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Assessing Asset Indices

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Abstract The use of asset indices in welfare analysis and poverty targeting is increasing, especially in cases in which data on expenditures are unavailable or hard to collect. We compare alternative approaches to welfare measurement. Our analysis shows that inferences about inequalities in education, health care use, fertility, and child mortality, as well as labor market outcomes, are quite robust to the economic status measure used. Different measures—most significantly per capita expenditures versus the class of asset indices—do not, however, yield identical household rankings. Two factors stand out in predicting the degree of congruence in rankings. First is the extent to which expenditures can be explained by observed household and community characteristics. Rankings are most similar in settings with small transitory shocks to expenditure or with little random measurement error in expenditure. Second is the extent to which expenditures are dominated by individually consumed goods, such as food. Asset indices are typically derived from indicators of goods that are effectively public at the household level, while expenditures are often dominated by food, an almost exclusively private good. In settings in which individually consumed goods are the main component of expenditures, asset indices and per capita consumption yield the least similar results.

Keywords Poverty measurement · Inequality · Assets · Welfare · Human development

Introduction

In this article, we explore the potential for carrying out welfare analysis in the absence of the typically used measure of household economic status: per capita

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household expenditures. In many situations, this preferred proxy for income is not available or is difficult to collect. While various solutions for overcoming this problem have been proposed, Filmer and Pritchett (1999, 2001) popularized an approach using an aggregate index based on consumer durable assets owned by household members, along with a set of housing characteristics, to rank households.

Filmer and Pritchett (1999, 2001) developed their index in the context of analyzing the associations between household economic status and schooling outcomes when using data sets that did not include information on household expenditures. The approach has since been used for a variety of purposes. For example, researchers have used asset indices to explain inequalities in health outcomes and behaviors (Bollen et al. 2002; Gwatkin et al. 2000; Schellenberg et al. 2003), in particular those related to fever and malaria (Filmer 2005; Njau et al. 2006), child nutrition (Sahn and Stifel 2003; Tarozzi and Mahajan 2005), child mortality (Fay et al. 2005; Sastry 2004), and early child development (Ghuman et al. 2005; Paxson and Schady 2005). The approach has also been used to analyze socioeconomic inequalities in schooling in subpopulations, such as orphans (Ainsworth and Filmer 2006; Bicego et al. 2003; Case et al. 2004; Evans and Miguel 2007) and children with disabilities (Filmer 2008). Others have used asset indices to analyze poverty change (Sahn and Stifel 2000; Stifel and Christiaensen 2007) and inequality (McKenzie 2005), or to control for economic status in program evaluation when expenditures data are not available (Rao and Ibanez 2005). The asset index approach has frequently been used to describe inequalities in health and education outcomes in international databases such as those in the World Bank's *World Development Reports* (World Bank 2003, 2005, 2006, 2011).

A similar approach of using an index of observable household characteristics has been used in a different context for the purpose of targeting public programs. For example, Ecuador uses an index of assets and other household characteristics (based on a census of households) to target cash transfers to poor households (Schady and Araujo 2008). Analogous proxy-means targeting approaches have been applied in other countries, such as Armenia, Brazil, Colombia, and Indonesia (see discussion in Coady et al. 2004).

The fact that expenditure data are expensive and time-consuming to collect makes it plausible that there will always be occasions when a proxy indicator of economic status is needed. Data used to construct asset indices are simple to collect and are frequently available. The literature to date suggests that economic gradients in education and health outcomes are similar when based on per capita expenditures or on an asset index. At the same time, however, the evidence suggests less-than-perfect agreement in ranking households—and thereby in identifying the poorest.[1] Although this evidence is compelling, it is typically partial; that is, studies usually assess only a single variant on an asset index at a time. In the remainder of this

[1] For a fuller account of the methodological literature to date, see Online Resource 1. Key issues and readings include comparisons of asset indices to expenditure measures, variations in aggregation methods, and sensitivity to specific indicators used in the index (Bollen et al. 2002; Case et al. 2004; Das et al. 2004; Ferguson et al. 2003; Filmer and Pritchett 2001; Houweling et al. 2003; Lindelow 2006; Lubotsky and Wittenberg 2005; Montgomery et al. 2000; Montgomery and Hewett 2005; Morris et al. 2000; Mukherjee 2006; Organisation for Economic Co-operation and Development (OECD) 2004; Paxson and Schady 2007; Sahn and Stifel 2000, 2003; Stifel and Christiaensen 2007; Wagstaff and Watanabe 2003; Wittenburg 2005).

article, we overcome this shortcoming by systematically assessing the effect of using different measures and aggregation methods in identifying the poor and analyzing inequalities in a variety of human development outcomes. In addition, we go beyond what previous studies have done by assessing the correlation of alternative welfare measures with other household attributes, such as demographic characteristics and urban or rural residence, and by analyzing the factors that lead to more or less congruence in the different economic status rankings.

Our approach is empirical in that it attempts to replicate the various approaches an analyst might use to construct an index when faced with a data set lacking expenditures—although we do so using data sets that *do* include expenditures so that the two classes of welfare measures can be compared. By applying this approach in a variety of settings and analyzing differences in "performance" across those settings, we identify regularities that we hope will help guide future analysts when using asset indices. By systematically comparing results across 11 surveys, we address three main questions: *Are* alternative measures of economic status different? If so, *does it matter* for the types of analysis that they are typically used for? And *when* are alternative approaches most likely to be different?

