to schooling also exceeds its effect on productivity in each country, but the extent differs widely. As before, the excess returns (the gap between the salary and productivity premiums) for experience and schooling are highest in Tanzania, at respectively, 4.8 percent per year of labor market experience and 6.0 percent per year of education. The gaps are sizeable in Kenya as well, at 2.8 percent and 3.3 percent. In Zimbabwe, the gaps are only 0.3 percent and 1.2 percent, and formal statistical tests do not reject equality of the returns (*p*-values are 0.81 and 0.75). In the two least-developed countries, equality of the returns to experience can be firmly rejected, even at a 1 percent significance level. The same holds for schooling in Tanzania (albeit only at a 10 percent significance level), but not in Kenya.

Second, given that the rejection of equality between wage and productivity premiums in Tanzania and Kenya is to a large extent driven by the experience premiums, we have reestimated the model, relaxing the assumption that workers with high and low experience are perfect substitutes. We introduce two separate labor aggregates ($\tilde{L}_X$ and $\tilde{L}_Y$) in the model; each is adjusted by multiplicative factors to control for the other worker characteristics—as in equation (5).[17] To be as flexible as possible on the production side, we adopted a constant elasticity of substitution (CES) specification, which allows not only the weight on each labor aggregate, but also the elasticity of substitution between the two aggregates to be determined by the data. This requires a modification in the test for equality between the two premiums, but we refer to Van Biesebroeck (2003; section 7.2) for details. The results are qualitatively similar to the results in table 11.3, where perfect substitutability is assumed. This is not surprising given that the estimates for the elasticity of substitution between young and experienced workers are relatively high: 3.0 for Kenya, 6.3 for Tanzania, and infinity for Zimbabwe. The *p*-value on the joint test for Kenya is even lower than in table 11.3.

Third, even though we did not observe the entire workforce for most firms, we could proceed with the estimation by using the sample of observed employees to estimate the fraction of male, educated (and so forth) workers at each firm. While these are estimated quantities, we have treated them as the true means. Van Biesebroeck (2003) reports results from two Monte Carlo exercises that investigate how sensitive the findings are to the noise that enters the estimation procedure in this way. A first exercise repeatedly samples for each firm a different sample of employees from the hypothetical workforce (as implied by the estimated means) and proceeds with the estimation as before. A second exercise uses Bayes' law (based on the estimated means) to assign probabilities to randomly generated values for each characteristic. These probabilities are then used as weights in the seemingly unrelated regression (SUR), where each firm is assigned randomly generated average characteristics.

For both exercises, the average *p*-values are slightly below the *p*-values for Tanzania and Kenya in table 11.3, rejecting equality strongly. In the second, exercise, the *p*-value for Zimbabwe is much reduced, although it remains more than twice as high as the one for Kenya. Given that, on average, a smaller fraction of each firm's workforce is sampled in Zimbabwe, it was expected that sampling would introduce greater variation for Zimbabwe. Still, the qualitative finding that "the likelihood of rejecting equality between wage and productivity premiums is decreasing with the level of development" still applies.

11.5.5 Trade Exposure

In addition to the differences between countries, there are bound to be differences between individual firms within each country. One crucial distinction between firms is to what extent they are exposed to competition

17. Data limitations force us to still use the entire workforce to estimate the fraction of male workers, highly educated workers, and so on. In principle, it is possible to let the ratio of male workers as well as the wage and productivity premiums associated with gender vary by experience category.

from foreign firms. Firms that operate in a highly competitive product environment might also have to compete harder on the labor market to attract good employees. To export successfully, firms need a high-quality product, possibly requiring more highly skilled workers. To survive in an industry facing a lot of import competition, producing efficiently is crucial and investments in human capital might be one way to achieve process innovations. In any case, strong competition in the output market will make it harder to offer wage premiums for worker characteristics that do not contribute to productivity.

