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Estimating Household Income to Monitor and Evaluate Public Investment Programs in Sub-Saharan Africa

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Contents

List of Tables

List of Figures

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ABSTRACT

Monitoring rural household income is important for governments, donors, nongovernmental organizations, researchers, and others involved with development strategies, because increasing rural household income is a primary objective for achieving many development goals, including reducing poverty, hunger, and food and nutrition insecurity. However, accurate assessment of rural household income is time consuming and costly.

Using an expenditure-based income measure, data on actual household expenditures per capita obtained from various national surveys for 28 Sub-Saharan African countries, this study used proxy indicators to estimate regression models and then predict and analyze changes in household income per capita between 1985 and 2006.

Over the 20-year period, the study predicted annual average real household monthly income per capita at $78 in 1993 international dollars. South Africa was ahead of the group of countries at $225, followed by Côte d'Ivoire and Lesotho at $117 and $91, respectively. Predictions for Nigeria and Zambia were the worst at $28 and $39, respectively. Looking at changes in income over time, Burkina Faso, Côte d'Ivoire, Uganda, Senegal, Mauritania, and Ghana (in declining order) experienced consistent positive growth. In contrast, Zambia, Kenya, and Lesotho showed declining trends, averaging –2.7 percent, –2.0 percent, and –1.3 percent per year, respectively, over the 20-year period. The latter results were not surprising given the low and sometimes negative growth rates in real GDP per capita and real agricultural value added per worker over the same period for those countries. The predicted trends were also consistent with observed trends in poverty and hunger, suggesting that the methodology is a useful and least-cost approach for monitoring household incomes to support evaluation of public investment programs.

Keywords: household income, monitoring and evaluation, proxy indicators

1. INTRODUCTION

Increasing rural household income is a central objective of strategies designed to reduce poverty, hunger, and food and nutrition insecurity and achieve the Millennium Development Goals. Tracking and evaluating the progress of development projects and programs demand consistent output of up-to-date information on the levels of and changes in rural household income. Moreover, the need for that information increases along with the importance of a poverty reduction strategy as a strategic planning tool. However, accurate assessment of rural household income and related indicators is costly and time consuming. For example, the World Bank's Living Strategy Measurement Study (LSMS)[1] and household budget surveys, which are common and excellent sources of rural and national household income, cost an estimated US$1.3 million to survey roughly 3,200 households over a one-year period (Grosh and Munoz 1996). The actual cost of an LSMS survey, however, has been between US$0.25 million and US$3.3 million, and a survey can take up to two years to complete. Even lighter-content surveys, such as the Core Welfare Indicators Questionnaire (CWIQ),[2] which is designed for monitoring purposes only, costs between US$0.2 million and 0.4 million and takes two to three months to complete. It is not surprising that information on household income and related indicators is rare in developing countries and in Sub-Saharan African countries in particular. The knowledge gap is frustrating governments and donor agencies that spend large sums of their scarce resources every year on development projects and programs to improve the well-being of rural households yet cannot fully know how their spending is impacting the actual incomes and well-being of households.

Given the cost and time constraints countries face in attempting to provide a consistent output of up-to-date information on the levels of and changes in household income and related indicators, developing cheaper and less time-consuming methods for providing that information in the absence of actual survey data is crucial. That was the aim of this study. First, we used household income data obtained from national surveys conducted in 28 Sub-Saharan African countries at various irregular periods between 1980 and 2000, as well as proxy indicators obtained from the database of the World Development Indicators (WDI; World Bank 2006a), to develop an econometric prediction model.[3] Then we used the model to predict and analyze changes in annual household income at the national level between 1985 and 2006.

The conceptual framework, empirical approach, and data are presented in Section 2. The results of estimating alternative prediction models and assessing their predictive accuracy are presented in Section 3, followed in Section 4 by an analysis of the levels and changes in household income from 1985 to 2006. Conclusions and implications are presented in Section 5.

[1] See http://www.worldbank.org/lsms.
[2] See http://www4.worldbank.org/afr/stats/cwiq.cfm.
[3] Proxy indicators are variables that are correlated with household income.

2. METHODOLOGY

Conceptual Framework

The underlying motive of the study was developing a regression prediction model that relates a set of proxy indicators (X) to observed household income (y) according to the following econometric equation:

$$y_t = \sum_k \beta_k X_{k,t} + e_t \tag{1}$$

where β is the set of coefficients (parameters) to be estimated that quantify the association of each proxy indicator to the observed household income, and e is the error term (see Greene 1993). With new information on the proxy indicators in, say, time $t + 1$, the corresponding household income ($\hat{y}_{t+1}$) could be estimated as follows:

$$\hat{y}_{t+1} = \sum_k \hat{\beta}_k X_{k,t+1} \tag{2}$$

Because the model is estimated only for predictive purposes, not for determination purposes, it would not be appropriate for making conclusions regarding any cause–effect relationships between household income and the proxy indicators. For example, the model could not be used to assess the impact of the variables on household income. Therefore, the magnitude and signs of the coefficients are not important in such prediction models. What matters is the level of correlation, or the R-squared value of the regression of y on X. Basically, models with R-squared values closer to 1 are preferred, because the likelihood that the predicted values will be closer to the observed values increases with larger R-squared values. Other measures for assessing the predictive accuracy of alternative models, which are also based on analysis of the errors, include the mean absolute error (*MAE*) and root mean-squared error (*RMSE*; Greene 1993):

$$MAE = \frac{1}{n} \sum_t \left| y_t - \hat{y}_t \right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_t \left(y_t - \hat{y}_t \right)^2} \tag{4}$$

where y and $\hat{y}$ are the observed and predicted values, respectively, and n is the number of observations. For choosing among competing models, those with smaller *MAE* and *RMSE* values (i.e., a lower margin of error) are better. In such predictive econometric models, however, the ability to predict turning points in the data is very important. Therefore, the R-squared, *MAE*, and *RMSE* values by themselves may not be sufficient for choosing between competing models. Analysis of changes in y, such as the Theil U_Δ statistic shown in equation 5 (see Greene 1993), become very useful, and here too competing models with smaller values of U_Δ are preferred.

$$U_\Delta = \sqrt{\frac{\sum_t \left(\Delta y_t - \Delta \hat{y}_t \right)^2}{\sum_t \left(\Delta y_t \right)^2}} \text{; where: } \Delta y_t = y_t - y_{t-1} \text{ and } \Delta \hat{y}_t = \hat{y}_t - y_{t-1} \tag{5}$$

Selecting Proxy Indicators

The conceptual framework shows that selection of proxy indicators is the foundation of a prediction model. Although the model is not appropriate for making conclusions regarding any cause–effect relationships, it is still important to have proxy indicator variables that have strong logical and empirical links to household income. The literature on the determinants of household income and poverty is well established, dating back from the literature on human capital development, economic growth, and poverty reduction (e.g., Schultz 1961; Welch 1970) to more recent analyses of household data (e.g. Hassan and Babu 1991; Lanjouw and Ravallion 1995; Simler et al. 2004; Otsuka and Yamano 2006). The main determinants include household size, the age and gender composition of the household, education, health, social capital, assets and endowments, and employment, among others. The effects of other factors that operate at higher levels than the household (e.g., rainfall, prices, infrastructure, etc.) are normally captured with fixed-effect dummy variables. The analysis in this paper, however, was done at the national level. Therefore, indicators of the variables measured at the national level are needed.

To identify those indicators, we drew from the literature on economywide models and how various sectors of the economy interact with the household sector in generating household income, particularly on the role of agriculture in economic development (e.g., Johnston and Mellor 1961; Hayami and Ruttan 1985) and on the divergence between a very few rich countries and the majority of poor countries (e.g., Landes 1999; Hayami 1997). The variables include resource endowments (i.e., land, labor, capital, climate, etc.) and their use in various production activities (agricultural vs. industry vs. services) and across space (e.g., rural vs. urban); human and physical capital accumulation; returns to factors of production (i.e., rents, wages, interest rates, etc.); terms of trade (i.e., relative price of outputs and inputs, imports vs. exports, agriculture vs. nonagriculture, foreign exchange rate, etc.); other macroeconomic factors (e.g., inflation); and institutions and policies governing the generation and distribution of public resources (i.e., governance, taxes, public expenditure, etc.).