After defining the different economic status measures and describing the data used in our analysis, we address each question in turn. First, we assess whether alternative approaches are different by analyzing how similarly they rank households; in so doing, we not only compare expenditures against an asset index but also compare alternative asset indices. Second, we assess whether using alternative approaches matters for inferences about the economic gradients in education, health, fertility, mortality, and labor force participation outcomes. We also assess whether the approach matters for inferences about the relative poverty status of urban versus rural households or of households of different demographic composition. Third, we explore the factors that lead to greater congruence and divergence in rankings, focusing on measurement error, transitory shocks, and household economies of scale.

Definitions and Data

Before turning to a discussion of results, in this section we define the different measures of economic status and describe the data on which our analysis is based. The motivation behind the use of asset indices is straightforward: in the absence of information on household expenditures (or income), can one use the information that is often collected in the context of surveys to characterize a household's economic status? An approach that has become popular in the past decade uses an "asset index" constructed from variables describing household ownership of durable goods and characteristics of housing. Asset indices typically follow the same basic form:

$$A_i = (b_1 \cdot a_{1\mathrm{i}}) + (b_2 \cdot a_{2i}) + \; \ldots + (b_k \cdot a_{ki}), \tag{1}$$

where A_i is the asset index for household i, (a_{1i}, a_{2i}, . . . , a_{ki}) are k indicators of asset ownership and housing quality variables, and (b_1, b_2, . . . , b_k) are weights used to aggregate the indicators into an index.

By aggregating observed measures of a household's material living conditions, the asset index captures a dimension of economic status. While it is reasonable to think that assets and housing characteristics reflect a dimension of wealth, it is clear that this is not wealth in the formal sense of the value of household assets owned minus liabilities.[2] Data on true household wealth are costly to collect and thus, like expenditures, are frequently unavailable.[3] Asset indices vary in terms of both the set of indicators included (i.e., a_{1i}, a_{2i}, . . . , a_{ki}) and how weights used to aggregate the indicators are derived (i.e., b_1, b_2, . . . , b_k). How these attributes of indices affect household rankings and our understanding of inequalities in outcomes and welfare levels is the focus of this article.

Defining Welfare Indices

Filmer and Pritchett (2001), Bollen et al. (2002), and Sahn and Stifel (2003) have all argued that per capita household expenditures should not necessarily be considered the "gold standard" against which asset indices are judged. Nevertheless, we take a practical approach: given that the main variable used in the poverty analysis literature is per capita expenditures, we assess the performance of asset indices relative to that benchmark (we discuss below how adjusting expenditures for household economies of scale affects the results).

In principle, calculating *reported per capita household expenditures* is straightforward: add all the responses to items on the survey questionnaire relating to expenditures, add the imputed value of home-produced goods that were consumed (e.g., homegrown food consumed by the household), and impute the "flow" values for items that are consumed in bulk and have long depreciation periods (such as expensive consumer durables or housing) or are provided free (such as water or other utilities that are provided without charge from government sources).[4] The use of expenditures for welfare measurement has a long history in economics (see the discussion in Deaton 1997). Much of the logic for using expenditures rests on the permanent income hypothesis (Friedman 1957) by which economic agents' long-run income (along with functioning capital markets) determines consumption. Deaton and Zaidi (2002) provide a thoughtful discussion of both the theory and practical issues underlying the use of expenditure aggregates in welfare analysis in developing countries. In particular, these authors discuss unsettled problems such as the exact set of questions (which varies across questionnaires—for example, the range of items asked about, or the time scale for certain types of purchases), the way durables are depreciated, and how their flow value is calculated, as well as a series of judgments about how to deflate values across space and time.[5]

[2] In previous papers (e.g., Filmer and Pritchett 2001), the index was often referred to as a *wealth index*. The term *wealth* in those papers was used to distinguish it from an expenditures-based measure. In order to use a term that more accurately reflects the measure, we refer to it as an *asset index* in this article.

[3] In addition, asset indices typically exclude productive assets that reflect household investments, assets that are not usually collected in the types of data sets for which analysts turn to an index approach.

[4] We use the term *expenditures* to refer to what is sometimes more precisely called *consumption expenditures*, the value of household consumption regardless of whether purchased or home-produced, excluding expenditures for nonconsumption purposes such as investment. This is also sometimes just called *consumption*. For consistency and compactness, we use the term *expenditures* throughout.

[5] For a discussion of the comparison between asset indices and total household expenditures (as opposed to per capita expenditures), see the discussion in the section devoted to congruence and divergence in rankings.

For five of the surveys analyzed here, we use the expenditure aggregates described by Deaton and Zaidi (2002),[6] and for the remaining six surveys we use the expenditure aggregate that was constructed for the main poverty report that resulted from the survey.[7] All expenditure aggregates are spatially deflated to adjust for regional price differences within countries.

