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WAGE RENTALS FOR REPRODUCIBLE HUMAN CAPITAL: EVIDENCE FROM GHANA AND THE IVORY COAST

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Evidence from Ghana and the Ivory Coast

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Abstract

Education, child nutrition, adult health/nutrition, and labor mobility are critical factors in achieving recent sustained growth in factor productivity. To compare the contribution of these four human capital inputs, an expanded specification of the wage function is estimated from household (LSMS) surveys of The Ivory Coast and Ghana. Specification tests assess whether the human capital inputs are exogenous, and instrumental variable techniques are used to estimate the wage function. Smaller panels from the Ivory Coast imply the magnitude of measurement error in the human capital inputs and provide more efficient instruments to estimate the wage equation. The conclusion emerges that weight-for-height and height are endogenous, particularly prone to measurement error, and heterogeneous in their effects on wages. Overall returns to these four forms of human capital are similar within each country for men and women, but education and migration returns are higher in the more rapidly growing Ivory Coast, and the wage effects of child nutrition proxied by height are greater in poorer, more malnourished Ghana.

Keywords: Endogenous Human Capital Returns, Health, Migration, Schooling, Africa, Physical Stature.

JEL codes: J24, I12, O15, J31

1. INTRODUCTION

Schooling, height, weight-for-height, and migration are attributes of workers associated with their current productivity. These forms of worker heterogeneity are to some degree reproducible: schooling and migration are created by well-described processes, whereas height and weight-for-height are formed by the biological process of human growth, in which the inputs of nutritional intakes, protection from exposure to disease, health care, and activity levels combine to exert a net cumulative effect on the individual's realization of their genetic potential. The impact of height and weight-for-height on labor productivity and well-being have been extensively documented by economic historians (Fogel, 1994, Steckel, 1995), and more recently studied in contemporary random surveys from low-income populations (Strauss and Thomas, 1995). These worker attributes are viewed here as indicators of human capital because they can be augmented by social or private investments, but they also vary across individuals because of genetic and environmental factors that are not controlled by the individual, family, or society. This paper estimates the productive payoff to the formation of these four human capital stocks in two low-income countries.[1] Because the cost of creating these stocks has not been accounted for, only estimates of the wage rental values of these stocks are offered here and not internal rates of return. Several questions are addressed.

First, how important for labor productivity is each of these four dimensions of worker heterogeneity considered jointly, for men and women separately, in two Sub-Saharan African countries where the conditions of health and nutrition are relatively poor?[2] Second, do the wage payoffs to forms of human capital change when one allows for human capital stocks to be endogenous, heterogeneous, and measured with random error. Finally, how do these forms of human capital interact in their determination of worker productive capacity; can complementarity between forms of human capital (interactions) be distinguished from changing "returns to scale."

In Section 2, a simple framework is outlined for guiding the estimation of an extended wage function that includes several, possibly endogenous, heterogeneous, and measured with error, human capital stocks. The data are described in Section 3. Empirical specification issues are discussed further in Section 4. Sections 5 and 6 report the estimates for cross sectional surveys from the Ivory Coast and Ghana. Then in Section 7, for a smaller two-year panel from adjacent years of the Ivory Coast surveys, measurement error is quantified and alternative estimates of wage functions are compared. Section 8 presents flexible form estimates to assess non-linearities, and Section 9 reconsiders the gender wage gap in terms of the human capital inputs. Section 10 summarizes the new evidence and suggests how further research might resolve some of the outstanding questions.

2. THE DEMAND FOR HUMAN CAPITAL AND THE WAGE FUNCTION

Household demand for human capital is represented as a derived demand for the services of these capital stocks, which is a function of the prices of inputs to produce these stocks, the discounted value of the increased output they produce, local public services and relevant conditions, as well as the credit available to parents, and the parents' own endowments. Four forms of human capital are considered here as an input, I_{ij} , where i refers to the individual and j to the type of human capital: H for adult height as an indicator of childhood nutritional status (Faulkner and Tanner, 1986; Behrman, 1993); E for years of education (Becker, 1993; Mincer, 1974; Griliches, 1977); B for body-mass-index (BMI = weight in kilograms divided by height in meters squared) as an indicator of adult nutritional status and current health (Fogel, 1994; Steckel, 1995; Strauss and Thomas, 1995) , and M for whether the individual has migrated from the region of birth (Schultz, 1982) :

$$I_{ij} = a_j Y_i + \beta_j X_i + \varepsilon_{ij}, \qquad j = H, E, B, M \tag{1}$$

where the critical distinction is between *Y* that affects the demand for human capital partly through its impact on wage structures which provide the labor market incentive to invest in human capital, as well as through other possible channels, and *X* that affects the demand for human capital without modifying the structure of expected wage opportunities. For example, the price of an input used in the production of the human capital might be specified as a variable in *X*, but would not affect the local wage returns to human capital, such as the local price of food or nutrients (Strauss, 1986), whereas residing in a rural area might be specified to Y which could capture the higher cost of obtaining health care in a rural area and also be associated with different wage returns from human capital in these areas. The parameters of behavioral demand and human capital production technology are not separately identified in these reduced-form parameters, α and β, that are estimated in (1). The errors, ε_{ij} , are assumed uncorrelated with *Y* and *X*.

A standard semi-logarithmic linear approximation of the wage function is expanded here to include the four noted human capital inputs and the vector of exogenous variables (Y) that additively affect the logarithm of wages:[3]

$$w_i = \sum_{j=l}^{4} \gamma_j I_{ij} + \delta y_i + v_i \tag{2}$$

The human capital inputs are exogenous in the wage function if the wage error is uncorrelated with the errors in the human capital demand functions, or the covariance (v_i, ε_{ij}) = 0, for j = 1, ..., 4. If this cross equation error covariance is not zero for some j, then the jth form of human capital is endogenous and ordinary least squares (OLS) estimates of the wage equation are biased.

To test for the exogeneity of the human capital inputs, the wage function parameters must be identified, possibly by an exclusion restriction, represented by the vector of X instruments in the human capital demand equation (1). A significant difference between the OLS estimates, consistent even if the inputs are exogenous, and instrumental variable (IV) estimates, consistent even if the inputs are endogenous, defines the standard specification test (Hausman, 1978). One way to specify appropriate instruments for this problem is to explore in more detail the probable sources of human capital input endogeneity.

One form of endogeneity could arise if there are exogenous unobserved differences across individuals in their original endowments, and these endowments could influence how parents and children invest in human capital, in possibly a compensatory or complementary manner. Examples of this type could be "ability" affecting the demand for education (Willis and Rosen, 1979), and "frailty" affecting the demand for health inputs (Rosenzweig and Schultz, 1983). These forms of innate heterogeneity that are not observed by the researcher could cause a correlation between the human capital inputs and the error in the wage function and thereby lead to biased OLS estimates of the wage function.[4] There are two approaches to this problem. Either measure the omitted variable, e.g., genetic ability, and include it in the wage function, or choose an instrument for the input such as market prices or random temporal and spatial shocks, e.g., rainfall, that are expected to influence human capital demands but not otherwise affect subsequent wage opportunities of the individual.

A second type of misspecification arises when two inputs are aggregated that have different productive effects on wages. If the instruments are more strongly correlated with one of the two inputs, the specification test may reject the exogeneity of the aggregated input, because the IV estimate will predict one component better than the other. For example, height across a birth cohort may be largely determined by the genetic capacities or genotype distributed across the population at conception, although its expression may be modified by subsequent resource allocations. Individual nutritional intakes, exposures to disease, treatment of these diseases, and variation in other environmental burdens determine net nutritional status, which then facilitates or stunts the expression of genetic potential for adult height. As a readily measured and objective index of healthiness, productivity, and well being, height encompasses a wide range of biological characteristics that are otherwise difficult to quantify and decompose (Faulkner and Tanner, 1986). Deviations of height from genetic potential are particularly sensitive to early childhood living conditions (Martorell and Habicht, 1986). The two components (genotype and phenotype) of height are equally relevant to economic or welfare outcomes. In a population that is closed to emigration or immigration and does not experience change in its mix of biological groups (e.g., by race), changes in average height over time may be plausibly attributed to changes in reproducible human capital investments, or changes in disease environments, or both. Yet, in the cross section, the fraction of the variance observed in height that can be explained by socioeconomic endowments and constraints may have a larger (or smaller) effect on productivity than the fraction of the variance in height that is not explained by socioeconomic variables and is presumably more likely to arise from genetic variability.

Aggregating these different sources of variation in height could lead to misleading inferences on the relative importance of augmenting height by lowering food prices or reducing the virulence of disease. This form of aggregation bias could also lead to the rejection of the exogeneity of height according to the standard Hausman-Wu specification test, if the X includes only socioeconomic endowments and constraints. The origin and interpretation of this type of aggregation bias differs from the first type of heterogeneity bias. Confronted by human capital inputs in the cross section with two such components, as with height and perhaps BMI, selecting instruments that determine behavioral demands for human capital and that are not correlated with genotypic variability in these inputs should improve estimates of the effect of the reproducible component in human capital. Those characteristics in the population which are more likely to be related to relevant genetic groups, e.g., race, language, or birthplace, may be included in the vector of control variables, Y, that enters both the wage and the human capital demand functions, in order to avoid relying on inter-group genetic variation to identify the wage effects of the reproducible component of human capital.[5]

Errors in measurement of the human capital inputs could also explain why the apparent wage effects of the inputs when directly estimated by OLS are downwardly biased compared with the IV estimates. This source of bias could be detected by the specification test and be corrected by instrumental variable estimation methods. If the measurement errors were random, due to, say, coding errors and numerical rounding mistakes, and were independent from one observation to the next for the same individual, it might be directly assessed in a panel. Averaging two periods, for example, would reduce such white noise and attenuate the bias due to this source of error. The matched observation on the same human capital input from another round of the survey could provide a relatively efficient instrument for this round's error-measured input observation, potentially correcting for this source of bias.

Thus, three alternative models could account for a specification test that rejects the exogeneity of human capital inputs. The bias due to omitted variables and errors-in-measurement could plausibly introduce off-setting effects on a human capital coefficient in a wage equation, such as with education (Griliches, 1977; Lam and Schoeni, 1993). These off-setting sources of bias could weaken the power of the specification test to reject exogeneity.

The functional form of the wage equation may also be more complicated than expressed in (2). Diminishing (or increasing) returns to the individual's accumulation of each form of human capital is often plausible from a biological or economic perspective. The empirical specification of the wage function should flexibly allow for this possibility. For example, the effect of nutrition on physical growth and adult productivity is expected to be subject to diminishing returns (Strauss, 1986; Strauss and Thomas, 1995). The proportionate increase in wages associated with a specific increase in nutrition may be greater for those who are especially malnourished. This nonlinearity in returns to nutrition has buttressed the efficiency wage hypothesis (Bliss and Stern, 1978) and motivated theories of malnutrition and inefficiency due to market failure (Dasgupta, 1993; Foster and Rosenzweig, 1993). The proportionate increase in wages associated with an additional year of schooling is often reported to be smaller at higher levels of schooling (Psacharopoulos, 1994). Although economists are accustomed to this empirical regularity suggesting diminishing returns to "scale" of human capital investments (Becker, 1993), the opposite pattern of increasing returns to education is also documented today, when bureaucratic bottlenecks or perhaps credit constraints hinder the economically efficient expansion of intermediate or higher levels of schooling.[6] Nonetheless, the predominant pattern, if not a rule, is for human capital returns to be higher at lower levels of investments. Consequently, investments in human capital could be equilibrating and if targeted to the poor could reduce economic inequality and also promote efficient growth.