Although several potential variables can be used as proxy indicators, it is important to minimize the error associated with the model, as shown in equations (3) through (5). Therefore, it matters which variables are included in the final model because the error associated with the model is a function of two trade-off factors: squared bias and variance (see Hastie et al. 2001). The squared bias can be reduced by including some transformations of the variables and interaction terms between the variables. However, doing so can increase the variance because more-complex models tend to have more statistically insignificant variables even though they may have high *R*-squared values. The variance is typically reduced by limiting the number of variables included. Doing so usually increases the statistical significance of the variables included, although the overall *R*-squared value will tend to be lower, thus increasing the squared bias. Therefore, it is important to select proxy indicators that will lead to a model with an *R*-squared value as close to 1 as possible while having all coefficients statistically significant.

A common approach for selecting variables is the stepwise regression method (Greene 1993), using either a forward or backward selection technique or a combination of the two. We used stepwise regression for our study. Based on all the potential proxy indicators and a specified level of statistical significance to use as a cutoff point for including variables in the final model or excluding them from it, we included a subset of the variables in the final model starting with an empty model (i.e., the forward selection technique) or removed a subset of the variables from the model starting with the full model (i.e., the backward selection technique). The variables are included in the model or removed from it one at a time based on starting with the most or least significant variable in the forward or backward selection technique, respectively. Sometimes variables that are included earlier in the process end up being insignificant in the final model following inclusion of some other variables. Combining forward and backward selection techniques can help resolve those problems. Similarly, with the backward selection technique, variables excluded early in the process could have been important in the final model. Therefore, variables considered very important can be forced into the final model. Given that no regression is ever truly correct, we used those various techniques to derive competing models to choose from.

Validating Model Predictions

To select among alternative prediction models and to validate predictions of the chosen model, it is ideal to split the data into three subsets. One data subset can be used to estimate the alternative models, and the second data subset can be used to make out-of-sample predictions to select one of them using the analysis of errors in equations (3) through (5). The third subset of data can then be used for out-of-sample predictions and validated using a test of differences in the predicted and observed values using a Chow test (Greene 1993). The data can also be split into two subsets and applied by combining the first two steps, estimation and model selection using in-sample prediction and analysis of errors (for further discussion, see Hastie et al. 2001).

The procedures described here, however, are luxuries to which the data set we used could not be subject without severe loss of estimation power. As we will explain in detail later, the entire data set is made up of 81 observations on household income for 28 Sub-Saharan African countries. However, only 12 countries have three or more observations (subtotal of 49 observations) to allow for turning points in the data set for any one country. Thus, because of the limited number of observations, we did not split the data and used only in-sample predictions and analyses or errors to select the best model.

Implementation

A common approach to implementing the proxy indicators concept is exemplified by the Tegemeo Institute, which developed a household income prediction model for use by donors and nongovernmental organizations in Kenya and Mozambique (Tschirley and Mathenge 2003). In its work in Kenya in 2000, the institute used data from a comprehensive survey of 1,500 households to identify appropriate proxy indicators and estimate a household income prediction model, as specified in equation (1). Then in 2002 the institute collected data on the proxy indicators and used that data set to predict household income in 2002, as specified in equation (2). In principle, the model can be applied as frequently as data on the proxy variables are collected. That approach is especially ideal for monitoring and evaluation at the project level, where the cost of the surveys and the time required to complete them are lower than for large public investment programs that require national-level household surveys. For example, Tschirley and Mathenge estimated the cost associated with the full and proxy surveys involving 1,500 households to be US$87,853 and US$29,225, respectively, and the time required to collect the data to be 32 and 11 weeks, respectively. For monitoring household income at the national level, however, such an approach can be costly because it requires larger surveys with adequate national-level representation. Besides the cost, the prediction model used by Tschirley and Mathenge is based on cross-sectional data of households rather than a panel of data. The disadvantage of cross-sectional data is that they may not capture the relative importance of proxy indicators over time.

Data from national-level household surveys, such as the LSMS and intervening years' monitoring questionnaires (e.g., CWIQ) or poverty scorecards (PSC), can also be used in a manner similar to the approach of Tschirley and Mathenge (2003). The selected proxy indicators are based on analysis of LSMS data, and the CWIQ and PSC surveys are used to collect information on the proxy indicators. Therefore, they share the same cost disadvantage. Also, data on the proxy indicators are not available for many years, which limits their usefulness for monitoring purposes. Another main drawback, even when data are available for several years, has to do with the comparability of the data over time, especially when the proxy indicators are qualitatively measured and their values cannot be observed or measured by the data collector. For reliable predictions, the sampling properties and survey instruments must be consistent over time.

A cheaper and less time-consuming approach, and the one we utilized, is using proxy indicators that are readily available annually and over long periods. Subnational-level data can be obtained from national statistics offices, line ministries, and other publicly available sources for analysis at the national level. For cross-country analysis, national-level data can be obtained from publicly available sources, such as the WDI database (World Bank 2006a) and the statistical database of Food and Agriculture Organization of the United Nations (FAOSTAT; FAO 2007).[4]

The main critique of cross-country analysis is that the conclusions drawn lack relevance because the parameters of the prediction model are identical across countries. Because it is not realistic to assume that all countries are on the same international income frontier, including region-specific dummy variables or estimating a fixed-effect model to capture cross-regional heterogeneity addresses some aspects of the problem.[5] Another way to reduce the problem is to include other constructed variables on groups of countries with common socioeconomic and growth characteristics.

[4] Data on potential proxy indicators are more readily available at the national level than at the subnational level, limiting use of the model for country-specific analysis.

[5] Including country-specific dummy variables is especially useful when the results will be used to predict the behavior of individual countries. However, because several variables in the final models do not vary much over time, they do capture most of the cross-country heterogeneity, which limits the use of country-specific dummy variables in this case.

3. DATA AND MODEL ESTIMATION

Data Sources

Household Income

The household income data used here were obtained from PovcalNet (World Bank 2006b) for 28 Sub-Saharan African countries, with the original raw data obtained from various national-level household surveys conducted during periods between 1980 and 2005 (Table 1). The data represent a total of 81 observations, although one-half of the 28 countries had only one or two data points, which does not allow for turning points in the data for those countries. That signals the impossibility of estimating a regression model at the national level separately for any one country. Therefore, we pooled the data when estimating the regression equation specified in equation (1).[6] Table 1 and the top panel of Figure 1 show the irregularity at which actual household income data have become available. The bulk of the data are in the 1990s, following popularization of the World Bank's LSMS and the targeting of donor funding for such surveys.

Table 1. Sources of household income data

Country	Year of household survey data	Country	Year of household survey data
Botswana	1985–1986, 1993–1994	Mauritania	1987, 1993, 1996, 1999–2000
Burkina Faso	1994, 1998, 2003	Mozambique	1996–1997, 2002–2003
Burundi	1992, 1998	Namibia	1993
Cameroon	1996, 2001	Niger	1992, 1995
Central African Republic	1993	Nigeria	1985–1986, 1992–1993, 1995–1996, 2003
Côte d'Ivoire	1985, 1986, 1987, 1988, 1993, 1995, 1998, 2002	Rwanda	1984–1985, 2000
Ethiopia	1981–1982, 1995, 2000	Senegal	1991, 1994–1995, 2001
Gambia	1998, 1992	Sierra Leone	1989
Ghana	1987–1988, 1988–1989, 1992–1993, 1998–1999	South Africa	1993, 1995, 2000
Kenya	1991–1992, 1994, 1997	Swaziland	1994–1995
Lesotho	1986–1987, 1993, 1995	Tanzania	1991, 2001
Madagascar	1980, 1993, 1997, 1999, 2001	Uganda	1989, 1992–1993, 1996, 1999–2000, 2002–2003, 2005–2006
Malawi	1997–1998, 2004	Zambia	1991, 1993, 1996, 1998, 2003
Mali	1994, 2001	Zimbabwe	1990–1991, 1995

Source: World Bank (2006b).
Note: See Appendix 1 for details on the types of surveys and number of households surveyed.