Results in table 11.5 are for two subsamples that pool firms from all countries, but separate firms that face international competition from those that do not. Firms "exposed to trade" are those that exported, or that indicated that the main source of competition they faced was from (a) imported goods, from (b) local production by foreign or multinational firms, or from (c) foreign firms on export markets.[18]

Results using the firm-level estimator are reported in the first two columns of table 11.5. To conserve space, the excess returns—the difference between the wage and productivity premiums—are reported directly. The pattern is clearcut. Firms that face international competition reward characteristics more in line with the productivity contributions they make. The average gap between wage and productivity premiums, even excluding the male premium, is 58.2 percent for firms that do not face international competition and 45.4 percent for firms that do. Even though the standard errors are somewhat smaller for the latter firms, the tests indicate that rejection of equality is more likely for firms not facing international competition.

The comparable average gap for the results with the individual-level estimator, reported in the last two columns of table 11.5, is 39.5 percent for domestically oriented firms and 25.1 percent for firms competing with foreigners. The tests for equality are not very different for the two samples, although p-values are always lower for the domestically oriented firms. This is mostly due to the much smaller gap for experience for firms exposed to trade. Using either estimation method, firms competing with foreigners are especially likely to equate wages to productivity premiums for the firm-specific characteristics, tenure and training. Given that these are controlled by the employee and can be adjusted over one's career, incentives will be more appropriate for employees of these firms. While the results in table 11.5 are somewhat sensitive to the controls included and to the way the samples are divided, it does provide some evidence for the importance of competition.

18. Alternative answers to the question asking about the main source of competition were (iv) none, or (v) domestic firms producing locally.

Table 11.5 Estimation on separate samples by trade exposure (pooling firms from all countries)

	Firm-level estimation		Individual-level estimation	
Trade exposure?	No	Yes	No	Yes
Male	–1.377	–0.278	–0.318	–1.703
	(1.47)	(.272)	(.312)	(.544)
Experience	1.054	0.560	0.773	0.251
	(.489)	(.323)	(.113)	(.128)
Schooling	0.404	0.586	0.488	0.497
	(.251)	(.297)	(.150)	(.151)
Tenure	0.447	–0.531	0.276	–0.216
	(.234)	(.811)	(.195)	(.233)
Received training	–0.423	0.138	–0.050	0.041
	(.552)	(.297)	(.222)	(.158)
Test for equality of coefficients in both equations (p-values)				
Joint test—without male	0.00	0.20	0.00	0.01
Joint test—general HC	0.04	0.06	0.00	0.01
Joint test—firm-specific HC	0.14	0.72	0.14	0.99
Observations	395	289	1988	1279

Note: Same estimation as in table 11.3, first two columns, and table 11.4, last two columns. Firms from all three countries are pooled: additional controls now include country-specific time, location, and industry dummies. The reported coefficients and standard errors are for the difference between the wage and productivity premiums, the 'excess return' for each characteristic. Groupings of characteristics for the joint tests are the same as in table 11.3.

11.6 Conclusions

A couple of findings are worth reiterating. First, wage premiums for a number of characteristics do not always match productivity contributions, and this failure is more pronounced for some countries than for others. Second, a lot of attention in the development literature is devoted to education, and rightfully so, because the returns in higher salary and output are important and we only capture a fraction 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. Third, a crucial aspect of remuneration is the trade-off between paying workers for general experience versus firm-specific tenure. This mirrors a similar trade-off between preemployment education and subsequent training. In Tanzania, and to a lesser extent in Kenya, general skills (experience and schooling) are rewarded relatively more than firm-specific skills (tenure and training). In Zimbabwe, wage premiums match the productivity gains that are associated with them more closely, and interestingly, the returns to firm-specific investments are higher than in the other countries. Fourth, we offer some suggestive evidence that firms facing higher product market competition are more likely to reward characteristics in line with their productivity contribution.

Data quality is often a concern when working with surveys from developing countries. As mentioned earlier, data issues have limited us to look at only three countries and at a limited set of human capital characteristics. It is our hope that these findings are sufficiently interesting to spur other researchers to check their robustness with other data sources and qualify and refine the results where needed.

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