The first asset index we consider is based on *predicted per capita household expenditures*. The weights for this index are derived from an ordinary least squares (OLS) regression of per capita expenditures on the asset and housing indicators, that is, the estimates of the βs in

$$Y_i = (\beta_1 \cdot a_{1i}) + (\beta_2 \cdot a_{2i}) + \ldots + (\beta_k \cdot a_{ki}) + \varepsilon_i. \tag{2}$$

These estimates of β_1 to β_k are then substituted for b_1 to b_k in Eq. 1. In the previous section, we motivated this analysis by referring to situations in which expenditures are unavailable. Predicted expenditures is, nevertheless, an interesting variable for our analysis. There are four main reasons for this. First, it represents the linear combination of these assets and housing characteristics that best predicts per capita expenditures. No other linear aggregation of the same indicators will come as close to giving the same ranking of households and, therefore, come as close to giving similar results to per capita expenditures. A predicted expenditures measurement therefore mimics the "best possible" linear prediction for situations in which indicators are available in one data set but can be related only to expenditures in another.[8] As such, it represents the best possible "economic" asset index, in the terminology of Stifel and Christiaensen (2007).

Second, this regression-based prediction is consistent with what is sometimes used in proxy-means-tested approaches to targeting populations for social programs. As discussed earlier, principal components analysis has sometimes been used for this purpose, but predicted expenditures are probably more commonly used (Coady et al. 2004).

Third, under some interpretations, predicted expenditures capture a stable component of expenditures. This argument has two variants. If expenditures are measured with substantial random error, then using the prediction is a way of

[6] These aggregates were graciously made available by those authors for Brazil 1996/1997, Nepal 1996, Panama 1997, South Africa 1993, and Vietnam 1992/1993. The other data sets we use were not available to those authors at the time of their analysis.

[7] Albania 2002, Ghana 1991/1992, Nicaragua 2001, and Papua New Guinea 1996 are available online (http://www.worldbank.org/lsms). Uganda 2000 and Zambia 2004 were made available by the agencies responsible for data collection or analysis. Note that all of these data sets use a methodology consistent with Deaton and Zaidi (2002) to calculate total expenditures. The questionnaire in Papua New Guinea was structured and collected slightly differently: the survey took place over two rounds, with expenditure data collected in the second round using the time between the first and second rounds as the reference period. Other surveys typically collected expenditure data based on fixed recall periods (e.g., last seven days, last month, last year).

[8] Note that this is consistent with the way the approach is often carried out (such as in Stifel and Christiaensen 2007)—although not with the "poverty mapping" approach, which includes area-level aggregates as well as interaction terms (in Alderman et al. 2002; and Elbers et al. 2002, 2003). Including various interaction terms into our construction of the predicted per capita expenditures measure typically yields an estimate that has slightly higher congruence with reported per capita expenditures but does not much affect the other comparisons.

purging this measurement error (it cannot, however, address potential systematic biases in the measurement of expenditures). Alternatively, if asset ownership and housing characteristics relate to the permanent component of expenditures (as a proxy for permanent income), using the prediction is a way of purging transitory shocks to income. Under this interpretation, predicted per capita expenditures forms a perhaps more "legitimate" comparison point for the other asset indices, as opposed to reported per capita expenditure, since predicted expenditures purges out this extra source of variability.

Fourth, in the context of regression analysis, an instrumental variables approach to estimating the impact of expenditures on an outcome is sometimes used as a way of purging the effects of statistical endogeneity: using predicted per capita expenditures in our analysis mimics such an approach. For example, in order to ensure that their estimates of the impact of household per capita expenditures (as a proxy for income) on school participation in Vietnam were not biased because of measurement error, reverse causation, or other sources of endogeneity, Behrman and Knowles (1999) used a set of consumer durables and other longer-run characteristics of households as instruments for expenditures. Benefo and Schultz (1996) used a similar approach when studying the impact of household per capita expenditures on fertility and child mortality in Cote d'Ivoire.

The second asset index we consider uses principal components analysis to derive weights: the *principal components index using all indicators* (sometimes shortened in this article to *principal components index*).[9] This method, along with factor analysis, has been used in much of the recent literature. Principal components analysis posits an underlying structure relating the indicator variables to a set of latent factors:

$$\begin{aligned}\widetilde{a}_{1i} &= (v_{11} \cdot A_{1i}) + (v_{12} \cdot A_{2i}) + \ldots + (v_{1k} \cdot A_{ki}) \\ &\ldots \\ \widetilde{a}_{ki} &= (v_{k1} \cdot A_{1i}) + (v_{k2} \cdot A_{2i}) + \ldots + (v_{kk} \cdot A_{ki}),\end{aligned} \tag{3}$$

where the $\tilde{a}$s are the k asset indicators (a's in Eq. 1) normalized by their means and standard deviations, as are the k principal components; and vs are the weights that relate the principal components to the ownership of the assets.[10] Since only the left side of these equations is observed, principal components analysis imposes a set of restrictions on the relationship between the components (they are orthogonal to one another) and on the vs (the sum of their squares sums to 1) to solve the system. Once the vs have been estimated, inverting the system (3) yields the following set of equations:

$$\begin{aligned}A_{1i} &= (b_{11} \cdot \widetilde{a}_{1i}) + (b_{21} \cdot \widetilde{a}_{2i}) + \ldots + (b_{k1} \cdot \widetilde{a}_{ki}) \\ &\ldots \\ A_{ki} &= (b_{1k} \cdot \widetilde{a}_{1i}) + (b_{2k} \cdot \widetilde{a}_{2i}) + \ldots + (b_{kk} \cdot \widetilde{a}_{ki}).\end{aligned} \tag{3'}$$

[9] See Jolliffe (2002) for a useful textbook treatment of principal components analysis.