As the bottom panel of Figure 1 shows, except in a few countries, real household income per capita grew very little over the survey periods. The annual average real household monthly income per capita was about $72 in 1993 international dollars (i.e., deflated using 1993 purchasing power parity).[7] Real household monthly income per capita rose substantially in Cameroon, Gambia, and Botswana and

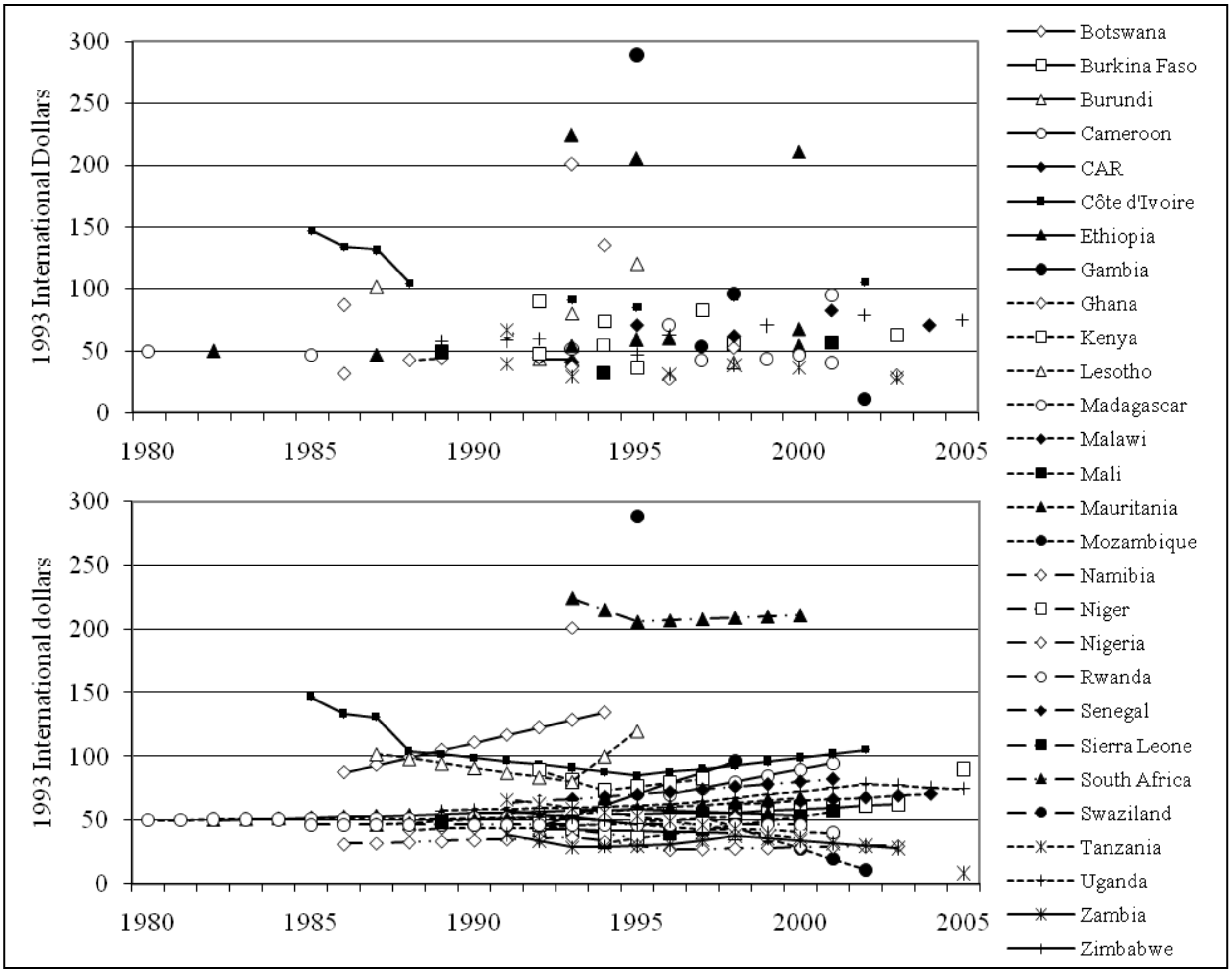
[6] For countries with several rounds of survey data, it is possible to undertake the analysis for a specific country if subnational-level data (e.g., from a district or province, depending on the level at which the survey is representative) are available for the proxy indicators.

[7] For comparing standards of living or incomes per capita across countries, using purchasing power parity values, which is a long-run equilibrium exchange rate, rather than nominal market foreign exchange rates are better for at least two reasons. First, nominal foreign exchange rates only reflect traded goods in contrast to nontraded ones. Second, currencies are traded for purposes other than trade in goods and services, and different interest rates, speculation, hedging, or interventions by governments and central banks can influence the foreign exchange market.

only modestly in Mauritania and Senegal. On the other hand, the trend was declining in Madagascar, Nigeria, Kenya, South Africa, Côte d'Ivoire, and Lesotho, although Lesotho seems to have recovered toward the end of the mid-1990s.

Two issues arose regarding the household income data we used: the data are based on household consumption expenditure, and the data are total household income rather than rural household income. On the first issue, although both consumption expenditure and income are useful aggregate money metrics of welfare, consumption expenditure seems increasingly to be the more favored measure.

Figure.1. Household monthly income per capita (1993 international dollars)



Notes: The top panel shows the actual data points. The bottom panel shows a linear extrapolation of actual data points to fill in values between any two survey years for which actual data are not available. CAR = Central African Republic.

Source: World Bank (2006b).

A fundamental argument for this is that although income can be interpreted as a measure of welfare opportunity, consumption expenditure can be interpreted as a measure of welfare achievement (for further discussion, see Simler et al. 2004). However, the notion that survey respondents are more willing to reveal their consumption behaviors than their incomes seems more compelling. Similarly, with a relatively large proportion of households engaged in self-employed or multiple income-generating activities with several in-kind payment forms, especially in developing countries, it becomes rather difficult to obtain an accurate measure of income. Therefore, it is not surprising that household surveys implemented to capture welfare tend to focus more on consumption expenditure. It is also not surprising that substantial differences in income and consumption expenditure from many household surveys have been observed.

In the case of Ghana, for example, the country's 1991–1992 and 1998–1999 living standards surveys show that mean annual consumption expenditures per capita were GH¢16.70 and 98.70, respectively (GSS 1995, 2000). On the other hand, the mean annual incomes per capita were GH¢10.70 and 52.70, which were lower than the consumption-based estimates by 36 percent and 47 percent, respectively. For several other cases, the measures based on income and consumption expenditure have tended to be fairly close. For example, survey estimates for Uganda show that household monthly consumption expenditures in 1997 and 1999–2000 were USh 101,600 and 141,700, respectively, compared with USh 98,100 and 141,000 for household monthly income in the same survey years; thus, the difference between the two measures is less than 4 percent (UBOS 2001). In the case of Zambia in 2002–2003, mean monthly consumption expenditure and income per capita were 111, 444 and 101,495 Kwacha, respectively, which represents a difference of about 9 percent (ZCSO 2004).

Despite the differences or similarities between the two measures, for policy analysis in general and for analyzing trends in particular, the two measures should produce fairly similar results because they both measure the ability of individuals and households to obtain goods and services.