Finally, human capital inputs may technically substitute or complement each other in their effect on labor productivity, depending perhaps on the nature of tasks the individual performs in the labor market. For example, weight may become less valuable for increasing the productivity of workers as they become more educated and qualify for white-collar jobs where physical strength and endurance are of less value. Existing empirical evidence on interactions between types of human capital does not consider human capital inputs as potentially endogenous or subject to variable returns to scale. Reported interactions that treat human capital as exogenous may not, therefore, serve as a reliable guide to the importance, or even sign, of the technical input interactions between endogenous forms of human capital.[7]

The wage function should be estimated, therefore, in a flexible form that allows for nonlinearity and interactions in addition to the multiplicative form implied by the standard semi-logarithmic wage function (Mincer, 1974). Consequently, a second-order approximation of the log wage function will be considered later in Section 8 (Fuss and McFadden, 1978), with the human capital inputs tested jointly for their exogeneity.[8]

$$w_i = \sum_{j=1}^{4} \gamma_j I_{ij} + \sum_{j=1}^{4} \sum_{k=j+1}^{4} \eta_{jk} I_{ij} I_{ik} + \sum_{j=1}^{3} \theta_j I_{ij}^2 + \delta Y_i + \nu_i . \tag{3}$$

Note that the squared effect of migration human capital is not estimated because it is measured as a dichotomous variable, equal to 1 if the individual has migrated away from their birthplace and zero otherwise. This more flexible form of the wage function (3) is obviously more difficult to estimate precisely because 13 input coefficients are now estimated (compared with 4 in (2)), and these additional variables are highly correlated with each other by construction. This multicollinearity problem is more serious if some of the input variables are subsequently assumed endogenous and must then be predicted on the basis of the same vector of instrumental variables (X). Practically, it should be expected that in this context only a few of the quadratic and interaction terms will prove statistically significant in modest-sized samples of only a few thousand individuals. Thus, a more parsimonious linearized specification is likely to be accepted strictly on grounds of parsimony and statistical fit (Rosenzweig and Schultz, 1983). Nonetheless, empirical evidence that certain higher-order terms in the expanded wage function (3) are statistically significant should not be entirely discounted because all such terms are not jointly significant. If any of these higher order terms are empirically decisive, they could increase the precision of inferences on how public and private expenditures are best deployed to increase labor productivity. Correlations may be expected between different forms of human capital across individuals, and the greater the magnitude of this intercorrelation of inputs the more difficult it may be to estimate the productive payoff to each input separately.[9]

Another problem in estimating the wage equation is the unrepresentativeness of the sample of individuals who report wages. To correct this potential sample selection bias, variables must be observed that are arguments in the sample selection decision rule that are theoretically restricted from affecting the market wage equation (Heckman, 1979). Conditional on the assumption that physical wealth and non-earned income identify the probit selection model, the correlation of the errors between the wage earner participation probit equation and the log wage equation are in the samples considered here generally insignificant. Estimated returns to schooling or adult health are robust to these corrections for sample selection bias (Schultz, 1993; Schultz and Tansel, 1997).[10] Sample selection bias will therefore be neglected here.

3. CHARACTERISTICS OF THE SAMPLES

Table 1 reports the average levels of the four indicators of human capital stocks for men and women from the Ivory Coast and Ghana, by age, according to the Living Standards Measurement Surveys circa 1985-1989.[11] Some individuals in the youngest age group, 15 to 19, are continuing to invest in education, and individuals in this age group are still growing toward their adult stature of height and BMI. Migration, because it is a cumulative measure of having ever migrated since birth, increases with age within a birth cohort, but may not increase across age groups in a cross section if mobility has been increasing over time for more recent birth cohorts.

Years of schooling completed began to increase sharply at least a decade earlier in Ghana than in the Ivory Coast. Men's education in the Ivory Coast increased in three decades nearly seven fold from .9 years for men age 50-65 to 6.0 for those age 20-29. In Ghana men's education more than doubled in this period from 3.6 to 8.3 years.[12] Women age 50-65 have only one-seventh as many years of education as do men in The Ivory Coast, whereas women 50-65 in Ghana have one-fourth as much education as do men. In the Ivory Coast women in the age group 20-29, who received their education approximately during the 1970s, have 69 percent as many years of schooling as do men, and women this age in Ghana have four-fifths as many years of education as do men. Women clearly receive substantially less education than do men in these two populations. Although this gender gap is closing, it still remains absolutely large at the secondary school level, particularly in The Ivory Coast (Schultz, 1993).

The indicator of migration peaks for women in The Ivory Coast in the ages 20-29 and for men at ages 30-39. In Ghana, where economic growth started earlier in this century but has been slower since the mid-1960s than in The Ivory Coast, migration is less frequent and more uniform across ages.

Height for males in the Ivory Coast shows an increase from 1.67 meters among the oldest group, age 50-65, to 1.71 among those age 20-29. This four-centimeter increase is larger than the two-centimeter increase observed among males in Ghana. Women in the Ivory Coast report a height gain of 3 centimeters between the same age groups, whereas the gain for women in Ghana is only one centimeter. In these three decades real GNP per capita increased about 70 percent in Ghana and 316 percent in The Ivory Coast (World Bank, 1991). These gains in height could plausibly reflect the improved nutritional status of youth maturing during the 1970s compared with those growing up during the 1940s and 1950s. As of 1990, 36 percent of the children under age 5 are still malnourished in Ghana, whereas only 12 percent are estimated to be malnourished in the Ivory Coast (World Bank, 1991).

The time trend in height across birth cohorts can also be estimated with greater precision at the individual level, by regressing height on age while controlling for membership in groups that may share a genetic component and which may have changed their proportions in the population over time, such as ethnic/language/religion and birthplace groups (Appendix Table A-1). Restricting the sample to men and women ages 20 to 60 to exclude most of those who are still growing or the elderly who may be shrinking, the ordinary least squares linear trend estimates imply a rate of growth in height of 0.52 cm per decade in Ghana for women (t=6.97) and 0.48 cm for men (t=5.18), and about one centimeter per decade for men and women in the Ivory Coast (1.1 cm (t=11.8) and .99 cm (t=13.7), respectively). These estimates are within the standard growth increments experienced during the second half of the 20th century of between 0.3-3 cm per decade (e.g. Cole 2003).[13]

Because the body-mass-index often increases with age, the tendency for BMI to peak for men and women in the age group 30-39, as shown in Table 1, does not clarify whether there has been an improvement over time in BMI in either country across birth cohorts. Controls for age differences in BMI, therefore, should be interpreted with caution, for they could capture both aging and changes over time in nutritional status.

The demand determinants (eq. 1) and the productive consequences (eq. 2) of the four human capital stocks are estimated in the next section for persons age 20 to 60, allowing for variation across the four age groups distinguished in Table 1 by including three dummy age group variables.

4. EMPIRICAL SPECIFICATION OF THE MODEL

If the human capital stock variables are measured with error, biologically heterogeneous, or are affected by unobserved characteristics of individuals, families, or communities that also affect wages, ordinary least squares (OLS) estimates of the wage equation (2) will be biased. To obtain consistent estimates in these circumstances instrumental variable methods may be used, in which the instruments are sufficiently correlated with the human capital variables, but strictly not correlated with the wage equation error. Conditional on the other variables included in the wage function (*Y*), good instruments (*X*) should then explain a statistically significant part of the variation in the demand for the human capital variables (Bound et al, 1995). The second criterion of a good instrument is that it not be information an employer would know and plausibly use to determine a potential worker's wage offer, while it might motivate the prior acquisition of any of the four forms of human capital analyzed here.[14]

First, there are productive characteristics of the worker that could be included in both the wage function and in the human capital demand function (*Y*): The age and ethnic/language group, rural/urban residence, region of birthplace, average annual rainfall, and whether the interview occurred during the biannual rainy (malarial) season in the north or south. In West Africa height and weight, as well as education and migration differ by ethnic group, and ethnicity may be correlated with other omitted forms of human capital and even genetic variability that could possibly influence worker productivity. The twice-a-year rainy season is associated with increased malaria and other water-borne diseases, which temporarily disable or reduce the productivity of many adults e.g., because of diarrhea. The derived demands for labor in agriculture are also affected by season and vary by climatic region, and should be expected to affect wages.

The instruments that are assumed to only affect the demand for human capital inputs (*X*) and identify the wage equation include: (1) community health infrastructure, water and sanitation conditions, the distance to a doctor and clinic, and distances to various school facilities and a permanent market; (2) eight to eleven community prices of food items; and (3) father and mother education and whether they worked in agriculture. The hourly wage rate, inclusive of income in kind, is deflated by a regional price deflator to approximate a real wage (Schultz and Tansel, 1993). Consequently, the relative prices of food staples in the community should capture the relative cost of nutrition that might influence current nutrition and BMI in particular (Strauss, 1986; Thomas and Strauss, 1996). Increasing distance to middle and secondary schools should discourage schooling by increasing its private cost. Community health infrastructure and access to medical care are expected to influence the prevalence of diseases and affect net nutritional status, as proxied by height and BMI.

However, many individuals have moved from their birthplace and human capital investments such as height and schooling, are partly determined by local conditions as a young child. Therefore, for migrants, local condition variables are set to the average conditions prevailing for respondents still living in the regions where the migrants were born. Because the surveys do not ask migrants whether they were born in a rural or urban area, it is assumed that they were born in rural areas, except for those reporting their birthplace as the capital city. Local conditions will have changed, moreover, since the respondent was a child. The statistical significance of these contemporary instruments in explaining past human capital inputs might thus be attenuated among older respondents.[15]

The birthplace region, of which eleven are distinguished in each country, may itself proxy unobserved regional variation in schooling and health facilities, and may contribute to migration, given the different regional levels of development and wage opportunities. Wages may differ by birthplace region for reasons other than the individual's accumulation of the four observed stocks of human capital, and that is allowed for within the model's specification by including birthplace in the wage equation. Parent education and occupation are assumed to influence the respondent's investment by means of changing the four observed forms of human capital. If parents also affect the formation of other unobserved skills and traits of children that enhance their offspring's productivity as adult workers, the parent education/occupation may be an invalid instrument. One approach to detect this problem is to also include the parent characteristics in the wage function directly, or assign them to Y rather than X (Lam and Schoeni, 1993). This approach may also bias down the estimated wage effects of the human capital inputs (Griliches, 1977), but in the case at hand, conditioning wages on parent characteristics does not significantly add to the explanatory power of the wage function.[16]

5. ESTIMATES OF THE EXTENDED WAGE FUNCTION

Different forms of human capital tend to be positively correlated with each other. In both countries and for both men and women, 20 out of the possible 24 correlations between the four human capital variables are positive and significant at the 1 percent level (Appendix Table A-2). An exception is BMI and height, in which BMI is constructed to be approximately orthogonal with height, as seen in The Ivory Coast, in order to facilitate multivariate studies of the joint effect of height and BMI on health outcomes (Fogel, 1994).

All of the forms of human capital are individually positively correlated with the log hourly wage variable in each of the 16 cases at a significance level exceeding .01 percent (Table A-2). Consequently, the estimated effect of any of the human capital variables on the log of hourly wage rate is likely to be upward biased, if other human capital variables are omitted from the wage function (Griliches, 1977). The nature of the bias could be complicated by possible nonlinear effects of the human capital inputs on the log wage and interactions with other variables. Indeed, the relationship between BMI and health is not only nonlinear, it appears to be non-monotonic; health outcomes such as mortality, chronic morbidity, or nonparticipation in the labor force among elderly men increases with BMI in excess of about 28 (Fogel, 1994; Costa, 1996).[17] The effect of years of education on log wages is often noted to be decreasing with scale, although instances of education returns increasing are also documented (Schultz, 1993). It is thus an empirical issue of how much estimates of the wage returns to education may be biased (presumably upward) by the omission of other forms of human capital in the wage function.

Table 2 reports estimates of the linear specification of the log wage equation for only the human capital coefficients, in which controls (Y) are also included. Columns (1) through (4) report ordinary least squares (OLS) estimates based on the assumption that the human capital inputs are exogenous, homogeneous, and measured without error. Adding sequentially migration, BMI, and height, according to their average correlations with education (Table A-2), to the more conventional wage equation reduces the initial estimate of the private returns on education (Cols. (1) through (4)) as was expected. If these human capital stocks are exogenous and measured without error the estimates of the wage returns to education appear to be biased upward by about 5 to 15 percent by the omission of these three other forms of human capital. Only height in the Ivory Coast among women is not statistically significant in the full multivariate exogenous specification of the wage function (4), just as it was least significant in the simple correlations with wages (Table A-2).