[10] Factor analysis allows for an indicator- and household-specific error term in these equations.

The equation with maximal variance is defined as the first principal component. The weights used to create the asset index are therefore the set (b_{11}, b_{21}, . . . , b_{k1}).[11]

The next asset index we consider is also based on principal components but uses only the indicators that reflect ownership of household consumer durables: *principal components using only assets*. As discussed in the previous section, there has been some discussion in the literature about which of the indicators should be included. Some authors have expressed concern about variables that affect outcomes directly (such as water source in health outcome analysis) as well as variables that reflect availability of publicly provided utilities (such as use of electricity for lighting). This variant of the principal components index explores the implications of excluding all indicators measuring housing quality, drinking water source, and type of toilet, as well as availability of electricity and source of cooking fuel.

The next index is derived from an item response theory analysis of the data, the *IRT index*. The underlying model assumes that each of the k indicators is determined through the following relationship:

$$\Pr(a_{ki} = 1|A_i) = \frac{\exp(\alpha_k(A_i - \beta_k))}{1 + \exp(\alpha_k(A_i - \beta_k))}, \tag{4}$$

where, in the IRT literature, α_k is called the "discrimination" parameter for the kth indicator, β_k is the "difficulty" parameter, and A_i is the latent factor (often called the "θ") for the ith household. The IRT methodology estimates the αs and βs after conditioning on A_i and then derives an *ex-post* estimate of A_i.[12]

The next index is the sum of the asset indicators in which each asset is weighted by the share of the population that does not own the asset, the *share weighted average*. More formally,

$$A_i = (w_1 \cdot a_{1i}) + (w_2 \cdot a_{2i}) + \ldots + (w_k \cdot a_{ki}), \tag{5}$$

[11] Principal components analysis produces k components. These are typically ordered from the one that has the largest variance (the first principal component) to the one that has the least. There is no theoretical basis for labeling the first component as representing economic status. The assumption underlying this interpretation is that it is economic status that explains the maximum variance (and covariance) of the various indicators. The evidence presented in this article lends credence to this assumption. It is much harder to interpret higher-order components. As discussed in Filmer and Pritchett (2001), visual inspection of the results suggests that the second component frequently "captures" rich rural households (in the sense that asset indicators associated with these households get high weight, and those that are not get low, or negative, weight). But this is not true across all the countries in the present analysis. Note that these higher-order components are, by construction, orthogonal to the first, so they will not bias the bivariate comparisons of the asset index and outcomes of interest. (See Filmer and Pritchett (2001) for further discussion.)

[12] The open-source software ICL was used for estimating the IRT model. It is available at http://www.b-a-h.com/software/irt/icl. Note that only binary variables can be included, which means that rooms per person is dropped. Moreover, only assets whose ownership increases with the latent factor can be considered in this index. Some assets or housing characteristics are therefore dropped in the construction of the IRT index. When we repeat the principal components on this slightly reduced set of indicators, the results are extremely similar. See van der Linden and Hambleton (1997) and Baker and Kim (2004) for textbook treatments of IRT.

where $w_k = \frac{1}{N}\sum_{i=1,N}(1 - a_{ki})$. That is, if a_k is a binary indicator of the ownership of indicator k, then w_k is the share of the population who does not own that asset.[13]

Next is the index created by simply summing the number of assets owned and indicators for housing quality, the *count index*. In this index, all of the bs of Eq. 1 are equal to 1:

$$A_i = a_{1i} + a_{2i} + \ldots + a_{ki}. \tag{6}$$

The last index we consider captures the value of assets owned divided by the number of household members: *per capita value of durable goods*. Since only durable goods have a readily defined resale value, this index includes only consumer durables and excludes the housing characteristic indicators. The value of each asset is defined as the current resale value reported by the household respondent in the questionnaire. The index is therefore

$$A_i = [(p_{1i} \cdot a_{1i}) + (p_{2i} \cdot a_{2i}) + \ldots + (p_{ki} \cdot a_{ki})]/H, \tag{7}$$

where ps are the reported resale value (the "price") of each asset and H is household size. Note that the resale value is household-specific and subject to the measurement error that it is reported by a respondent who has not actually tried to sell the item at the reported price.

Data

The data sets we use are from the Living Standards Measurement Study program (www.worldbank.org/lsms) or from similarly designed large-scale household surveys (details are in Table 6 in the Appendix). The data are from 11 countries: four data sets are from sub-Saharan Africa (Ghana, South Africa, Uganda, and Zambia), three are from Latin America (Brazil, Nicaragua, and Panama), three are from Asia/the Pacific (Nepal, Papua New Guinea, and Vietnam), and one is from Europe (Albania). The percentage of the population living on less than \$1 a day ranges widely: six of the surveys are from countries with a very high share of the population living in extreme poverty (more than 30% live on less than \$1 a day in Ghana, Nepal, Nicaragua, Papua New Guinea, Uganda, and Zambia), two are from countries with a high share in extreme poverty (between 10% and 18% in South Africa and Vietnam), and three are from countries with a relatively small share of the population living in extreme poverty (less than 10% in Albania, Brazil, and Panama).