The other issue regarding use of total household income rather than rural household income results from data availability constraints. Personal conversation with the person in charge of the World Bank's PovcalNet website revealed that rural–urban disaggregation of the household income and consumption expenditure data will be available by the end of the year, at which time the analysis can be redone at a very low marginal cost. However, because most households surveyed in the respective countries were in rural areas (Table 2), results of the analysis from using total household income analysis is still very useful for inferring changes in rural household income.

Table 2. Coverage of rural households in a sample of national surveys in Sub-Saharan Africa

Country/survey year	Rural households surveyed (% of total)	Country/survey year	Rural households surveyed (% of total)
Ghana		Mozambique	
2002	62.7	2002	53.9
1998–1999	65.0	1996	70.6
1991–1992	65.0	Uganda	
Kenya		2002–2003	83.0
1997	87.2	1999–2000	84.0
Mali		1992–1993	87.0
1994	43.5	Zambia	
2001	62.8	2003	50.2

Source: World Bank (2006b).
Note: See Appendix 1 for details on the types of surveys and number of households surveyed.

Proxy Indicators

The proxy indicators used were obtained mainly from the WDI database (World Bank 2006a), supplemented with FAOSTAT (FAO 2007) and other data sources. We constructed several variables capturing the conceptual factors discussed in the conceptual framework, including some interaction terms and transformations (e.g., squared values and natural logarithms of continuous variables). Given the panel-like nature of the data, we considered proxy indicators that changed over time and varied across countries. Then we screened all the variables and used as the starting point those that were significantly correlated with household income, using a partial correlation coefficient with significance at the 90 percent or higher level as the cutoff point.[8]

[8] Because we estimated the regression model for prediction purposes only, not for determination purposes, multicollinearity is not an issue. We thank an anonymous reviewer for pointing this out to us.

We used forward and backward selection techniques within a stepwise regression analytical framework to select the proxy indicators for alternative regression prediction models. In the first model (model 1), we used the forward selection technique with a 0.1 level of significance as the cutoff point for including variables in the model. In model 2, we used the backward selection technique, also with a 0.1 level of significance as the cutoff point for removing variables from the model. In the third model (model 3), we used a combination of the two, starting with forward selection and 0.2 as the level of significance for the cutoff point, followed by backward selection with 0.15 as the level of significance for the cutoff point. Detailed descriptions of the dependent variable and the full set of proxy indicators, organized by conceptual factor are given in Table 3.

Table 3. Description and summary statistics of dependent variable and proxy indicators

Variable	**Description**
Dependent variable	
Per capita income	Household monthly consumption expenditure per capita in 1993 international dollars
Proxy indicators	
Production and returns to factors	
GDP share (cf., Ag–GDP)	Value-added as percent of GDP (comparative base is agriculture)
Services–GDP	Services value-added as percentage of GDP
Industry–GDP	Industry value-added as percentage of GDP
Ag labor productivity	Agricultural valued-added per agricultural labor in 1993 international dollars
Non-ag labor productivity	Nonagricultural valued-added per capita in 1993 international dollars
Resource endowment and employment of factors	
Capital–tractors	Number of tractors per 1,000 agricultural workers
Capital–gross	Gross capital formation in 1993 international dollars per capita
Pop density	Rural population per square km of arable land
Pop density × Pop density	
Agricultural land	Hectare of agricultural land per agricultural worker
Agricultural population	Percentage of total population dependent on agriculture
Rural population	Percentage of total population living in rural areas
Agricultural population × Ag–GDP	
Dependency ratio	Dependents to working-age population
Health	Percentage of children aged 12–23 months immunized against diphtheria and measles
Foreign aid and terms of trade	
Aid	Aid per capita in 1993 international dollars
Import–export ratio	Value of imports of goods and services divided by value of exports of goods and services
Exchange rate	Index of local currency per US$1 dollar (official rate), 2000 = 100
Inflation	
CPI	Consumer price index (2000 = 100)
PPP rate	Purchasing power parity rate (local currency per one international dollar)
Fixed effects	
Regional location (cf., West Africa)	Dummy variable for regional location of country (comparative base is West Africa)
Region–SA	Dummy variable equal to 1 if country in southern Africa; 0 otherwise
Region–ECA	Dummy variable equal to 1 if country in eastern or central Africa; 0 otherwise
Large country	Dummy variable equal to 1 if large country (population of 50,000 or more); 0 otherwise
Time factor	
Year–1980s	Dummy variable equal to 1 if year of data is 1980s; 0 otherwise
Year–1990s	Dummy variable equal to 1 if year of data is 1990s; 0 otherwise

Sources: World Bank (2006a, 2006b) and FAO (2007).
Note: Continuous variables are transformed by natural logarithm.

Table 4. Stepwise regression results for predicting real household monthly income per capita in selected Sub-Saharan African countries

Variable	Restricting sample to countries with three or more observations on income per capita						Total sample					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Services–GDP	0.013	2.71	0.118	8.17	0.120	12.41	0.088	8.13	0.093	9.88	0.027	6.70
Industry–GDP			0.115	7.52	0.113	9.63	0.072	5.88	0.076	7.19		
Ln Ag labor productivity	-0.438	-3.56	0.660	6.26	0.572	6.60						
Ln Non–ag labor productivity	0.825	5.24										
Ln Capital–tractors			-0.263	-2.65	-0.186	-2.30						
Ln Capital–gross	0.406	8.27	0.160	1.68	0.058	1.12	0.044	1.07				
Ln Pop density	0.238	2.10	8.245	2.14					1.926	1.95		
Ln Pop density × Ln Pop density			-0.744	-2.13					-0.189	-2.04		
Ln Agricultural land per worker							-0.114	-2.63	-0.103	-2.70		
Agricultural population			-0.018	-1.73	-0.028	-5.79	-0.049	-7.69	-0.055	-10.79	-0.021	-6.48
Rural population			-0.013	-1.50			0.010	1.63	0.018	3.57		
Agricultural population × Ag–GDP			0.001	4.50	0.001	8.02	0.001	5.68	0.001	6.97		
Dependency ratio			1.199	1.68								
Health							-0.003	-1.32			-0.004	-1.69
Ln Aid	-0.149	-2.91	-0.297	-6.07	-0.249	-6.45						
Import-export ratio	0.145	3.87			0.086	3.57	-0.094	-2.32	-0.109	-2.98		
Exchange rate			0.318	3.12								
Ln PPP rate	0.122	3.19	-0.399	-3.24			-0.027	-1.46			-0.055	-2.69
Region–SA	-0.966	-9.45	-0.338	-3.09	-0.602	-7.74	-0.338	-2.90	-0.362	-4.14		
Region–ECA			0.243	1.40	0.120	1.63	-0.034	-0.25			0.387	3.40
Large country	-0.588	-2.56	-1.864	-8.23	-1.650	-8.99	-1.303	-6.99	-1.278	-7.38	-0.705	-3.84
Year–1980s									0.143	1.65		
Intercept	-0.039	-0.05	-28.914	-2.91	-5.783	-6.23	-0.072	-0.08	-5.891	-1.99	4.791	15.38
R-squared	0.904		0.968		0.957		0.786		0.800		0.632	
Number of observations	49.000		49.000		49.000		79.000		79.000		79.000	

Sources: World Bank (2006a, 2006b) and FAO (2007).

Notes: Dependent variable is household monthly consumption expenditure per capita in 1993 international dollars. See Table 3 for detailed descriptions of the other variables. Ln = transformation by natural logarithm. Model 1 uses forward selection technique, with 0.1 level of significance as the cutoff point for including variables, starting with an empty model; Model 2 uses backward selection technique, with 0.1 level of significance as the cutoff point for dropping variables, starting with a full model. Model 3 uses a combination of forward and backward selection with 0.2 and 0.15 levels of significance as the cutoff points, respectively.