According to the OLS estimates in Column (4), a year of completed schooling has an average effect of increasing wages by 11 percent for men and 7 percent for women in the Ivory Coast and 4.4 percent for men and 3.8 percent for women in Ghana. This larger return to education in the Ivory Coast than in Ghana could be attributed to the larger initial supply of educated workers in Ghana or to the slower economic growth in Ghana since independence that may have depressed the relative derived demands for more skilled workers. Migration from region of birth is associated with a larger gain of 72-89 percent in wages in The Ivory Coast than the 35-53 percent in Ghana, probably related to the greater integration of the national labor market in Ghana than in the Ivory Coast and the correspondingly larger wage differentials favoring Abidjan than those prevailing in Accra. The cultural-political barriers to movement across tribal regions may inhibit interregional migration to a greater extent in The Ivory Coast than in Ghana. Change in a unit of BMI is associated with similar percentage changes in wages in both countries, 4.2 to 6.1 percent, but sample variability in BMI is greater among women than men, with standard deviations about 4.2 versus 2.6, respectively (Appendix Table A-1). The association between wages and height is stronger in Ghana than in the Ivory Coast suggesting that malnutrition among children is more often a binding constraint on adult height in Ghana. An individual who is one centimeter taller (the standard deviation is 6-7 cm.) receives in Ghana a wage that is 1.3 to 1.5 percent higher, whereas taller men in the Ivory Coast receive a wage that is .95 percent higher per centimeter, and women receive a wage that is .25 percent higher. These OLS estimates reinforce the standard view that education is the dominant reproducible form of human capital, with migration second, followed by significant but relatively small effects related to height and weight-for-height. However, the question arises how might these estimates be biased by the econometric problems discussed earlier?

6. ENDOGENOUS DEMANDS FOR HUMAN CAPITAL INPUTS

Table 3 summarizes in Column (1) the overall explanatory power of the first-stage estimates of the human capital input equations, in Column (2) the increment to the R^2 contributed by only the identifying instruments, and in Column (3) the F ratio test of their joint statistical significance. In addition to the 22 identifying instrumental variables in the Ivory Coast and 30 in Ghana (Table A-1), interactions of the instruments with the controls and quadratic terms in parent education are also included as identifying variables (48 variables in the Ivory Coast and 54 in Ghana) to improve the fit of the later estimates of the second-order approximation of the wage equation (3). Despite the large number of instruments, the F test is statistically significant in all 16 cases at the 6 percent level or better, with education and migration being significant at .01 percent level (Bound et al, 1995). Two-fifth to two-thirds of the variation in education and migration is explained, while the increment accounted for by the instruments is between 8 and 29 percent. A smaller share of the variation in height and BMI is explained, between 8 and 17 percent, whereas the instruments in these cases account for only 3.5 to 8.7 percent of the sample variance. Observed variations in height and BMI are clearly not well-explained by the socioeconomic instruments, suggesting that these indicators of nutrition and stature are dominated by genetic variability or at least they are not readily explained by common household or community characteristics.

Specification tests may help assess whether the human capital inputs are related to unobservables that are correlated with wages. The Hausman (1978)-Wu (1973) test of exogeneity is performed with respect to each of four human capital inputs individually, where the other three inputs are all assumed exogenous. The identifying instruments include local food prices, health and education services and infrastructure, and parent education and occupation. The exogeneity of height is rejected at the 10 percent level of confidence in three out of four gender/country samples, as is BMI at the 5 percent level (Table 3, Column 4). Migration is never rejected as being exogenous at conventional levels, whereas education is rejected at the five percent level in only one out of four samples, for females in Ghana. Either BMI and Height are measured with more error than schooling or migration, or they are endogenously affected by omitted factors, which are also correlated with the wage rates. The failure to reject migration as exogenous may be due to the low explanatory power of the instruments for migration, which reduces the power of the specification test. Without complete agreement in these tests across the four gender/country samples, Column (5) in Table 2 reports instrumental variable (IV) estimates assuming all four human capital variables are endogenous, whereas Column (6) assumes that only BMI and height are endogenous, which the Hausman test supports at the 10 percent level of confidence in all four samples, and at the .5 percent level in the two larger Ghanian samples. The regression standard errors in Table 2 are corrected to take account of the fact that the human capital regressors in the last two columns are now predicted.

Specification tests of the exogeneity of human capital variables in the wage function are not commonly reported. Angrist and Krueger (1991) note that the OLS and IV estimates of the wage rental value of education do not differ substantially in the United States in recent censuses, suggesting that education can be viewed as exogenous. Migrants are often noted to be more productive than natives at destinations after a period of assimilation, which has been hypothesized to be due to the positive self-selection of migrants with respect to their market productivity and motivation (Chiswick, 1978; Schultz, 1982, 1988). It might be expected, therefore, that the exogeneity of migration would be rejected, but it is not in these two African countries. Weight for height (or BMI) is assumed endogenous in some recent studies of wage function in low-income countries, but specification tests are not formally reported (Strauss, 1986; Strauss and Thomas, 1995). The only analysis where height is treated as an endogenous determinant in the wage function is by the author based on the same surveys (Schultz, 1995). Heterogeneity of height and BMI, possibly representing genetic and reproducible components, which have different effects on labor productivity, is a hypothesis that warrants further study.

To assess the validity of the over-identification restrictions on the model, the residuals from the IV wage equation from Column (5) in Table 2 are regressed on the identifying instrumental variables. The R squared from this residual regression multiplied by the sample size is distributed as chi squared with the degrees of freedom equal to the number of such identifying instruments (Angrist and Newey, 1991). The over-identification restriction is accepted for men and women at the 5 percent level in The Ivory Coast (men imply a chi squared (70) = 60.91 and women = 103.84) and for men in Ghana (chi squared (84) = 106.2), but it is rejected at this level for women in Ghana (= 145.9). Thus, the over-identifying restrictions implied by the instruments is not rejected in The Ivory Coast for both sexes and for men in Ghana, but are rejected at the 10 percent level for women in Ghana. Omitting from the identifying set of instruments the food prices, the interactions between distances to markets, hospitals and doctors, and parents education and occupation, I assessed the robustness of the IV wage equation estimates analogous to Column (6), Table 2. Few substantial changes were noted in the wage rental estimates.[18]

If all human capital inputs are treated as endogenous, estimated private returns on education do not change substantially for men and women in The Ivory Coast and increase for women and decrease for men slightly in Ghana. The estimates of endogenous migration are larger for women in the Ivory Coast and smaller for men than when they are estimated as exogenous, but decrease substantially in Ghana. Only in Ghana is there any evidence that the endogeneity of migration exerts the anticipated upward bias to OLS estimates of the wage impact of migration as would be expected if migration was selected on unobservables that increased labor productivity, e.g., market motivation to succeed. BMI has a larger effect on wages when it is endogenized, and the estimated IV effect of height on wages increases markedly for men and women in Ghana, but ceases to be significant for men in The Ivory Coast (Table 2). The mixed estimates in Column (6) of Table 2 are preferable, because they rely on the more efficient OLS estimates for education and migration, based on their apparent exogeneity, and use IV techniques to correct for the potential endogeneity and errors in measurement of height and BMI.[19] The estimated effects of an increase in height by one centimeter are now insignificant for men and women in The Ivory Coast and 5.6 and 7.6 percent in Ghana for men and women, respectively. A unit increase in BMI is associated with a 9 percent increase in women's wages in The Ivory Coast and in Ghana. A unit of BMI increases men's wages by 15 percent in the Ivory Coast and by 7 percent in Ghana.[20]

These estimates of the expanded linearized approximation of the log wage equation (Col. (6), Table 2) imply that a standard deviation (Table A-1) increase in all four human capital inputs would be associated in the Ivory Coast with an increase in male wages of 134 percent and in female wages of 99 percent, while in Ghana such an increase in human capital is associated with an increase in male wages of 92 percent and in female wages of 195 percent. However, the variation in human capital stocks across a population may have two sources—one due to investments of individuals, families and states, and the other due to genetic endowments that are not affected by these human investment activities—and our estimates are designed to assess the returns on the former source of reproducible variation. Therefore, it might be more realistic to simulate only that fraction of the sample standard deviation that is accounted for by the identifying instruments, as reported in Col. (2) of Table 3. This counterfactual would suggest a wage gain for males of 11 percent and females of 18 percent in the Ivory Coast, and for males of 8 and females of 13 percent in Ghana. One-third of the gains in Ghana are now attributable to proxies for nutritional status, BMI and height, whereas in the Ivory Coast these anthropometric inputs account for only a sixth to a tenth of the apportioned wage gain. Thus, education and migration remain the dominant inputs in this human capital accounting of wage variation even in this West African setting where health and nutrition are poor by world standards.[21]

The most important finding in Table 2 is the tendency for the wage effects of physical stature to increase when they are estimated by instrumental variables rather than by ordinary least squares in Ghana and in the Ivory Coast in the case of BMI. Although the explanatory power of the first-stage human capital demand equations are relatively low for BMI and especially for height, the identifying variables remain statistically significant jointly, as seen from the joint F statistics (p values) reported in Column (3) of Table 3. Three possible explanations for why OLS and IV estimates systematically diverge were postulated in Section 2: unobserved heterogeneity in individuals and families; different productive effects from reproducible and exogenous (e.g., genetic) components of human capital; and errors in measurement of these inputs. To consider the importance of these alternative explanations, the next section analyzes two-year rotating panels for subsamples of the Ivory Coast surveys.[22]

7. MEASUREMENT ERROR AND PANEL ESTIMATES FROM THE IVORY COAST

To simplify the interpretation of the data, it is assumed that the true human capital inputs do not change between observations a year apart. Education can increase at most one year, but there are only 3 female wage earners in school in the first year of our sample and 13 males. The migration variable can increase for an individual, but if they migrate, they leave our sample of matched (addressed) households. Therefore, there should be no valid changes in migrant status between years. Height is regarded as essentially fixed by age 20, although it is possible that malnutrition might delay the adolescent growth spurt and some males could still experience a small amount of "catch-up" growth in their early 20s. Only BMI can actually vary from year to year, violating my working assumption.[23]

The "classical" and simplest model of measurement error assumes that each human capital input is measured with an additive, serially uncorrelated error that is distributed independently of the true human capital inputs and independently of other input errors or control variables. With this framework, the OLS estimates of the human capital input effect on wages are biased downward, toward zero, in proportion to the ratio of the variance of the error to the variance of the measured input. This proportional attenuation bias due to errors in measurement is evaluated below. The magnitude of measurement error in a cross section can in certain cases be assessed from panel data.[24] However, panels can also introduce their own error, because some persons may be mismatched.[25] To improve the quality of the panel data some "criteria" may be applied to "clean" the data and eliminate mismatches that would otherwise overstate measurement error.[26] For example, there are 809 males in the Ivory Coast survey age 20 to 60 who have the same household number and individual roster number in two adjacent annual survey rounds from 1985 to 1988 (Appendix Table A-3). Forty-one are reported to be females in the second round, suggesting a mismatch. There are also 26 of the remaining males who report an age in the second cycle of the survey that is more than ten years different from that expected after aging one year. Another 30 men are removed from the sample if the tighter restriction is imposed that their second age should be within five years of that expected on the basis of the first age. Finally, to arrive at the working panel sample analyzed in this section, 27 individuals are eliminated because their years of education changes by more than five years between the adjacent survey cycles. Clearly, different restrictions on what represents a valid match implies different estimates of measurement error, but the pattern of results discussed below across inputs are not greatly affected by retaining in the panel estimation sample those persons with larger and less plausible intercycle changes in age and education.