The data are all from surveys that were designed to be nationally representative (typically with sampling weights, which are used throughout this analysis), with sample sizes ranging from 1,141 households in Papua New Guinea to more than 10,500 in Uganda.[14] Most of the surveys were carried out in the 1990s, but four of them were fielded after 2000.

[13] This index, like the count index, uses the same reduced set of indicators as the IRT index because only binary assets or characteristics whose ownership increases with the index can be included.

[14] In rare cases, parts of the country were excluded. For example, the Brazilian survey covers only the southeast and northeast regions of the country. In Uganda, one region of the country was not sampled because of security reasons. Surveys typically used cluster sampling; robust standard errors are used for inference in this analysis.

The asset indicators used in each of these data sets are similar to those in situations in which the asset index approach is typically used, for example, the analysis of Demographic and Health Survey data. The indicators cover household ownership of consumer durables, such as a radio, a television, a bicycle, a car; and characteristics of the dwelling in which the household lives, such as characteristics of the flooring, the roofing, main source of drinking water, type of toilet facilities, main source of lighting, and cooking fuel. We use all available indicators (as a typical analyst might). We note that the set of indicators varies across countries, potentially introducing an additional source of variability in the approach across countries.[15] The data sets contain between 12 (Uganda) and 29 (Nicaragua) indicators of asset ownership, and between 4 (Ghana) and 12 (Albania) indicators of housing characteristics (Zambia is an exception at 37).[16]

Results

We begin this section by assessing how household rankings differ when the alternative approaches to measuring economic status are used; we then assess how gradients in outcomes differ; and we end by assessing the variation in household attributes, such as rural/urban location, size, and composition.

Relative Rankings

We use two approaches to compare household rankings. The first compares the simple correlation of household rankings across the different measures. This gives an indication of the difference across the entire population. The second estimates the share of the population that is simultaneously ranked in the poorest quintile by different measures. This focuses on the way in which these types of aggregations are often used—namely, identifying individuals and households in the poorest tail of the economic status distribution.

Household Rankings

The various measures yield statistically significantly related household rankings. The Spearman rank correlation between per capita expenditures and all the asset indices is typically greater than .5 (top panel of Table 1).[17] Unsurprisingly, predicted per capita expenditures yield the most similar household rankings to per capita expenditures: the rank correlation coefficients range from .42 in Zambia to .84 in Brazil, with a mean of .66 across the 11 countries (Table 1, column 2). The rank correlation of per capita expenditures with the other indices averages about .5. For the principal components index that uses all indicators, the rank correlation with per capita expenditures ranges from .39 in Zambia to .72 in Brazil (Table 1, column 3).

[15] Importantly, our results are robust to reducing the list of indicators to the set of "durable goods" only, which are more similar across countries. Also, the degree of congruence between expenditures and asset indices is not related to the number of asset indicators used.
[16] The full list of indicators for each data set is in Online Resource 2.
[17] Correlations of rankings in this article refer to Spearman rank correlations.

Table 1 Rank correlation coefficients between welfare indices across households

	Per Capita Household Expend. (1)	Predicted per Capita Household Expend. (2)	PC Index, All Indicators (3)	PC Index, Assets Only (4)	IRT Index (5)	Share Weighted Average (6)	Count Index (7)	Per capita Value of Durable Goods (8)
Correlation with ranking by per capita household expenditures								
Albania	1	.64	.47	.45	.45	.45	.44	.63
Brazil	1	.84	.72	.71	.72	.68	.68	—
Ghana	1	.47	.43	.37	.44	.30	.34	.33
Nepal	1	.60	.48	.41	.43	.42	.44	.53
Nicaragua	1	.77	.71	.67	.69	.64	.66	.71
Panama	1	.79	.70	.67	.68	.65	.66	.65
Papua New Guinea	1	.57	.47	.46	.47	.48	.49	.53
South Africa	1	.79	.67	.60	.66	.59	.58	—
Uganda	1	.68	.55	.39	.53	.45	.41	—
Vietnam	1	.71	.61	.62	.59	.61	.59	.62
Zambia	1	.42	.39	.37	.38	.40	.40	.53
Average	1	.66	.56	.52	.55	.52	.52	.57
Correlation with ranking by principal components index which uses all indicators								
Albania	.47	.81	1	.95	.99	.94	.96	.73
Brazil	.72	.85	1	.99	.99	.97	.99	—
Ghana	.43	.89	1	.89	.98	.79	.86	.44
Nepal	.48	.86	1	.81	.95	.96	.94	.58
Nicaragua	.71	.94	1	.96	.99	.88	.93	.82
Panama	.70	.90	1	.98	1.00	.95	.97	.70
Papua New Guinea	.47	.77	1	.92	.96	.92	.88	.73
South Africa	.67	.84	1	.93	.98	.93	.93	—
Uganda	.55	.86	1	.76	.96	.87	.80	—
Vietnam	.61	.84	1	.89	1.00	.97	.98	.73
Zambia	.39	.92	1	.89	.95	.96	.95	.74
Average	.56	.86	1	.91	.98	.92	.93	.68

Notes: A dash indicates that data are not available. Cross-country averages are unweighted.