Model Estimation, Results, and Predictive Power

We pooled the data for all 28 Sub-Saharan African countries. Data on the proxy indicators were available until 2004, so the 2005–2006 data point on household income for Uganda was excluded, leaving 79 observations for the estimation. Because most countries have only one or two observations on household income, creating a severely unbalanced panel, quite a lot of noise tends to enter the analysis. Thus, we also estimated the model using only data on the 12 countries with three or more data points, giving 49 observations for the estimation. STATA software (StataCorp 2008) was used for the analysis.

Table 4 shows details of the results of the three alternative prediction models. Although the magnitudes and signs of the individual coefficients were not important in our study, they are presented here for interested readers. The models estimated with the restricted data set performed better, confirming our concern about the noise in the full data set, which is a severely unbalanced panel. Therefore, we used only the models estimated with the restricted sample in subsequent analyses. With the *R*-squared values in excess of 0.9 for each of the models when we used the restricted data set, we would expect any of the models to have very good predictive power, although model 2 would be preferred because it had the highest *R*-squared value.

Table 5. Relative predictive accuracy of real household monthly income per capita

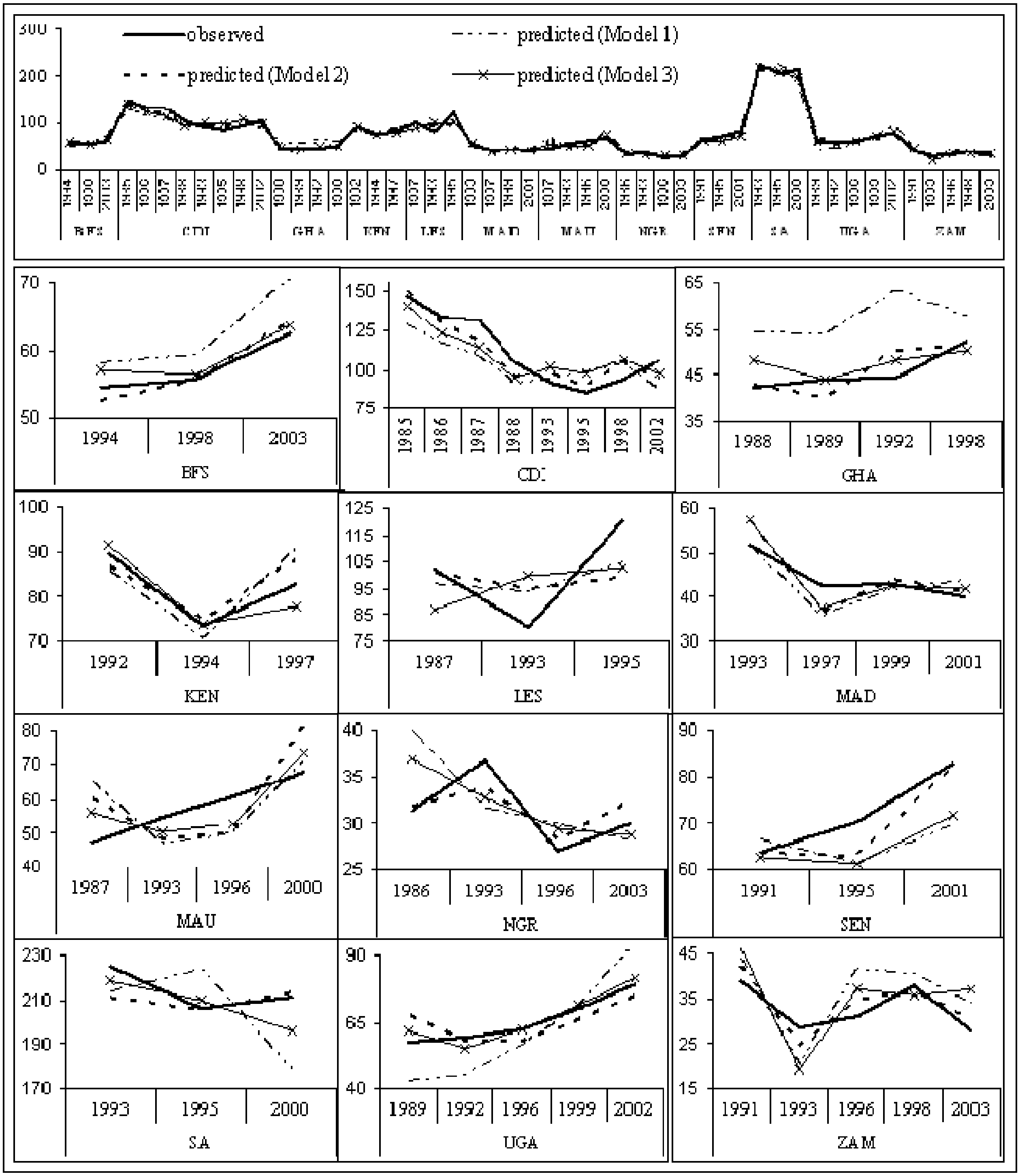
Country	Model 1			Model 2			Model 3		
	MAE	*RMSE*	U_Δ	*MAE*	*RMSE*	U_Δ	*MAE*	*RMSE*	U_Δ
All countries	9.46	11.58	0.31	5.07	6.95	0.18	6.26	7.99	0.21
Burkina Faso	4.99	5.37		1.17	1.39		1.48	1.72	
Côte d'Ivoire	14.60	15.80	1.12	7.71	8.47	0.65	10.89	11.36	0.87
Ghana	11.36	12.36	2.68	2.76	3.49	0.86	3.01	3.65	0.55
Kenya	4.84	5.23		3.09	3.52		2.23	3.01	
Lesotho	11.45	12.32		12.43	15.04		17.45	17.57	
Madagascar	2.99	3.93	0.83	3.26	3.98	0.62	3.29	4.01	0.58
Mauritania	9.80	11.27	1.10	10.65	11.10	1.44	6.69	6.95	0.86
Nigeria	4.57	5.24	0.53	1.81	2.06	0.36	3.27	3.64	0.43
Senegal	8.28	9.25		2.82	4.28		6.97	8.18	
South Africa	20.40	22.25		5.42	7.94		8.18	9.48	
Uganda	10.08	11.68	1.78	4.85	5.71	0.61	2.49	3.03	0.43
Zambia	6.33	6.90	0.92	2.76	2.94	0.36	6.65	7.15	0.90

Notes: *MAE*, *RMSE*, and U_Δ are mean absolute error, root mean-squared error, and Theil's statistic, respectively; see equations (3) through (5). U_Δ was not estimated for countries having less than four data points. A shaded cell indicates the model with the best performance indicator.

Table 5 shows the relative predictive accuracy of the three models in terms of comparing the predicted incomes against the observed incomes using the three analysis-of-error measures (*MAE*, *RMSE*, and U_Δ; see equations [3] through [5]). For the entire data set—that is, taking all 12 countries together—as well as for many of the countries separately, model 2 is preferred because it has the lowest *MAE*, *RMSE*, and U_Δ values. However, it is evident that there are differences in the predictive accuracy of the three models when comparing them country by country. In many cases, those differences are inconsistent with the model chosen by using the overall *R*-squared values as the selection criterion. This is expected and primarily caused by the limited data on observed household income and potential differences in the importance of the proxy indicators for each country. By comparing the values of *MAE*, *RMSE*, and U_Δ across countries as well, the differences suggest that any particular model predicts better in some countries than in others, which also is expected for the reason previously mentioned.