The means and variances of the matched sample of the input variables do not change substantially in adjacent years (Table 4). However, the correlation of one year's input with that input in the adjacent year is far from perfect. Although education is correlated at .98, migration falls to .93 for men, and .80 for the less educated women, and height and BMI are lower still.[27] There is a substantial difference between the heights of women in the two years; the variance of the measurement error appears to be almost a fourth of that of the signal, given the working assumptions of the model.[28] This evidence would lead one to expect a larger downward bias in OLS estimated returns to height and BMI than to education or even to migration for men in this panel. Indeed, this is the pattern of differences between OLS and IV cross sectional estimates reported in Table 2.

Table 5 reports the human capital coefficients in the wage function based on six specifications for the panel of matched sample from the Ivory Coast. Columns (1) and (2) confirm the expected decline in the traditional estimate of the return to education when controls are added for the other three human capital inputs. All except height are statistically significant even for these much smaller samples of 687 men and 397 women. Column (3) is estimated from the average of the input values in the adjacent two years to reduce the measurement error bias. As expected, the coefficients on BMI increase by 10-20 percent, height by 20 percent for women, while the coefficient on education increases trivially, and migration decreases slightly. Conditional on the assumed simplified model of measurement error, averaging two years of input data should reduce the variance in the noise by half, suggesting that the downward measurement bias on BMI is on the order of 30 percent while on education it is only 6 percent. For women the averaging of inputs implies the measurement error accounts for a 68 percent downward bias on the OLS estimate for BMI, a 50 percent downward bias on height, and a 2.4 percent downward bias on education. This estimate of measurement error corresponds roughly with that implied by the IV estimates in Column (4) predicted with the adjacent year's input observation. The errors on migration do not correspond with those in our simplified framework.

Column (5) reports IV estimates based on the same identifying variables as used in cross section estimates reported in Table 2. These instruments have the weakness that they are not as highly correlated with the current input variables as the adjacent year's input, and the strength that they are suggested by the behavioral model of human capital demands. The IV estimates in Col. (5) should be robust to serial correlation in the input measurement errors and be asymptotically free of bias due to heterogeneity in the individual/family or in the differential effect of socioeconomic predictions of the inputs and their residual (e.g., genetic) as detected by the Hausman tests in both these panels and in the previous larger cross sections.

When the instruments are the local conditions at the region of birth, local residence prices, and parent characteristics in Col. (5) the precision of the estimates decrease compared with those in Col. (4), as anticipated. The returns to education for males increase from the OLS value of .113 in Col. (2) to .117, the effects of migration increase from .924 to 1.20, that of BMI increase from .0408 to .0670, while height for males remains insignificant but changes sign.

For the female sample the return on education decreases more, from .0759 to .0540, migration from .714 to .601, whereas BMI increases 2.4 fold from .0469 to .112, and the effect of height for women also changes sign and is insignificant.

The panel estimates confirm a serious problem of measurement error in BMI and possibly height, and its minor importance for interpreting returns on education. Although the measurement error of BMI and height goes some way toward explaining the increased magnitude of IV over OLS estimates, there is still an unexplained downward bias due to heterogeneity of individuals or distinct social and biological components in the observed input as it affects labor productivity.[29]

8. SECOND-ORDER APPROXIMATIONS OF THE WAGE FUNCTION

If the human capital inputs are exogenous and measured without error, the second-order approximation of the semilog wage function is efficiently estimated without bias by OLS, and these estimates are reported in Column (1) of Table 6. As other researchers have noted, there is evidence in all four gender/country samples that the log wage returns to education are higher beyond primary school than they are at the primary level. The quadratic terms for BMI and height are not statistically significant, despite scattered evidence from other studies that they are individually subject to diminishing returns, but probably not in the very low range of values obtained in these two countries (Fogel, 1994; Costa, 1996).[30] Among the six interactions terms, those with respect to education are the only set of three that are jointly significant at the 5 percent level. According to these tests of zero restrictions for the OLS second-order approximation, a more parsimonious specification is adopted in Column (2) of Table 6 that includes only the squared education and the education interaction variables in addition to the linear effects. The joint tests on the variables that include education, migration, BMI, and height are each statistically significant, with the same exception as before of height for women in the Ivory Coast. Education appears to be a substitute for BMI in three out of four samples, implied by the negative sign of the cross effect on wages. Migration and education in Ghana are substitutes for women, and complements for men implied by the positive sign of the cross effect on wages.

Identified by the original vector of prices, local infrastructure, and parent characteristics, and their interactions, the IV estimates of the parsimonious wage specification are reported in Column (3) of Table 6, assuming all inputs are endogenous. The IV estimates confirm a positive quadratic term for education, but the linear term is no longer estimated precisely. BMI is a significant substitute for education for women in the two countries, but not for men. Height is a significant substitute for education only in the case of men in the Ivory Coast. This last result does not sustain the view that schooling and better child nutrition (proxied by height) are complements in increasing school achievements and later labor productivity (Moock and Leslie, 1986; Behrman, 1993). The negative cross effect of BMI on education in conjunction with the positive correlations between stature and education (Table A-2) could account for the diminishing wage returns attributed to BMI as inferred from bivariate relationships (Strauss and Thomas, 1995: Fig. 34.3). The OLS estimates of the interactions between migration and education are mixed across genders, but positive and significant in the IV estimates in the Ivory Coast. The effect of education on returns from migration probably depends on the skill intensity of the derived demands for labor in the expanding regions, which may differ across countries and possibly by gender. These estimates of the second-order approximation of the wage function are not sufficiently robust across men and women or countries to draw any firm conclusions as to the complementarity (or substitutability) among human capital inputs in West Africa at this time. Larger samples and better instrumental variables may in future research provide more precise predictions of the tradeoffs among human capital inputs that could be useful for setting public sector investment priorities in the human resource area.

9. MALE-FEMALE WAGE DIFFERENCES

In addition to wage returns, the gender composition of human capital in a society is related to non-wage social externalities. Women's market productivity relative to men's is widely associated with lower fertility, child mortality, and population growth, as well as increased schooling and human capital investments per child in the subsequent generation (Schultz, 1993). How much of the difference between the logarithm of male and female wages is accounted for by the gender differences in human capital using Oaxaca's (1973) decomposition procedure is suggested by Table 7. In the working sample age 20 to 60, men received an average 2.9 more years of education than women and are more likely to be a migrant than women. Equalizing educational investments between women and men is also likely to narrow the gender gap in migration. There is probably a biologically determined difference between male and female stature. This difference between men and women may vary over time and across environments because of development which could affect the need for and access to consumption and health care, or social discrimination which could modify the resources available to men and women to satisfy these needs, or technological change which could influence endemic diseases and the environment which impacts distinctly the stature of men and women. If we restrict the wage coefficients to be the same for men and women, except for an intercept, comparison of Columns (1) and (2) indicates that the difference in education alone between women and men in the Ivory Coast reduces the log wage advantage of men to women from .59 to .21, or by .38 log points, and in Ghana from .27 to .12, or by .15 log points, which represents in both countries a reduction in the initial gap by one half. Because of the off-setting effect of BMI, the gender wage gap increases to .24 when all four human capital endowments are equalized in the Ivory Coast in Col. (3), and in Ghana the wage gap decreases further to .05, because of the substantial coefficient on height. Column (4) allows the human capital endowments and all other conditioning variables to affect log wages differently for men and women, which is equivalent to the estimates in Col. (4), Table 2 with complete disaggregation by sex. Note, the returns to education benefit men significantly more than women in the Ivory Coast whereas migration benefits women significantly more than men in Ghana. The intercept differences between men and women are no longer statistically significant with this fully interacted specification, but this result is conditional on the other included controls (i.e., ethnic, age, birth region, etc.).

10. CONCLUSIONS AND DIRECTIONS FOR FURTHER WORK

The effects on log wages of four measures of human capital — height proxying childhood nutritional status, education, migration, and body-mass-index proxying adult health — are estimated here for men and women separately for the Ivory Coast and Ghana from household surveys collected during the late 1980s. These four human capital inputs are initially treated as measured without error, homogenous, and exogenous. Under these working assumptions, OLS estimates are unbiased and efficient, and they confirm what other studies have found: wage differentials associated with education are substantial in the Ivory Coast and moderate in Ghana, which can be explained by both the relatively larger supply of educated workers in Ghana and the relatively slow growth of the national economy from 1960 to 1990 in Ghana compared with the Ivory Coast. Wage returns are large for migration in the Ivory Coast and Ghana, substantial for BMI in all four samples, and for height in all samples except women in the Ivory Coast. The first finding is then that the estimated wage returns to schooling are reduced by 10-20 percent with the addition to the wage function of these other three key human capital inputs (Table 2, Columns (1)-(4)).

Although the conventional assumption in the wage function literature is that human capital inputs are exogenous, Hausman tests of this specification choice indicate that the exogeneity of height and BMI is more often rejected than not, whereas the exogeneity of migration and education cannot be rejected in more than one out of the four samples. The biologically fixed variation in height and BMI may exert smaller effects on labor productivity than does the human capital induced variation in these measures of stature, contributing to the Hausman test rejecting the equality of the effect of overall variation in stature on wages compared with the effect of the reproducible variation in stature explained by the instruments (Schultz, 2002). Schooling is relatively well explained by the availability of schools and parent education, providing powerful instruments, which imply schooling selection is not a source of bias in estimating educational returns. Migration exerts a large and uncertain effect on wages, and the instruments may not be sufficiently powerful in explaining the human capital component of migration to distinguish between the effect of the random and human capital component of migration on wages. Instrumental variable estimates are reported based on the assumption that the health/school infrastructure, food prices of the local childhood community, and the parent's education and occupation influence the household's demand for these four human capital inputs, but that these instruments do not enter the wage equation. In addition to obtaining IV estimates in Table 2, Column (5) assuming all four inputs are endogenous, the preferred IV estimates in Column (6) rely on the Hausman tests and assume that education and migration are exogenous, and only height and BMI are estimated as endogenous.

The notable finding in Table 2 is that the IV estimates of the productive payoff to BMI and height are larger than the OLS estimates in Ghana the poorer and less well nourished country, and they are also larger in Cote d'Ivoire for BMI, if not for height. There are at least three possible explanations for this result. The errors in measuring BMI and height are larger than those in measuring education and migration, or heterogeneity in individuals and families accounts for an omitted variable bias, or the productive consequences of reproducible and innate components of human capital differ and the instrumental variable estimates approximate the payoff to the reproducible component which exceeds the returns to the unexplained genotypic variation in stature.

To distinguish among these alternative hypotheses for the unanticipated cross sectional IV estimates, smaller panels of repeated observations on the same individual are analyzed from the Ivory Coast.[31] If errors in measurement of each human capital input are independent over time, and uncorrelated with other errors or with other control variables, averaging of adjacent years of the human capital inputs should decrease by half the attenuation bias caused by the random measurement error. Consistent with this "classical" framework, the panel estimates of the wage effects based on the two-year average values increase marginally for education but increase 10-30 percent for BMI and height (Table 5, Columns (2) versus (3)). This pattern of IV estimates confirms much larger errors in measurement for the anthropometric indicators than for education (Table 5, Columns (2) versus (4)).

The second approach is to estimate by instrumental variables the human capital effects on wages, using the adjacent year's value of the input to predict the current input's value. These IV estimates for BMI and height are about 50 percent larger than those obtained by OLS, whereas those for education increase by less then 10 percent (Table 5, Column (2) versus (5)).

The third approach to the panel is to use the local community food prices, health and schooling infrastructure in the region of birth, and parent characteristics to instrument for the human capital inputs, as in the larger cross section. The

IV estimates for BMI increase further for women and are of the same magnitude for men as they were for the prior IV estimates, whereas the estimates of height for which the instruments are weakest lose their statistical significance. The panel evidence reaffirms that the returns to education and migration are not substantially biased by the assumption that these forms of human capital are measured without error and are exogenously determined. BMI and height will require much further study as potentially heterogeneous and endogenous inputs to the wage function, which are also subject to substantial amounts of measurement error in these surveys.