The range is similar for the other indices, and Ghana and Zambia always have the lowest and Brazil always has the highest rank correlation. Although these rankings are related, the correlations are not systematically high.

The rank correlation among the various asset indices is very high. The correlation between the ranking derived from principal components using all indicators and the other asset indices is typically greater than .8 (bottom panel of Table 1). Even predicted per capita expenditures is highly related to the principal components index: the correlation ranges from .77 (Papua New Guinea) to .94 (Nicaragua) and has an average of .86 across the countries. The correlation between the principal components index and the other asset indices is typically even higher.[18]

The per capita value of durable goods is not closely correlated with the other asset indices. While it has about the same rank correlation with per capita expenditures as the other indices, its correlation with the principal components index using all indicators is lower (.66 versus more than .90 for the others). However, the mean rank correlation is higher between the per capita value of durables and the principal components index (.68) than between the per capita value of durables and per capita expenditures (.57)—and this is true for every country. The asset indices are therefore more closely related to the per capita value of durables than they are to per capita expenditures.

Overlap in Classifications

Not quite half the people categorized as being in the poorest quintile by per capita expenditures are also in the poorest quintile according to the other welfare measures (top panel of Table 2). The overlap for per capita expenditures and predicted per capita expenditures—the benchmark for the "best" linear prediction of per capita expenditures given the asset indicators—ranges from 42% (Zambia) to 72% (Panama), with a mean of 50%. The overlap for the principal components index using all indicators is only slightly lower, with a range of 40% (Zambia) to 71% (Panama), a pattern that holds across all the other asset indices. The overlap is bigger within the class of asset indices: typically around 70% of people classified as being in the poorest quintile by one asset index are also so classified by another asset index (bottom panel of Table 2). The exception, again, is the measure of the per capita value of durable goods. Among asset indices, the principal components ranking is most closely related to the IRT index ranking (85% overlap, on average, with more than 95% overlap in Brazil, Panama, and Vietnam).

When people are classified as being in a different quintile, how much of a mismatch is there? Of the people in the poorest quintile by per capita expenditures, the asset indices classify on average about 75% in the poorest two quintiles (top panel of Table 3). Virtually all of those classified in the poorest quintile by the principal components index using all indicators are classified as being in the poorest two quintiles by the other indices (bottom panel of Table 3).

In sum, households are certainly re-ranked by different measures of economic status. There is a fairly tight matching, however, among the various asset indices—including predicted per capita expenditures. But between per capita expenditures and the asset indices, the reclassification is by more than one quintile for a quarter of all individuals. If one believes that transitory shocks or measurement error are large, one could argue that asset indices capture permanent income (as argued by Filmer and Pritchett (2001) and Sahn and Stifel (2003)) and might therefore be preferable for identifying the more permanently poor. Without panel data, it is hard to conclusively

[18] Some of the differences between the PC index and the IRT, share-weighted, and count indices come from the fact that the latter set uses a slightly reduced list of indicators. Repeating the analysis but using only the same set of indicators for the PC index increases the rank correlation coefficients by between 0 and .07 points, with an average increase of .02 points.

Table 2 Overlap in the classification in the *poorest quintiles*

	Per Capita Household Expend. (1)	Predicted per Capita Household Expend. (2)	PC index, All Indicators (3)	PC index, Assets Only (4)	IRT Index (5)	Share Weighted Average (6)	Count Index (7)	PC Value of Durable Goods (8)
Proportion of the population classified in the poorest 20% by per capita household expenditures who are in the poorest 20% according to other welfare indices								
Albania	1	.47	.42	.41	.41	.37	.38	.47
Brazil	1	.68	.64	.62	.63	.57	.63	—
Ghana	1	.37	.42	.39	.40	.33	.38	.32
Nepal	1	.36	.34	.32	.30	.32	.30	.35
Nicaragua	1	.56	.51	.46	.50	.48	.49	.52
Panama	1	.72	.71	.69	.70	.65	.70	.65
Papua New Guinea	1	.36	.34	.27	.32	.32	.33	.34
South Africa	1	.48	.43	.38	.43	.43	.42	—
Uganda	1	.52	.48	.43	.51	.47	.48	—
Vietnam	1	.54	.49	.50	.47	.49	.48	.49
Zambia	1	.42	.40	.40	.40	.41	.42	.40
Average	1	.50	.47	.44	.46	.44	.46	.44
Proportion of the population classified in the poorest 20% by the principal components index using all indicators who are in the poorest 20% according to other welfare indices								
Albania	.42	.74	1	.83	.91	.70	.83	.68
Brazil	.64	.82	1	.93	.96	.81	.93	—
Ghana	.42	.71	1	.68	.78	.38	.50	.26
Nepal	.34	.71	1	.58	.81	.86	.81	.46
Nicaragua	.51	.81	1	.80	.85	.50	.63	.53
Panama	.71	.91	1	.87	.96	.81	.88	.72
Papua New Guinea	.33	.46	1	.77	.61	.39	.38	.24
South Africa	.44	.54	1	.57	.85	.73	.66	—
Uganda	.48	.74	1	.66	.85	.78	.72	—
Vietnam	.49	.67	1	.71	.95	.84	.88	.63
Zambia	.40	.77	1	.76	.80	.79	.80	.62
Average	.47	.72	1	.74	.85	.69	.73	.52

Notes: A dash indicates that data are not available. Cross-country averages are unweighted.

address this issue. In this article, we limit ourselves to the less ambitious goal of documenting data regularities and exploring correlates of differences.