The relative predictive accuracy of the alternative models across countries is better visualized in Figure 2, which depicts the ability of the models to predict turning points in the data. It is evident that all the models do very well in predicting real household monthly income per capita at the aggregate level (see the top panel of Figure 2). At the country level, model 2 performs very well in most of countries, but in a few countries (such as Uganda), it is clear that one of the other two models performs better, which is consistent with the results in Table 5. In conjunction with the results presented in Table 5, different models do well in predicting household income in different countries. Model 1 performs best in Lesotho and Madagascar; model 3 in Kenya, Mauritania, and Uganda; and model 2 in the remaining group of countries, which comprises Burkina Faso, Côte d’Ivoire, Ghana, Nigeria, Senegal, South Africa, and Zambia.

Figure 2. Accuracy of alternative models in predicting real household monthly income per capita (1993 international dollars)



Notes: BFS = Burkino Faso; CDI = Côte d’Ivoire; GHA = Ghana; KEN = Kenya; LES = Lesotho; MAD = Madagascar; MAU = Mauritania; NGR = Nigeria; SEN = Senegal; SA = South Africa; UGA = Uganda; ZAM = Zambia.

4. HOUSEHOLD INCOME AND CHANGES, 1985 TO 2006

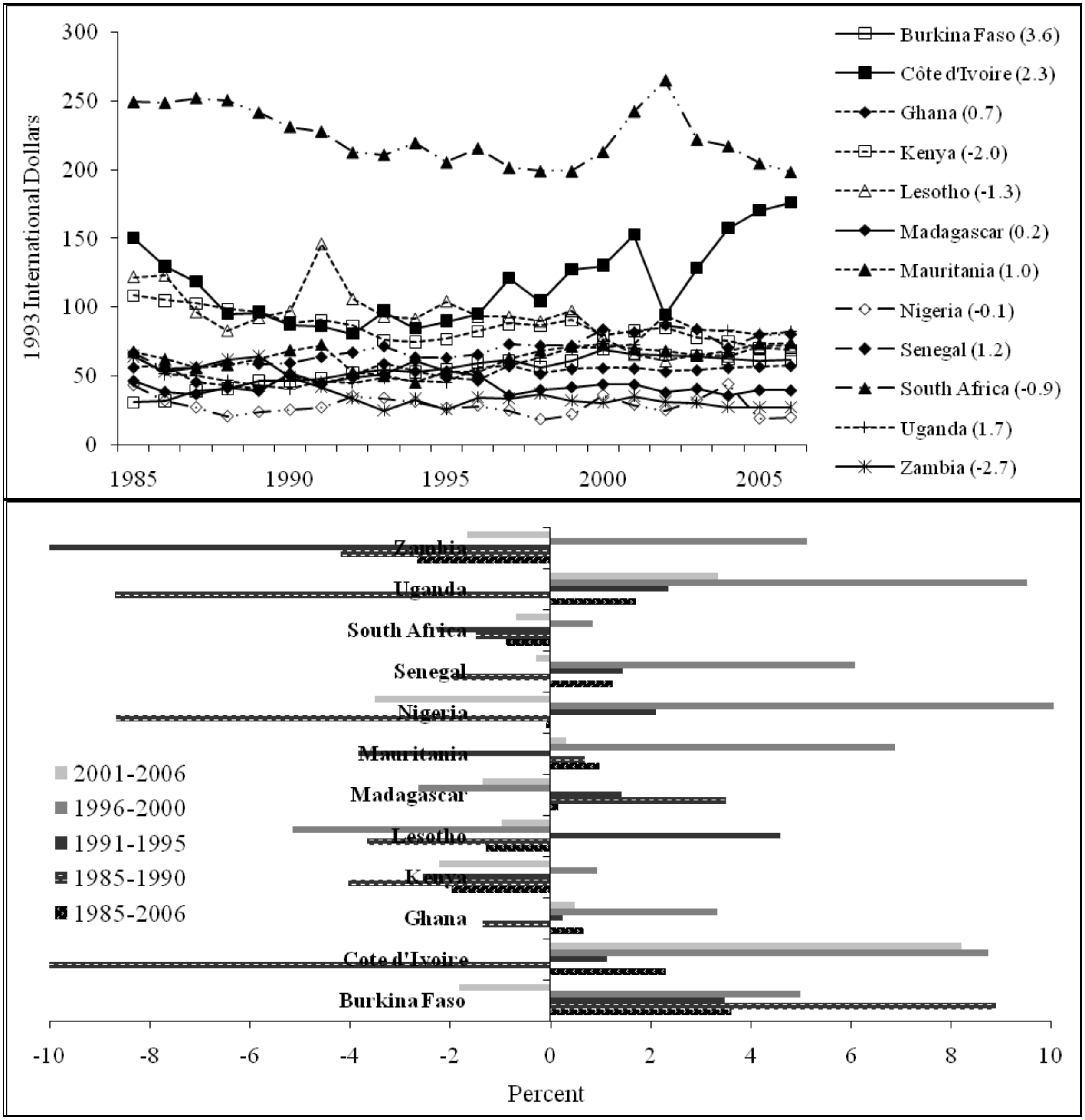
To fill the knowledge gap in the levels of and changes in household income over a long period, the best-performing model for each country was used to estimate household monthly incomes per capita between 1985 and 2006 to complement the actual survey estimates shown in the top panel of Figure 1. To obtain the estimates, we used the estimated coefficients and data on the relevant proxy indicators for the respective years in equation (2). Data from the WDI database on the proxy indicators were mostly available up to 2004 (World Bank 2006a). For the 2005 and 2006 data points, we first calculated the average annual growth rate for each variable and then used the growth rates to project the proxy values forward for 2005 and 2006. Again, we restricted the analysis to countries having three or more data points on observed household income. The results are shown in Figure 3.

We found substantial variation in predicted real household monthly income per capita across countries. The average was \$78 (in 1993 international dollars). South Africa was ahead of the pack at \$225, followed by Côte d'Ivoire and Lesotho at \$117 and \$91, respectively. Nigeria and Zambia fared the worst at \$28 and \$39, respectively. In terms of dynamics over the period, Burkina Faso, Côte d'Ivoire, Uganda, Senegal, Mauritania, and Ghana (in declining order) experienced consistent positive growth in real household income per capita, whereas Zambia, Kenya, and Lesotho showed declining trends, averaging –2.7 percent, –2.0 percent, and –1.3 percent per year, respectively, over the 20-year period.

Validation of Predictions

To assess the validity of the above predictions, household income observed from actual survey data, which was not used in estimating the prediction model, is needed to compare with the predicted values. An ideal way to do that is to split up the data and use one subset for the estimation and the other subset for the prediction and validation. Because of the limited number of observations in our data set, we were unable to use that procedure. For Uganda, however, we compared the predicted value for 2005–2006 (\$81.46) with the observed value for the same period (\$75.05). The difference is quite small (about 8.5 percent), suggesting that the predictions and analysis in the previous section are reliable. More data are needed to do similar comparisons for the same country as well as for the other relevant countries to be able to apply the Chow test discussed earlier.

Figure 3. Estimated household monthly income per capita, 1985–2006 (1993 international dollars)



Notes: The top panel shows levels, and the numbers in parentheses are average annual percentage growth rates over the entire period. The bottom panel shows average annual percentage growth rates for specific periods.