Extending the analysis to a comparison of men and women, a form of the Oaxaca wage decomposition of the gender wage gap can be performed with the OLS estimates in Table 7. In the Ivory Coast the gender wage gap is wider, with men receiving wages that are 58 percent larger than those of women. Three-fifths of this gap is accounted for by the differences in the four human capital endowments of men and women, weighting them by the wage function coefficients averaged for both sexes. In Ghana the wage gap is 23 percent, and the human capital inputs account for four-fifths of the gap (Table 7).

Returns to the human capital inputs are expected to vary with the scale of investment, and interactions between all pairs of inputs need not be uniformly complementary as implied in the standard semilog-linear specification of the wage function. A more flexible functional form is therefore estimated (Table 6). Yet, the demands on these data to define this second-order approximation of the wage function may be excessive, for few strong empirical regularities emerge, except that returns to schooling increase after primary schooling, which is confirmed by other studies of these countries.

What specific programs, policies, and relative prices in a local community encourage greater investments in the four human capital inputs distinguished in this paper? Community questionnaires could be better focused and more useful for policy analysts, if they knew how to intervene with public resources to increase the quantity of human capital demanded by families. Large household surveys of workers might be more valuable, if they collected not only information on adult education and wages, but also height, weight, and migration histories. Reducing measurement error in collecting the adult anthropometrics should be a priority, and describing policy relevant features of the respondent's childhood home will require retrospective instruments. Extended wage functions may then be routinely estimated and become a more reliable tool for setting human resource priorities. Thomas and Strauss (1996) have made an innovative start at this type of research for Brazil, but their assumption that height is exogenous in the wage function should be reappraised, and migration histories could be exploited to synchronize instrumental variables to capture more precisely the conditions at birth and during adolescent development. Economic historians have interpreted the relationships between anthropometric indicators of stature and productivity, health, and welfare (Fogel, 1994). The empirical study of wage functions in low-income countries may now refine these historical insights, extend the framework of Mincer (1974) to accommodate a richer portfolio of human capital, and model explicitly the household's demands for various forms of reproducible human capital.

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Table 1

Sample Means of Four Indicators of Human Capital Stocks by Age and Sex for Côte d'Ivoire and Ghana [a]

Sample: Country, Sex Variable	15-19	20-29	30-39	40-49	50-65	All
Côte d'Ivoire: Males Sample Size	1196	1414	994	824	1034	5642
Education (yes)	5.46	6.00	5.78	2.68	.876	4.37
Migration (1 or 0)	.289	.426	.581	.490	.300	.410
BMI (Wt/[Ht*Ht])	20.3	21.8	22.6	22.6	22.3	21.9
Height (Meters)	1.66	1.71	1.70	1.69	1.67	1.68
Côte d'Ivoire: Females Sample Size	1283	1925	1287	1019	1065	6579
Education	3.77	3.20	1.80	.326	.125	2.09
Migration	.333	.430	.424	.325	.206	.357
BMI	21.8	22.8	23.2	22.8	21.8	22.5
Height	1.59	1.59	1.59	1.58	1.56	1.58
Ghana: Males Sample Size	1073	1389	1075	766	731	5034
Education	7.05	8.26	7.88	6.70	3.64	7.02
Migration	.171	.258	.360	.394	.306	.289
BMI	18.4	20.7	21.1	21.0	20.5	20.3
Height	1.60	1.70	1.69	1.69	1.68	1.67
Ghana: Females Sample Size	1034	1818	1254	803	945	5854
Education	5.60	5.71	4.77	2.59	.852	4.27
Migration	.214	.296	.329	.270	.222	.273
BMI	20.4	21.5	22.8	22.7	21.6	21.8
Height	1.56	1.58	1.58	1.57	1.57	1.58

[a] Based on all persons in the surveys reporting age, sex, and the four human capital inputs.

Table 2
Coefficients on Four Indicators of Human Capital Inputs in Wage Functions by Sex with Controls for Region, Ethnic Group, and Season: Côte d'Ivoire and Ghana [a]

Country Gender Variable	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV
Côte d'Ivoire Males: Sample Size 1692						
Education	.121 (18.4)	.115 (17.4)	.112 (16.9)	.109 (16.4)	.107* (3.88)	.113 (17.0)
Migration		.567 (6.97)	.547 (6.74)	.715 (8.73)	.691* (3.09)	.713 (8.55)
BMI			.0441 (4.44)	.0451 (4.55)	.159* (3.00)	.154* (3.47)
Height				.862 (2.00)	-1.25 (.51)	-1.05* (.56)
Females: Sample Size 1180						
Education	.0747 (7.17)	.0744 (7.18)	.0713 (7.01)	.0730 (7.18)	.0731* (3.58)	.0758 (7.29)
Migration		.377 (3.76)	.339 (3.45)	.891 (8.26)	.961* (4.80)	.951 (8.55)
BMI			.0634 (7.10)	.0613 (6.88)	.0950* (2.71)	.0937* (2.95)
Height				.416 (.62)	-4.35* (1.78)	-4.18* (1.83)
Ghana Males: Sample Size 3414						
Education	.0521 (11.7)	.0475 (10.7)	.0449 (10.1)	.0437 (9.86)	.0445* (2.46)	.0445 (9.95)
Migration		.388 (7.48)	.360 (6.97)	.348 (6.75)	.218* (2.26)	.295 (5.34)
BMI			.0542 (6.93)	.0530 (6.80)	.0793* (1.95)	.0658* 1.76)
Height				1.48 (5.02)	5.69* (3.45)	5.56 (3.58)
Females: Sample Size 3400						
Education	.0481 (9.23)	.0425 (8.22)	.0395 (7.69)	.0375 (7.26)	.0356* (2.69)	.0346 (6.56)
Migration		.617 (9.85)	.537 (8.55)	.531 (8.46)	.361* (2.989)	.447 (6.51)
BMI			.0425 (7.72)	.0420 (7.63)	.0981* (4.11)	.0881* (4.32)
Height				1.29 (3.63)	7.48* (3.44)	7.62* (3.80)

[a] Other control variables include region of birth, ethnic group, age and season of interview. Beneath regression coefficient is the absolute value of the t ratio on parentheses in Cols. (1) – (4) and asymptomatic t ratio in Cols (5) – (6).

* Variable is assumed endogenous and estimated by instrumental variables, which includes parent education and occupation, local health infrastructure, and food prices.

Table 3
Diagnostics on Two Stage Estimates

Sample and Input Variable	R^2 (1)	First State Estimates Incremental R^2 (2)	F Ratio (p<value) (3)	Hausman Test of the Exogeniety of Human Capital t (p<value) (4)
Côte d'Ivoire				
Males: 1692				
Education	.408	.076	2.94, 70 (.0001)	-.74 (.46)
Migration	.583	.139	7.60, 70 (.0001)	-1.13 (.26)
BMI	.087	.052	1.30, 70 (.0530)	-2.60** (.009)
Height	.131	.053	1.41, 70 (.0158)	.18 (.85)
Females: 1180				
Education	.500	.221	6.83, 70 (.0001)	.15 (.88)
Migration	.685	.191	9.56, 70 (.0001)	-.85 (.40)
BMI	.146	.083	1.5170, (.0049)	-.85 (.40)
Height	.157	.088	1.61, 70 (.0014)	1.84* (.066)
Ghana				
Males: 3414				
Education	.421	.059	3.99, 84 (.0001)	-1.38 (.17)
Migration	.663	.290	33.9, 84 (.0001)	.26 (.80)
BMI	.112	.062	2.76, 84 (.0001)	-1.98** (.048)
Height	.090	.048	2.07, 84 (.0001)	-3.36*** (.0008)
Females: 3400				
Education	.441	.148	10.4, 84 (.0001)	-2.48** (.013)
Migration	.672	.279	33.4, 84 (.0001)	.76 (.45)
BMI	.170	.087	4.13, 84 (.0001)	-3.81*** (.0001)
Height	.077	.035	1.47, 84 (.0036)	-4.28*** (.0001)

* = statistically significant at 10 percent level.
** = statistically significant at 5 percent level.
*** = statistically significant at 1 percent level.

Table 4
Human Capital Input Measured in Adjacent Years of Survey in Côte d'Ivoire

Year, Input and Sex Sample	Mean		Variance		Correlation
	(1)	(2)	(1)	(2)	(1,2)
Education:					
Males	5.95	5.97	32.7	32.7	.984
Females	3.49	3.49	26.1	26.0	.984
Migration:					
Males	.632	.636	.233	.232	.928
Females	.491	.494	.251	.251	.803
BMI:					
Males	22.9	22.9	8.50	8.50	.798
Females	24.4	24.4	20.5	20.4	.835
Height:					
Males	1.70	1.70	.00435 .00427		.906
Females	1.59	1.59	.00345 .00351		.788

Table 5

Human Capital Input Coefficient in Wage Function Based on
Côte d'Ivoire Panel Observations for two Adjacent Years [a]

Gender of Sample (Size) Input Variable	OLS Traditional Wage Function (1)	OLS Expanded Wage Function (2)	OLS Averaged Two Year's Inputs (3)	IV Other Year's Input is the Instrument (4)	IV Location and Parents are Instruments (5)	IV Location and Parents are Instruments (6)
Males (687)						
Education	.144	.113	.116	.120*	.117*	`.118
	(14.1)	(10.8)	(11.0)	(11.3)	(3.80)	(11.3)
Migration		.924	.885	.821*	1.20*	.960
		(7.14)	(6.88)	(6.36)	(3.99)	(7.43)
BMI		.0408	.0469	.0569*	.0670*	.0733*
		(2.77)	(3.05)	(3.09)	(1.33)	(1.65)
Height		.837	.845	1.04*	-1.84*	-1.17*
		(1.27)	(1.25)	(1.43)	(.76)	(.57)
Females (397)						
Education	.0926	.0759	.0768	.0796*	.0540*	.0740
	(5.55)	(4.64)	(4.72)	(4.88)	(1.99)	(4.45)
Migration		.714	.682	.618*	.601*	.715
		(3.84)	(3.70)	(4.66)	(2.45)	(3.79)
BMI		.0469	.0605	.0801*	.112*	.100*
		(3.19)	(3.96)	(4.66)	(3.14)	(2.97)
Height		1.91	2.38	3.04*	-.272*	-.669*
		(1.69)	(1.99)	(2.11)	(.11)	(.27)

[a] Beneath regression coefficients is the absolute value of the t ratio in parentheses in Cols. (1) – (3) and asymptotic t ratios in Cols. (4) – (5). See notes to Table 2.

* Assumed to be endogenous or measured with error and estimated by instrumental variable methods.

Table 6A

Quadratic Approximation of Wage Function in Cote d'Ivoire and by Sex [a]

Human Capital Input Variables	Male			Female		
	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)
Education	.480 (3.36)	.391 (2.85)	-.271 (.41)	.354 (1.30)	.376 (1.44)	.689 (.85)
Education Squared $(x10^{-2})$	.331 (3.19)	.333 (3.22)	.362 (.74)	.706 (4.11)	.709 (4.14)	1.14 (1.97)
Education* Migration	-.0147 (1.06)	-.0142 (1.04)	.139 (2.45)	-.0045 (.25)	-.0051 (.29)	.0722 (1.95)
Education* BMI	-.0034 (1.83)	-.0028 (1.58)	-.0108 (.92)	-.0046 (2.21)	-.0050 (2.46)	-.0139 (1.82)
Education* Height	-.193 (2.44)	-.149 (1.94)	.269 (.69)	-.161 (.99)	-.169 (1.08)	-.297 (.59)
Migration	-.179 (.11)	.757 (7.43)	.0017 (.01)	.989 (.45)	.911 (7.98)	.656 (2.82)
Migration* BMI	.0036 (.17)	–	–	-.0319 (1.83)	–	–
Migration* Height	.512 (.57)	–	–	.418 (.31)	–	–
BMI	-.540 (1.98)	.0626 (4.15)	.220 (2.23)	.254 (.94)	.0783 (7.38)	.186 (3.75)
BMI Squared $(x10^{-2})$	.0248 (.12)	–	–	-.132 (1.10)	–	–
BMI* Height	.348 (2.37)	–	–	.0549 (.33)	–	–
Height	-18.3 (1.23)	1.57 (2.67)	-1.43 (41)	-2.37 (.09)	.512 (.67)	-5.15 (1.59)
Height Squared	3.48 (.84)	–	–	1.26 (.16)	–	–
R^2	.3531	.3505	–	.3351	.3322	–
F	25.09	28.90	12.0	16.04	18.42	11.70

[a] See Notes to Table 2.