Differences in Education, Health, and Labor Market Outcomes

The previous discussion focused on how household rankings changed with the use of different economic status measures. A frequent concern, however, is the extent to

Table 3 Overlap in the classification in the *poorest quintile* by one measure and the *poorest two quintiles* by another

	Per capita Household Expend. (1)	Predicted per Capita Household Expend. (2)	PC index, All Indicators (3)	PC Index, Assets Only (4)	IRT Index (5)	Share Weighted Average (6)	Count Index (7)	Per capita Value of Durable Goods (8)
Proportion of the population classified in the poorest 20% by per capita household expenditures who are in the poorest 40% according to other welfare indices								
Albania	1	.73	.68	.68	.68	.65	.66	.78
Brazil	1	.93	.90	.90	.90	.87	.88	—
Ghana	1	.65	.69	.65	.69	.63	.64	.61
Nepal	1	.63	.59	.60	.50	.55	.54	.65
Nicaragua	1	.88	.87	.84	.86	.80	.82	.86
Panama	1	.93	.91	.91	.92	.90	.90	.89
Papua New Guinea	1	.63	.65	.64	.65	.65	.68	.63
South Africa	1	.79	.76	.74	.77	.75	.75	—
Uganda	1	.78	.73	.69	.75	.73	.72	—
Vietnam	1	.81	.77	.79	.75	.76	.75	.78
Zambia	1	.73	.71	.68	.70	.72	.72	.70
Average	1	.77	.75	.74	.74	.73	.73	.54
Proportion of the population classified in the poorest 20% by the principal components index using all indicators who are in the poorest 40% according to other welfare indices								
Albania	.68	.95	1	1.00	1.00	.95	1.00	.91
Brazil	.88	.97	1	1.00	1.00	.99	1.00	—
Ghana	.66	.97	1	.94	1.00	.72	.83	.50
Nepal	.60	.92	1	.90	1.00	1.00	.97	.70
Nicaragua	.79	.99	1	1.00	1.00	.91	.96	.87
Panama	.91	.99	1	1.00	1.00	.99	1.00	.93
Papua New Guinea	.60	.88	1	.96	1.00	.97	.96	.87
South Africa	.71	.87	1	.99	1.00	.95	1.00	—
Uganda	.71	.94	1	.97	1.00	.96	.99	—
Vietnam	.73	.91	1	1.00	1.00	.99	1.00	.89
Zambia	.65	1.00	1	.99	1.00	1.00	1.00	.87
Average	.72	.94	1	.98	1.00	.95	.97	.59

Notes: A dash indicates that data are not available. Cross-country averages are unweighted.

which findings or inferences about inequalities in outcomes or behaviors might differ by the economic status measure used. To shed light on this issue, we look at a set of outcome and behavioral indicators in the areas of education, health, and labor markets. The specific indicators used—enrollment rate and primary school completion, the use of medical care, fertility, child mortality, and labor market participation—were chosen as being typical in the analyses of social sector outcomes as well as being systematically definable across the data sets used here. In each case, the variable of interest is regressed on dummy variables for quintiles (with the poorest quintile as the reference group) and dummy variables for age and gender.[19] Figures 1 through 5 display, for each country and for each economic status measure, the predicted average outcome for each quintile, setting the dummy variables for the other quintiles to zero and the other correlates to their means.

Figure 1 displays inequalities in the school participation rate among youths 7 to 19 years old and in the completion of grade six among youths 15 to 19 years old.[20] In Brazil, for example, 67% of 7- to 19-year-olds in the poorest per capita expenditure quintile are in school, compared with 97% in the richest quintile—as predicted from the multivariate regression that controls for age and gender. In contrast, 64% of youths in the poorest principal component quintile (using all indicators) are in school, as compared with 98% in the corresponding richest quintile. The difference-in-differences (i.e., the difference between the rich-poor gap using the principal component index and the rich-poor gap using per capita expenditures) ranges from −2 percentage points (in Nepal) to 17 percentage points (in Zambia). The values are positive in all but one case (Nepal) and statistically significant in 7 of the 11 countries (the small negative value in Nepal is not statistically significant).

In general, for the two education outcomes, the pattern is similar across all countries: the different economic status measures yield extremely similar rich-poor gaps in outcomes. The difference between the richest and poorest quintiles in school participation and sixth-grade completion are statistically significantly different from zero for all countries and for all economic status measures. The rich-poor gaps tend to be larger when asset indices are used than when per capita expenditures are used, and this difference-in-differences is often (but not always) statistically significant.