Relation to Poverty and Hunger Reduction

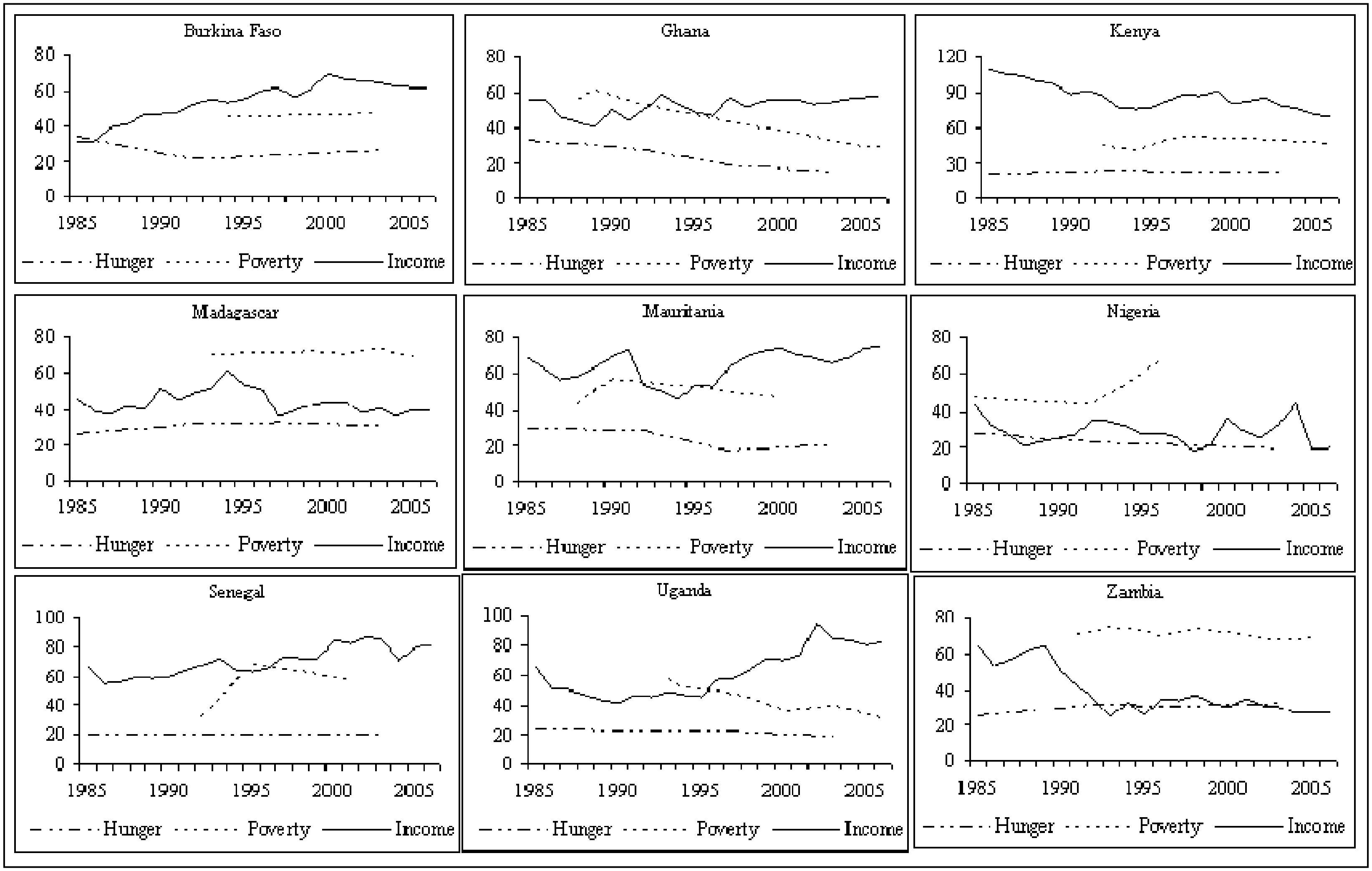
As mentioned at the outset, increasing rural household income is a central objective to reducing poverty and hunger. A vicious circle of poverty and hunger, which is both intra- and inter-generational, leads to poor health, lower learning capacity, and diminished physical activity, and thus to lower productivity and incomes. Consequently, it is useful to compare the predicted trends with observed changes in poverty and hunger. The results of the comparisons for countries on which we were able to obtain data on poverty and hunger are shown in Figure 4.

With the exception of one or two cases, predicted real household incomes and observed poverty and hunger underwent consistent change. Ghana, Mauritania, and Uganda show a consistent story of increasing real household incomes and declining poverty and hunger, suggesting that national policies and investment strategies, backed by development partners, are having the desired impacts and that the benefits of those investments and growth are translating into household incomes that actually lead to substantial reductions in poverty and hunger. Although the rate of hunger reduction has been slower in Uganda, it seems to be creeping up a little in Mauritania, where growth in real household income has also been relatively erratic. Ghana shows the largest reduction in hunger, which is also consistent with marked improvements in access to sanitation, health, and education over the period. In Nigeria, we found consistency in increasing real household incomes and declining hunger, although at much lower rates than in the three countries previously mentioned. The spike in poverty during the early 1990s, which appears to be a data problem, corresponds to the decline in real household income.

Also showing consistency in changes in real household incomes and changes in poverty and hunger are Kenya, Madagascar, and Zambia, but the outlook is bleak. Although poverty seems to have declined in recent years, real household incomes have stagnated or declined, while the proportion of the population that is hungry has increased or remained unchanged. The case of Zambia is particularly interesting because, although it has not been engaged in any wars, it has been indirectly affected by the civil wars in Angola and Mozambique, which created an influx of refugees from those neighboring countries. Zambia is among the countries at the bottom of the global hunger index (WHH and IFPRI 2006) and has one of the highest HIV prevalence rates in the world. The declining price of copper, its major export commodity, has also taken its toll. Therefore, Zambia, as well as Kenya and Madagascar, will require much higher growth rates if they are to meet their Millennium Development Goal targets for reducing poverty and hunger.

The results for Burkina Faso and Senegal are mixed. In Burkina Faso, although real household income has been increasing, poverty and hunger have been increasing. In Senegal, real household income has been rising, hunger has remained unchanged. As in Nigeria, the spike in poverty during the early 1990s, which seems like a data problem, also corresponds to the decline in real household income.

Figure 4. Trends in predicted real household income, poverty and hunger



Notes: Hunger is measured by the Global Hunger Index (WHH and IFPRI 2006) linearly extrapolated over the years using actual data for 1981, 1992, 1997, and 2003. The Global Hunger Index is based on undernourishment of the population and child nutrition deficiency and mortality. Poverty is measured by the headcount poverty index, also based on linear extrapolation of a few data points that were obtained from various Poverty Reduction Strategy Papers and other government publications, mostly corresponding to the survey data years discussed in Section 3. Income is based on the authors' estimations and measured in 1993 international dollars (see Figure 3).

5. CONCLUSIONS AND AREAS FOR FURTHER RESEARCH

Monitoring rural household incomes is important because increasing rural household income is at the heart of achieving many development goals, including reducing poverty, hunger, and food and nutrition insecurity. However, accurately assessing rural household income is time consuming and costly. Using an expenditure-based income measure, actual monthly household expenditures per capita obtained from national surveys for 28 Sub-Saharan African countries, and proxy indicators that are measured and easily available at the national level, we estimated regression models and then used those models to predict and analyze changes in household income per capita between 1985 and 2006.

From our predictions, we found that over the 20-year period, the annual average real household monthly income per capita was $78 (in 1993 international dollars). At $225, South Africa had the highest income, followed by Côte d'Ivoire and Lesotho at $117 and $91, respectively. Our predictions revealed that Nigeria and Zambia fared the worst, with average incomes per capita of $28 and $39, respectively. Looking at changes in income over time, Burkina Faso, Côte d'Ivoire, Uganda, Senegal, Mauritania, and Ghana (in declining order) were predicted to have consistent positive growth. Zambia, Kenya, and Lesotho, on the other hand, experienced declining trends, averaging –2.7 percent, –2.0 percent, and –1.3 percent per year, respectively, over the 20-year period. The latter results are not surprising given the low and sometimes negative growth rates in real GDP per capita and real agricultural value added per worker over the same time period for those countries. Our predictions are also consistent with observed trends in poverty and hunger, suggesting that the methodology is useful for tracking household incomes to support monitoring and evaluating public investment programs.