Table 6B

Quadratic Approximations of Wage Function in Ghana and by Sex [a]

Human Capital Input Variables	Male			Female		
	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)
Education	-.0408	-.0397	.561	.198	.195	.600
	(.43)	(.39)	(.79)	(1.70)	(1.73)	(.84)
Education Squared	.478	.476	.545	.487	.482	1.05
$(x10^{-2})$	(7.33)	(7.33)	(1.60)	(5.14)	(5.09)	(2.62)
Education*	-.0205	-.0205	.0118	.0181	.0200	.0114
Migration	(2.62)	(2.65)	(.53)	(1.87)	(2.10)	(.53)
Education* BMI	-.000	.000	.0084	-.0034	-.0030	-.0219
	(.04)	(.22)	(1.14)	(3.27)	(3.02)	(3.85)
Education* Height	.0100	.0035	-.463	-.0968	-.0990	-.122
	(.19)	(.07)	(1.13)	(1.33)	(1.41)	(.27)
Migration	-.582	.503	.177	.0742	.447	.187
	(.54)	(6.76)	(.88)	(.00)	(6.01)	(1.18)
Migration* BMI	-.0014	–	–	.0245	–	–
	(.09)			(2.18)		
Migration* Height	.660	–	–	-.0643	–	–
	(1.06)			(.08)		
BMI	.197	.0479	-.0043	-2.06	.0551	.217
	(.98)	(3.47)	(.05)	(1.40)	(7.70)	(5.59)
BMI Squared	.0956	–	–	-.0482	–	–
$(x10^{-2})$	(.59)			(62)		
BMI* Height	-.111	–	–	.176	–	–
	(.98)			(1.96)		
Height	2.73	1.48	8.20	14.9	1.73	8.29
	(.27)	(3.21)	(2.59)	(1.20)	(3.73)	(2.60)
Height Squared	1.85	–	–	-5.40	–	–
	(.62)			(1.40)		
R^2	.1871	.1864	–	.1886	.1858	–
F	19.91	22.74	15.20	20.03	22.58	18.65

[a] See notes to Table 2.

Table 7

Wage Function Estimates for Men and Women Combined with Human Capital Returns
Restricted to be Equal and Allowed to Vary by Gender

Explanatory Variables	Côte d'Ivoire (2872)				Ghana (6814)			
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Male	.589 (11.2)	.209 (4.02)	.244 (3.81)	1.30 (.85)	.271 (8.97)	.115 (3.64)	.0512 (1.27)	-.806 (.94)
Education		.118 (21.0)	.0937 (16.6)	.0730 (7.71)		.0489 (14.3)	.0395 (11.7)	.0375 (7.71)
Migration			.767 (11.7)	.891 (8.87)			.448 (11.1)	.531 (8.98)
BMI			.0582 (8.88)	.0613 (7.38)			.0458 (10.5)	.0420 (8.10)
Height			.706 (1.90)	.416 (.66)			1.36 (5.89)	1.29 (3.85)
Education *Male				.0357 (3.03)				.0062 (.91)
Migration *Male				-.176 (1.33)				-.183 (2.27)
BMI *Male				-.0162 (1.21)				.0110 (1.12)
Height *Male				.446 (.58)				.181 (.39)

Table A-1

Means and Standard Deviations for Variables for Earners Age 20 to 60 in
Côte d'Ivoire and Ghana by Sex [a]

	Côte d'Ivoire		Ghana	
	Male	Female	Male	Female
A. Dependent Variables				
Log Hourly Wage Rate	5.77	5.19	3.40	3.17
	(1.38)	(1.53)	(1.21)	(1.38)
Years of Education Completed	5.57	2.72	7.13	4.28
	(5.45)	(4.46)	(5.47)	(5.06)
Migration (moved from birthplace region at time of Survey – 1) [b]	.652	.529	.333	.282
	(.476)	(.499)	(.471)	(.450)
Body of Mass Index (Kg./Meters ^{2})	22.7	24.0	20.9	22.3
	(2.95)	(4.41)	(2.52)	(4.22)
Height in Meters	1.70	1.59	1.69	1.58
	(.0671)	(.0576)	(.0661)	(.0622)
B. Individual Explanatory Variable:				
Age	38.2	36.5	36.5	36.3
	(10.4)	(10.3)	(10.9)	(11.4)
Rural Resident [b]	.276	.292	.413	.360
Ethnic Group (CI/G) [b]	.223	.257	.432	.480
Akan				
Krou/Ewe	.104	.069	.172	.172
Mande South/Gaadangbe	.081	.123	.086	.096
Mande North/Dagbani	.083	.087	.039	.025
Voltaic/Hausa	.061	.060	.020	.023
Other/Other	.170	.114	.238	.193
---/Nzema	--	--	.012	.011
Birthplace Region	(11)	(11)	(11)	(11)
Religion [c]	--	--	.012	.011
C. Parent Characteristics:				
Mother's Years of Education	.0714	.144	.627	.811
	(.633)	(.1.06)	(2.36)	(2.80)
Father's Years of Education	.667	.825	2.31	2.67
	(2.24)	(2.71)	(4.61)	(4.95)
Father's Education Unknown [b]	.011	.015	.008	.011
Years Mother Worked in Agriculture	.513	.581	.656	.626
Years Father Worked in Agriculture	.764	.772	.712	.679
D. Sample Cluster or Community Characteristic:				
Health Problems (first or second) [b]	.036	.045	.423	.403
Malaria				
Diarrhea	.051	.069	.154	.156
Measles	.050	.043	.268	.267
Water/Sanitation Problems [b]	.030	.033	.169	.155
Distance to Hospital or Clinic (km/miles)	2.97	2.34	4.17	3.56
	(7.42)	(6.67)	(7.08)	(6.10)
Distance to Nurse or Doctor (km/miles)	3.58	2.83	3.53	2.99
	(9.38)	(7.77)	(6.75)	(5.89)
Prices of Food Items and Staples [d]	(8)	(8)	(11)	(11)

Rainfall Annual (mm)	112. (18.1)	111. (18.3)	49.7 (14.5)	49.2 (14.5)
Interview Occurred in Rainy Season [b]	.111	.108	.077	.056
North				
South	.525	.527	.557	.548
Immunization Campaign (in last years = 1) [b]	f	f	.469	.473
Anti Malaria Campaign (in last 5 years) [b]	f	f	.284	.274
Preventive Public Health Expenditures per capita [e]	f	f	93.0 (20.3)	92.1 (20.3)
Community Characteristics (cont.)				
Curative Public Health Expenditures per capita [e]	n/a	n/a	226. (77.7)	228. (78.7)
Distance to Market (km/miles)	.761 (2.63)	.814 (3.11)	3.06 (6.55)	2.94 (6.14)
Distance to Primary School (km/miles)	.0904 (.635)	.0398 (.343)	.307 (1.11)	.256 (.962)
Distance to Middle School (km/miles)	f	f	1.25 (2.61)	1.01 (2.35)
Distance to Secondary School (km/miles)	7.94 (16.6)	7.53 (14.8)	8.39 (12.7)	7.21 (11.5)

Notes:

[a] Sample was restricted to individuals reporting the following: 1.4 < Height < 2.0; 35 < weight < 115; 12 < BMI <45; and 19< Age < 61. Except for age the anthropometric restrictions eliminated 1 to 7 persons each.

[b] Dummy variable. Standard variation of variable is equal to $\sqrt{m(1-m)}$, where m denotes the mean of binary variable.

[c] Christian, Muslim, Traditional, and other.

[d] In Côte d'Ivoire prices refer to Beef, Fish, Rice, Onion, Peanut Butter, Palm Oil, Manioc, and Banana. In Ghana prices refer to Cassova, Maize, Banana, Onion, Tomato, Eggs, Fish, Palm Oil, Peanuts, Sugar and Antibiotic.

[e] Available from Government Budget allocations by regions only for Ghana in 1987.

[f] Not appropriate to Côte d'Ivoire educational system or no questions asked.

Table A-2

Correlations Between Wage and Human Capital Variables:
Côte d'Ivoire and Ghana by Sex [a]

Côte d'Ivoire	Female: (1) Log Wage	(2) Education	(3) Migration	(4) BMI	(5) Height
Male:					
1. Log Hourly Wage	_	.346 (.0001)	.211 (.0001)	.271 (.0001)	.110 (.0002)
2. Education Years	.484 (.0001)	_	.051 (.081)	.116 (.0001)	.177 (.0001)
3. Migration	.253 (.0001)	.171 (.0001)	-	.097 (.0008)	.101 (.0005)
4. Body Mass Index	.228 (.0001)	.159 (.0001)	.101 (.0001)	_	.039 (.180)
5. Height Meters	.112 (.0001)	.131 (.0001)	.097 (.0001)	.028 (.255)	_
Ghana	Female:				
Male:					
1. Log Hourly Wage	_	.219 (.0001)	.109 (.0001)	.207 (.0001)	.088 (.0001)
2. Education Years	.232 (.0001)	_	.078 (.0001)	.147 (.0001)	.126 (.0001)
3. Migration	.135 (.0001)	.074 (.0001)	_	.139 (.0001)	.044 (.0101)
4. Body Mass Index	.161 (.0001)	.172 (.0001)	.076 (.0001)	-	.048 (.0049)
5. Height Meters	.097 (.0001)	.056 (.0010)	.042 (.0148)	.048 (.0046)	_

[a] Sample of all persons age 20 to 60 reporting information needed to construct hourly wage rate. Sample size is 1692 for men and 1180 for women in Côte d'Ivoire and 3414 for men and 3400 for women in Ghana. Beneath the reported zero order correlation is the p value at which the correlation is statistically significant.

Table A-3

Size of Côte d'Ivoire Panel Sample when Restrictions are Imposed to Determine a "Matched" Individual Record

Sample Restrictions	Males	Females
All Persons Age Initially between 20-60 with Identical Household and Individual Number	809	498
Same Sex in Two Periods	768	462
Age Within 10 Years, i.e., $[Age_1 + 1 - Age_2] \leq 10$	742	427
Age Within 10 Years, i.e., $[Age_1 + 1 - Age_2] \leq 5$	712	409
Age Within 2 Years	662	357
Working Sample: Age Within 5 Years and Education Within 5 Years	685	397

Table A-4

OLS and IV Coefficients on Four Human Capital Inputs in Wage Function Within Two Age Groups, by Sex for Côte d'Ivoire and Ghana [a]

Sex	Males				Females			
Age	20 – 34		35 – 60		20 – 34		35 - 60	
(Sample Size)	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Côte d'Ivoire	(711)		(981)		(554)		(626)	
Education	.112	.115*	.103	.0966*	.0853	.112*	.0811	.0374*
	(12.6)	(2.15)	(10.6)	(2.24)	(6.65)	(3.92)	(4.36)	(.53)
Migration	6.43	.890*	.720	.541*	.624	.627*	1.13	1.01*
	(5.38)	(2.23)	(6.35)	(1.35)	(3.70)	(1.80)	(7.79)	(3.35)
BMI	.0458	.322*	.0414	.0706*	.0488	.180*	.0615	.0676*
	(2.82)	(2.72)	(3.25)	(.71)	(3.51)	(2.24)	(5.13)	(1.22)
Height	-.269	.582*	1.77	7.64*	.0256	2.05*	.426	-1.59*
	(.43)	(.14)	(2.99)	(1.97)	(.03)	(.53)	(.48)	(.31)
Ghana	(1646)		(1768)		(1737)		(1663)	
Education	.0432	.0656*	.0425	.100*	.0348	.0549*	.0430	.0472*
	(6.22)	(2.15)	(7.30)	(3.85)	(4.90)	(2.81)	(5.58)	(2.54)
Migration	.357	.331*	.340	.132*	.561	.200*	.519	.287*
	(4.61)	(2.03)	(4.88)	(.97)	(6.47)	(1.10)	(5.57)	(1.43)
BMI	.0506	.135*	.0548	.0431*	.0492	.222*	.0373	.102*
	(3.81)	(1.74)	(5.65)	(.73)	(5.36)	(5.16)	(5.30)	(3.15)
Height	1.50	2.31*	1.49	2.97*	.684	1.05*	2.00	11.9*
	(3.38)	(.92)	(3.80)	(1.07)	(1.40)	(.29)	(3.78)	(3.94)

[a] With the same controls as in Table 2, analogous to Cols. (4) and (5).

[*] Estimated by instrumental variables.

Table A-5a

Human Capital Demand Equations Used to Instrument Inputs in Wage Function in Côte d'Ivoire: Selected Variables [a]

Country, Sex Explanatory Variable [b]	Male				Female			
	Education	Migration	BMI	Height	Education	Migration	BMI	Height
Mother's Education	.165 (.90)	0070 (.50)	.114 (.95)	.0003 (.14)	.371 (3.42)	-.0099 (1.02)	-.212 (1.55)	.0051 (2.86)
Father's Education	.257 (4.43)	.0033 (.75)	.0325 (.85)	.0013 (1.54)	.387 (8.19)	.0006 (.15)	.0439 (.74)	-.0010 (1.35)
Father's Education Unknown	3.75 (3.53)	.120 (1.48)	1.82 (2.61)	.0300 (1.90)	1.70 (2.00)	-.0963 (1.27)	.104 (.10)	-.0329 (2.37)
Mother Employed in Agriculture	-1.50 (6.22)	-1.53 (8.32)	-.310 (1.96)	-.0082 (2.29)	-.998 (4.05)	-.167 (7.56)	-.93 (3.00)	-.0040 (.99)
Father Employed in Agriculture	-.219 (.70)	.0235 (.98)	.266 (1.29)	-.0077 (1.66)	-1.29 (4.19)	.0179 (.65)	-2.13 (.55)	-.0049 (.98)
Rural Resident [c]	.654 (1.3)	.752 (20.9)	.326 (1.05)	-.0047 (.67)	-.471 (1.14)	.798 (21.7)	-.142 (.27)	-.0042 (.62)
Rainfall [c]	.0740 (2.92)	-.0069 (3.55)	.0068 (.41)	.0009 (2.33)	.0032 (.21)	-.0114 (8.31)	.0105 (.54)	-.0002 (.86)
Health Problems: Malaria	1.01 (1.92)	-.0238 (.36)	-1.12 (1.96)	.0120 (.93)	-.327 (49)	-.170 (2.87)	-.388 (.47)	-.0088 (.81)
Diarrhea	-1.47 (1.92)	-.130 (2.22)	.181 (.36)	-.0149 (1.31)	-.0800 (.13)	-.111 (2.08)	-1.21 (1.61)	-.0044 (.45)
Measles	-.823 (.85)	.0721 (.97)	.127 (.20)	.0074 (.52)	-1.36 (1.51)	-.330 (4.10)	-1.17 (1.04)	-.0265 (1.79)
Sanitation and Water	-.608 (.59)	-.287 (3.61)	.448 (.66)	.0105 (.68)	-1.28 (1.50)	-.277 (3.65)	-2.74 (2.56)	-.0090 (.64)
Distance to Clinic or Hospital	-.0265 (.67)	.0108 (3.59)	-.0426 (1.64)	-.0003 (.52)	.0169 (.33)	.0408 (8.99)	.0687 (1.08)	.0003 (.40)
Distance to Nurse or Doctor	.0162 (.52)	-.0102 (4.29)	.0400 (1.96)	.0002 (.44)	.0020 (.05)	-.0199 (5.51)	-.0723 (1.42)	.0004 (.61)
Distance to Permanent Market	-.0541 (.95)	-.0118 (2.69)	-.0200 (.53)	-.0016 (1.88)	-.0370 (.83)	-.0252 (6.34)	-.0812 (1.45)	-.0012 (1.62)
Distance to Primary School	.0808 (.42)	-.0074 (.50)	-.0741 (.58)	.0062 (2.18)	.188 (.61)	.144 (5.20)	.438 (1.13)	-.0067 (1.31)
Distance to Secondary School	.0187 (1.03)	-.0031 (2.23)	-.0174 (1.45)	.0002 (.86)	.0166 (1.02)	.0043 (2.94)	.0116 (.57)	.00058 (2.18)

[a] Beneath regression coefficient in parentheses is absolute value of t.

[b] Other control variables include 4 age dummies, 6 ethnic groups, 10 regions, 10 local food prices, and 5 rainy season malaria interactions.

[c] These variables are also in the wage function, and thus do not represent identifying instrumental variables, i.e., they are in *Y* and not in *X*.

Table A-5b

Human Capital Demand Equations Used to Instrument Inputs in Wage Function in Côte d'Ivoire: Selected Variables [a]

Country, Sex Explanatory Variable [b]	Male				Female			
	Education	Migration	BMI	Height	Education	Migration	BMI	Height
Mother's Education	.0779 (2.13)	-.0007 (.27)	-.0300 (1.45)	.0006 (1.03)	.226 (8.16)	-.0014 (.70)	-.0528 (1.88)	.0000 (.13)
Father's Education	.122 (5.63)	.0025 (1.72)	.0425 (3.67)	.0000 (.15)	.209 (11.4)	.0014 (1.07)	-.0148 (.80)	.0003 (1.16)
Father's Education Unknown	.687 (.81)	-.0147 (.26)	-.684 (1.41)	.0215 (1.66)	-.116 (1.75)	-.0339 (.72)	.742 (1.10)	.0029 (.28)
Mother Employed in Agriculture	-.725 (3.97)	-.0774 (6.24)	-.605 (5.81)	-.0126 (4.54)	-.904 (5.34)	-.101 (8.42)	-1.51 (8.80)	-.0031 (1.16)
Father Employed in Agriculture	-.424 (2.03)	-.0014 (.10)	.108 (.91)	-.0019 (.60)	-.605 (3.21)	-.0066 (.49)	-.412 (2.16)	-.0058 (1.97)
Rural Resident [c]	.101 (.46)	.921 (61.4)	.165 (1.32)	.0069 (2.09)	-.0333 (.16)	.889 (62.3)	.629 (3.08)	.0067 (2.12)
Rainfall [c]	.0063 (.46)	-.0059 (6.32)	.0153 (1.96)	-.0003 (1.68)	.0102 (.86)	-.0047 (5.65)	-.0113 (.94)	-.0003 (1.62)
Health Problems: Malaria	-.769 2.47)	-.0647 (3.06)	-.339 (1.92)	-.0143 (3.03)	.299 (1.08)	-.0237 (1.21)	-.275 (.98)	.0017 (.40)
Diarrhea	-.204 (.78)	-.136 (7.62)	.117 (.79)	-.0000 (.01)	-.0752 (.32)	-.160 (9.60)	-.601 (2.51)	.0051 (1.38)
Measles	.506 (1.70)	-.141 (6.96)	-.239 (1.41)	.0065 (1.43)	-.111 (.40)	-.0995 (5.15)	-.0975 (.35)	.0043 (.99)
Sanitation and Water	.274 (1.00)	.142 (7.62)	.0397 (.26)	-.0031 (.76)	.276 (1.09)	.187 (10.4)	-.139 (.52)	-.0062 (1.56)
Immunization Campaign in 5 years	-.231 (.64)	-.0922 (3.74)	-.180 (.88)	-.0019 (.35)	-.994 (3.03)	-.104 (4.50)	-.533 (1.60)	-.0037 (.72)
Distance to Nurse or Doctor	.0282 (1.22)	-.0021 (1.37)	.0131 (1.00)	.0005 (1.32)	.0279 (1.25)	-.0002 (.13)	.0179 (.79)	.0000 (.16)
Distance to Permanent Market	.0069 (.38)	-.0106 (8.65)	-.0031 (.37)	.0005 (1.32)	.0279 (1.25)	-.0002 (.13)	-.0223 (1.36)	.0002 (.67)
Distance to Primary School	-.198 (1.69)	-.503 (6.32)	-.0778 (1.17)	-.0042 (2.27)	-.0539 (.45)	-.0253 (2.99)	-.196 (1.61)	-.0011 (.56)
Distance to Middle School	-.199 (3.85)	-.0373 (10.6)	-.0399 (1.36)	.0007 (.87)	-.124 (2.31)	-.0368 (9.69)	-.0820 (1.51)	.0012 (1.38)
Distance to Secondary School	-.0283 (2.49)	-.0076 (9.86)	-.0011 (.16)	.0005 (2.66)	-.0189 (1.68)	-.0073 (9.26)	-.0223 (1.96)	-.0002 (1.34)

[a] Beneath regression coefficient in parentheses is absolute value of t.

[b] Other control variables include 4 age dummies, 6 ethnic groups, 10 regions, 10 local food prices, 5 rainy season malaria interactions, state level per capita public expenditures on preventive and curative health programs in 1987 and anti malaria campaign in last five years.

[c] These variables are also in the wage function and thus do not represent identifying instrumental variables, i.e., they are in *Y* and not in *X*.

APPENDIX FIRST-STAGE HUMAN CAPITAL INPUT ESTIMATES

The coefficients on some of the identifying instrumental variables (X) in the linear human capital input demand equations are reported in Tables A-5a and A-5b for Côte d'Ivoire (the Ivory Coast) and Ghana. A few regularities might be noted. Parent educations are particularly important in determining the child's education. The father's education has a somewhat larger coefficient than the mother's in the son's education equation, but in the daughter's education equation they have about the same magnitude (C.F. Thomas, 1994). Having a mother employed in agriculture has a uniformly negative and substantial effect on all four human capital inputs for males and females in both countries. Residing a greater distance from a permanent market, and with various local health problems, reduces the chances of out migration. The effects of distance to primary and secondary schools reduce educational attainment in Ghana, as it also is negatively correlated with migration and often height and weight. It should be noted that rural residence and rainfall, which are strongly related to out migration, are not identifying variables, because they also enter the wage function directly.

Given the high degree of intercorrelation between the local sample cluster characteristics, individual variables may exhibit erratic relationships with the input demands due to multicollinearity, e.g., the distance to doctors and hospitals are correlated at about.8 (Schultz and Tansel, 1997). It should also be recognized that because all of the instruments, with the exception of the parent characteristics, they are measured at the level of the sample cluster, of which there are only about one hundred, the standard errors on these and other variables may be slightly downward biased. Deaton (1997) has stressed the need to adjust the standard errors when such "aggregated" variables are used to condition a relationship. The larger sample of individuals overstates the true sample size in the calculation of significance levels for the community variables. In the IV estimates reported in the paper, the instruments in Table A-5 are also interacted with rural residence, rainfall and quadratics in mother's and father's education added to the interacted instrument list as discussed in the text.

Endnotes

[1] Another human resource program that should be analyzed as an argument in the wage function is family planning. Family planning performs several functions, one of which helps women avoid unwanted births by reducing the cost of effective birth control. Unwanted births may be associated with women sacrificing their career objectives, if that career is imperfectly compatible with childbearing. In studies of Malaysia and the United States, an unanticipated or unwanted birth is associated with women receiving a wage in the labor market that is 10 percent lower (Schultz, 1992: Table 5.1).

[2] Social externalities associated with human capital are not accounted for in this study but might be addressed with micro data with a sufficiently structured model describing the source and scope of the diffusion of the externality. For example, Foster and Rosenzweig (1995) consider the effects on a farmer's profits of learning from a neighbor's innovative adoption of new productive inputs in India. Health may also increase the capacity to work in addition to its effect on wage rates that is estimated here. Schultz and Tansel (1997) discuss and estimate wage and labor supply effects of adult illness.