Although several techniques might be used to improve our analysis, two things may add the greatest value: using rural disaggregated household income data when they become available at the PovcalNet website (World Bank 2006b), and searching for more data on actual household income to improve the database for each country, because several countries included in the current analysis had only one or two available data points. Another possible improvement is including other countries in the study, particularly for the countries that would benefit most from the analysis. As the database is improved, the regression models might also be reevaluated and improved in terms of the proxy indicators used.

APPENDIX

Table A.1. Descriptions of household survey data and monthly consumption expenditures per capita

Country	Year of survey	Type of survey	Sample size	Household monthly consumption expenditure per capita (1993 international dollars)
Botswana	1985–1986	Income/Expenditure/Household Survey	2,077	87.71
Botswana	1993–1994	Income/Expenditure/Household Survey	3,608	135.06
Burkina Faso	1994	Priority Survey	8,642	54.46
Burkina Faso	1998	Priority Survey	8,500	55.67
Burkina Faso	2003	n.i.	n.i.	62.68
Burundi	1992	Income/Expenditure/Budgetary Survey	n.i.	43.10
Burundi	1998	Priority Survey	8,500	40.24
Cameroon	1996	Priority Survey	1,700	70.61
Cameroon	2001	Priority Survey	10,992	94.86
Central African Republic	1993	Priority Survey	7,500	40.98
Côte d'Ivoire	1985	LSMS/Integrated Survey	1,588	146.89
Côte d'Ivoire	1986	n.i.	n.i.	133.70
Côte d'Ivoire	1987	LSMS/Integrated Survey	1,600	131.23
Côte d'Ivoire	1988	LSMS/Integrated Survey	1,600	104.39
Côte d'Ivoire	1993	Priority Survey	n.i.	91.52
Côte d'Ivoire	1995	Priority Survey	1,200	85.29
Côte d'Ivoire	1998	Priority Survey	4,200	93.31
Côte d'Ivoire	2002	n.i.	n.i.	105.52
Ethiopia	1981–1982	Income/Expenditure/Household Survey	n.i.	50.26
Ethiopia	1995	Income/Expenditure/Household Survey	11,687	59.20
Ethiopia	2000	Income/Expenditure/Household Survey	17,332	54.49
Gambia	1992	n.i.	n.i.	45.42
Gambia	1998	Integrated Survey	2,002	96.07
Ghana	1987–1988	LSMS/Integrated Survey	3,200	42.48
Ghana	1988–1989	LSMS/Integrated Survey	3,456	44.11
Ghana	1991–1992	LSMS/Integrated Survey	4,565	44.58
Ghana	1998–1999	LSMS/Integrated Survey	5,998	52.49
Kenya	1992	Welfare Monitoring Survey	12,050	89.71
Kenya	1994	Welfare Monitoring Survey	n.i.	73.74
Kenya	1997	Welfare Monitoring Survey	12,000	82.86

Table A.1. Continued

Country	Year of survey	Type of survey	Sample size	Household monthly consumption expenditure per capita (1993 international dollars)
Lesotho	1986–1987	Income/Expenditure/Budgetary Survey	7,640	101.93
Lesotho	1993	Income/Expenditure/Budgetary Survey	1,700	80.16
Lesotho	1995	Income/Expenditure/Household Survey	4,850	120.33
Madagascar	1980	Income/Expenditure/Household Survey	n.i.	50.14
Madagascar	1993	LSMS/Integrated Survey	4,504	51.79
Madagascar	1997	n.i.	n.i.	42.69
Madagascar	1999	Priority Survey	5,120	42.96
Madagascar	2001	Priority Survey	5,080	40.28
Malawi	1997–1998	Integrated Survey (non-LSMS)	10,698	62.34
Malawi	2003–2004	n.i.	n.i.	71.00
Mali	1994	Priority Survey	9,700	32.47
Mali	2001	n.i.	n.i.	56.73
Mauritania	1987	LSMS/Integrated Survey	1,600	46.93
Mauritania	1993	Priority Survey	5,260	54.53
Mauritania	1996	LSMS/Integrated Survey	3,450	60.53
Mauritania	1999–2000	Integrated Survey	5,865	67.98
Mozambique	1996–1997	Integrated Survey	8,274	52.98
Mozambique	2002–2003	LSMS/Integrated Survey	8,700	63.49
Namibia	1993	Income/Expenditure/Budgetary Survey	4,750	200.79
Niger	1992	Income/Expenditure/Budgetary Survey	2,070	47.07
Niger	1995	Priority Survey	4,383	36.17
Nigeria	1985–1986	Income/Expenditure/Budgetary Survey	10,000	31.45
Nigeria	1992–1993	Integrated Survey	10,000	36.79
Nigeria	1996–1997	Income/Expenditure/Budgetary Survey	12,000	27.06
Nigeria	2003	n.i.	n.i.	29.98
Rwanda	1984–1985	Income/Expenditure/Budgetary Survey	1,200	46.63
Rwanda	1999–2000	n.i.	n.i.	46.69
Senegal	1991	Priority Survey	9,960	63.70
Senegal	1994–1995	Income/Expenditure/Budgetary Survey	3,277	70.49
Senegal	2001	n.i.	n.i.	82.67
Sierra Leone	1989	Income/Expenditure/Budgetary Survey	3,500	48.97
South Africa	1993	LSMS/Integrated Survey	1,558	224.59
South Africa	1995	Integrated Survey	29,700	206.10
South Africa	2000	Integrated Survey	n.i.	211.11

Table A.1. Continued

Country	Year of survey	Type of survey	Sample size	Household monthly consumption expenditure per capita (1993 international dollars)
Swaziland	1994–1995	Income/Expenditure/Budgetary Survey	6,246	288.85
Tanzania	1991	Income/Expenditure/Budgetary Survey	1,047	66.22
Tanzania	1999–2000	n.i.	n.i.	36.43
Uganda	1989	Income/Expenditure/Budgetary Survey	4,694	57.57
Uganda	1992–1993	LSMS/Integrated Survey	9,929	59.29
Uganda	1996	Priority Survey	29,745	62.35
Uganda	1999–2000	Priority Survey	10,596	70.38
Uganda	2002–2003	n.i.	n.i.	78.88
Uganda	2005–2006	Priority Survey	n.i.	75.05
Zambia	1991	Income/Expenditure/Budgetary Survey	2,930	39.09
Zambia	1993	Income/Expenditure/Budgetary Survey	4,500	28.70
Zambia	1996	Priority Survey	11,800	31.11
Zambia	1998	Priority Survey	16,636	37.86
Zambia	2002–2003	n.i.	n.i.	28.03
Zimbabwe	1990–1991	Income/Expenditure/Budgetary Survey	15,000	57.98
Zimbabwe	1995	Income/Expenditure/Budgetary Survey	n.i.	47.17

Sources: All data obtained from World Bank (2006b), except for data for Ghana 2005–2006 (GSS 2007), Mozambique 2002–2003 (GOM 2004), and Uganda 2005–2006 (UBOS 2006) where values in local currency units were converted into 1993 PPP values by the authors.
Notes: n.i. = no information; LSMS = Living Strategy Measurement Study; PPP = purchasing power parity (see Appendix 2).

Table A.2. 1993 Purchasing power parity conversion rate (local currency per international dollar)

Country	PPP conversion rate	Country	PPP conversion rate
Botswana	1.3879	Mauritania	81.77
Burkina	103.39	Mozambique	807.99
Burundi	56.31	Namibia	1.48
Cameroon	142.4	Niger	100.62
Central African Republic	108.51	Nigeria	11.52
Côte d'Ivoire	159.1	Rwanda	54.83
Ethiopia	1.30	Senegal	127.66
Gambia	2.45	Sierra Leone	234.01
Ghana	323.92	South Africa	1.67
Kenya	11.77	Swaziland	1.21
Lesotho	1.12	Tanzania	118.13
Madagascar	530.32	Uganda	259.97
Malawi	1.52	Zambia	223.42
Mali	124.89	Zimbabwe	2.2845

Sources: World Bank (2006b)

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