[3] There are several hypotheses for why the inputs might be correlated which stem from heterogeneity and technology: (1) exogenous family wealth relaxes the budget constraint allowing more wealthy families to invest more in all forms of human capital in their children, driving down the marginal returns to these investments due to the family's lower than average opportunity cost of capital; (2) an individual's biological endowment may raise the returns to several forms of human capital, as for example, it is hypothesized that ability increases the returns to education (Becker, 1993; Griliches, 1977); (3) heterogeneity in preference of families could also lead to differences across individuals in amounts of all human capital investments; and finally (4) types of human capital may technically complement (or substitute) for each other in the wage function, leading individuals who maximize their joint returns on all human capital investments to concentrate on complementary inputs and specialize between substitute inputs.

[4] The first three hypotheses for an intercorrelation in human capital inputs conditional on household and regional variables that were listed in endnote 3 could also be used to justify the treatment of these inputs as endogenous to the wage function. They operate across inputs as an unobserved constraint on the household—unobserved wealth, individual endowments, and preferences—and could therefore equally well-affect wages through other unspecified channels as well as through their effect on the demand for observed forms of human capital.

[5] The same framework could be extended to education, where some portion of the variation in education is determined by the genetic distribution of ability and the remainder is potentially reproducible.

[6] Unobserved heterogeneity in individuals may also explain why those who invest more in any particular form of human capital may earn lower (or higher) returns at the margin. As noted above, these sources of heterogeneity bias in input demands would be corrected when the inputs are treated as endogenous to the wage function.

[7] For example, it has been noted that children who are taller for their age (or of greater weight for age) perform better in school (Moock and Leslie, 1986). More educated individuals are more likely to migrate, even when controlling for wage and unemployment rates at origin and destination (Schultz, 1982). If either migration or education is determined endogenously, then a positive effect of the human capital interaction variable based on the assumption they are exogenous in the wage function may not be a valid indication of their technological interactions (Vijverberg, 1993). Similar doubts attach to the hypothesis that longevity should enhance the returns to, and hence demands for, educational human capital (Ram and Schultz, 1979).

[8] This production function retains the logarithmic transformation of the dependent variable, the wage rate, because the residuals from wage equations estimated in logarithms are more nearly normally distributed than are the residuals to a wage function estimated in absolute levels. Box-Cox transformation analyses of wage data often indicate that the log transformation does not perfectly fit wages, but tends to be a better approximation than the linear specification. The translog function is another commonly used second-order approximation, in which all inputs may only take on positive values, which education and migration generally violate (Fuss and McFadden, 1978). The translog specification was not superior to the Leontief-Diewert estimates reported here, with the minimum value of education assumed to be one year. Interactions between age and the human capital inputs probably also need to be re-appraised (Angrist and Newey, 1991), which could reflect the different productive value of each human capital input at different biological ages, or it could reflect the different quality of that input produced at different times embodied in different birth cohorts.

[9] There are several reasons one might expect human capital inputs to be correlated across individuals in equation (1), due to observable variables, unobservable variables, preferences, and technology. Unfortunately, in the form of the model estimated here it is not possible to distinguish among these possible causes: (a) Lifetime full wealth constraints

could induce demand for various human capital inputs in a child, to the extent that these inputs enter the parent's utility as a normal altruistic consumption good. (b) Wealth might also reduce the cost of parent borrowing, relax credit constraints, and thereby encourage the derived demand of wealthier parents for the services of child human capital. Evidence that economic shocks to parents lead to responses in child health and schooling investments do not, therefore, satisfactorily distinguish between the role of credit constraints on parents and the value of child human capital as a parental consumption good (Foster, 1995; Jacoby, 1993). (c) Characteristics of the individual, such as ability, that are omitted from the wage function may affect the returns to several forms of human capital, such as schooling and migration (Schultz, 1982). (d) Parents or society may respond to heterogeneity as in (c) by compensating or reinforcing behavior, depending on their relative preferences for equality and efficiency (Becker, 1993). (e) Differences in parent preferences for child human capital could explain why some parents invest relatively more in all forms, and some parents invest in less. (f) The technology of human capital production and its utilization in the labor market may cause different forms of child human capital to be complements or substitutes from the family's perspective, enhancing or depressing the returns to other forms.

[10] These wealth variables are theoretically expected to increase the individual's labor productivity in non-wage employment and increase demand for leisure, both of which tendencies would raise the market reservation wage and reduce the likelihood of participating as a wage earner. Estimation of the probit for being an earner that includes all of the variables in the wage function plus the physical wealth identifying variables indicated that these physical wealth variables are significantly associated with a reduction in wage earning participation in these samples.

[11] For the Ivory Coast, the three years 1985-87 are combined for a total sample of about 40,000 persons. For wage earners and self-employed who reported labor earnings and hours worked in that activity, a wage rate is derived. This group of earners between the ages of 15 and 65 is comprised of 1602 men out of 5642 and 768 women out of 6579. Ainsworth and Muñoz (1986) describe the design of these surveys. For Ghana, two years of surveys are combined from 1987-88 and 1988-89 with a sample of about 30,000 persons. The wage-earner sample yielded 3521 men out of 5034 between the ages of 15 and 65, and 3408 females out of 5834. The anthropometric variables (i.e., height and BMI) were not collected for all individuals, which also restricted the size of these working samples slightly. The later analysis of labor earnings is restricted to men and women age 20 to 60 reporting positive labor earnings and hours last month or last year. The means and standard deviations on all variables for these working samples are reported in appendix Table A-1.

[12] The summary measure of years of education completed does not weight the much larger private opportunity cost of a year of secondary or tertiary schooling compared with primary schooling, or the likelihood that the "quality" of a year of schooling has changed over time. Nor does this measure of stocks of education capture adequately past national investments, because international migration is selective for education. Better-educated Ghanaians emigrated in large numbers during the 1970s and 1980s, whereas the growing economy of Ivory Coast attracted immigrants from lower-income neighboring countries (Schultz and Tansel, 1997).

[13] And similar to that reported for Japan among men reaching age 20 for the 45 years 1892 to 1937 of .88 cm./decade (Shay, 1994).

[14] An empirical criterion for identification as originally proposed by Basmann (1960) relies on testing the explanatory power of adding X to the wage equation (2). A significant correlation between X and v calls into question the validity of X instrument for estimating 1 in the wage equation.

[15] Surprisingly, the instrumental variable auxiliary equation for higher yields to a larger coefficient of determination for older than younger persons in both the Ivory Coast and Ghana (C.F. Table A-4)

[16] This does not appear to be a serious source of bias in the case studied here because the five parent characteristics are not strongly related to the wage of their child, although they are often related to the child's human capital inputs. When the five parent variables are added to the OLS estimates of the wage function (Table 2, Col 4), they are never statistically significant at the 5 percent level, i.e., the F ratios with five and n-32 degrees of freedom are less than the critical value of 2.3 in the four contry/sex samples.

[17] In these African samples relatively few individuals are siffuciently obese that BMI would decrease health, with only 1-2 percent of the men reporting BMI in excess of 28 and 6-10 percent of the women. Efforts to estimate non-linearities in the wage equation with all of the other controls (Table 6). See Strauss and Thomas (1995) for other evidence of the non-linear patterns between nutritional inputs and wage rates and income.

[18] The joint F test of the statistical significance of the identifying instrumental variables provides an indication of the

power or reliability of the IV estimates. See discussion of Bound et al., 1995.

[19] Note however, that education and migration and their interaction are not treated as part of the information set to condition the predictions of the endogenous inputs and their interactions.

[20] Another investigation of the Ghana survey found that the instrumental variable estimate of the effect of height, BMI, and schooling on child cognitive ability found the schooling IV and OLS estimates were similar, but the IV estimates for height and BMI increased 4-6 fold (Behrman and Lavy, 1995). This outcome may also be explained by the distinction drawn in this paper between the differential effect of reproducible and innate anthropometric variation as well as the measurement error embodied in these human capital inputs.

[21] An alternative counterfactual would concentrate on particular changes in (exogenous) policy variables, and reckon their effects on human capital accumulation and wage changes. But these estimates of the human capital input demand equations are not offered as structural equations pivoting on well measured variation in policy regime for which future changes might be forecast, but a reduced form equations for human capital demands with many exogenous but highly correlated conditioning variables for which any single or group of estimated effects could be misleading. Another approach is to consider how some of the key conditioning variables have changed between the older and younger generation, or in the case of education between the parent and child's generations. If the equation continued to predict outcomes in the next generation, we would then have some basis for projecting change in the human capital inputs and being able to translate these input changes into predicted wage changes.

[22] The panel structure to the survey in Ghana could not be recovered because the household and individual identification numbers were not replicated.

[23] To assess the accuracy of observations of BMI the changes in BMI were plotted against the number of days in the last month the individual was ill and unable to work, separately for the first and the second year of each panel. The correlations were not statistical significant, although these patterns suggested that those who were sick more days in the second year were more likely to have reduced their BMI between the years, as expected.

[24] The effect of measurement error on estimates of models based on panel data is explored by Griliches and Hausman (1986), in which serial correlation in botht he outcome variable and in the measurement error are discussed. Because the input variables are not sugject to valid or substantial variation, with the possible exception of BMI, it is not possible here to estimate the wage function from first differences. Also, to require that the individual report wages in both survey cycles reduces further the small working sample examined here.

[25] The re-interviewer is instructed to return to the same household and confirm that the occupants are the same, by identifying the same head of household or their spouse. A new household member is assigned to the occupants if neither the head of household or the spouse is the same. Individuals in the matched household are then matched to the individual names and unique identification numbers from the first round household roster. Given the larger size and more complex kinship structures of households in the Ivory Coast and Ghana than in most high-income countries, it would not be surprising if mismatches are more common in these two low-income countries. The economic incentives for the survey interviewers are also likely to favor reported matches to save their time, even when there is reasonable doubt about the validity of the match.

[26] The household survey interviewers have little incentive to report the residents at a specific sample address as changed from the previous year, for this will necessitate their interviewing a new "replacement" household. Similarly, if individuals in a household change between annual interviews, it is possible that a new person in a household will be coded to match that of an individual enumerated before but absent at the time of the second interview.

[27] Without any restrictions on the consistency of reporting of age and education in the two panel observations leads to a lower serial correlation of education of .95 and lower correlations for the other matched human capital inputs as well.

[28] The variance in measured women's height is estimated as .0035 in Table 4, whereas the correlation between height in adjacent years if .788, indicating that the variance in measurement error is about .0008 = (1-.788)*.0035, or roughly one-fourth the magnitude of the variance of the signal of .0027. In the case of female education, the variance of the signal is estimated from Table 4 as 25.6, and the variance in the measurement error of female education is .42, suggesting a signal to error ration of about 60.

[29] One possible cause of heterogeneity is the omitted variable of pregnancy, a condition which may affect negatively labor productivity and affect positively BMI, and thus reduce OLS estimates of the positive effect of BMI on the wage of women. However, because fertility is to some degree a choice variable, the probability of becoming pregnant need not be independent of human capital demands. Consequently, conditioning the wage function on pregnancy status could itself bias other estimates, for example, biasing downward the wage return to a woman's education. Lacking a suitable instrument that might identify the fertility decision rule as distinct form other human capital investments (X) or wage determinants (Y), it is not obvious how the casual relationship between pregnancy and productivity can be empirically assessed here. This source of heterogeneity bias could help to explain why IV panel estimates of BMI in Table 5 are more than twice as large as OLS estimates for women, but only half again larger for men.

[30] Height and BMI variable were also fit in logarithms but did not improve standard fit measures, in either the linear or quadratic forms (C.F. Strauss and Thomas, 1995).

[31] The true human capital inputs should be nearly perfectly correlated in adjacent years, because height and migration cannot validly change, and education and BMI should vary little. Instead the serial correlation of education is .98 while that for BMI and height varies from .79 to .91 confirming again the greater importance measurement error in height and BMI than in education.