Figures 2 and 3 display inequalities in the use of health services; Fig. 2 is limited to children less than 5 years old, while Fig. 3 is limited to people 16 and older. The top panel refers to the proportion in each quintile who have visited a medical provider in the past month, and the bottom panel refers to the proportion who have visited a private-sector provider.[21] The results are more variable than those for education. Economic status gradients are similar across the set of asset indices; however, the pattern in the comparison between per capita expenditures and the asset indices is less systematic. For example, the rich-poor gap in the proportion of children obtaining medical care is smaller with asset index quintiles than with per

[19] We use linear probability models throughout this analysis. We experimented with probit and logit models and compared marginal and predicted probabilities. The results are extremely similar and the conclusions are unaffected.

[20] Statistical significance for the estimates underlying Figs. 1, 2, 3, 4 and 5, based on robust standard errors that allow for clustering, are in the tables in Online Resource 3. Tests of the significance of differences in the estimates of coefficients across models are based on simultaneous equations modeling using seemingly unrelated regressions estimation (SURE).

[21] Consistent with Dow (1996), these estimates do not condition on self-reported health status, which may be systematically related to socioeconomic status. We do not study self-reported illness directly because of the potential problem of biased self-reporting: if the poor are less likely to recognize illness—perhaps because the implicit cost of doing so is high—then it is unclear what the economic status gradient in self-reported illness actually represents. This issue is discussed in Butler et al. (1987), Deolalikar (1998), Sindelar and Thomas (1991), and Strauss and Thomas (1996).

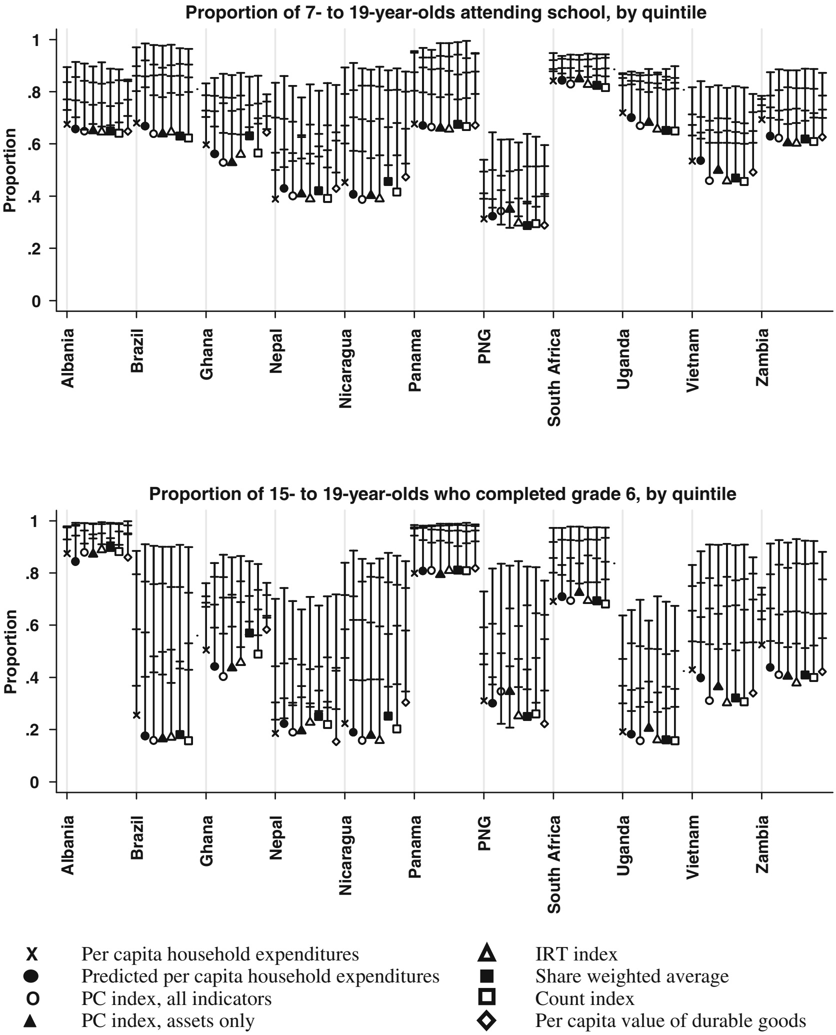

Fig. 1 Differences in education outcomes by quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile after controlling for dummy variables for age and gender. PNG refers to Papua New Guinea

capita expenditure quintiles. This difference-in-differences is statistically significant in Brazil, South Africa, Uganda, and Vietnam.

In two countries, different measures yield statistically significantly different implications about the importance of economic status as a correlate of medical care visits. In Brazil, being in the richest per capita expenditure quintile is associated with an 8.7 percentage point higher likelihood of having consulted a medical provider, compared with the poorest quintile; but the gap derived from the principal components index is only 1.2 percentage points and is not statistically significantly different from zero. In Zambia, the sign of the gap switches: poor children are more likely to have been taken to a medical provider when the asset indices are used to derive quintiles. In both these countries, the results are driven by the fact that poor

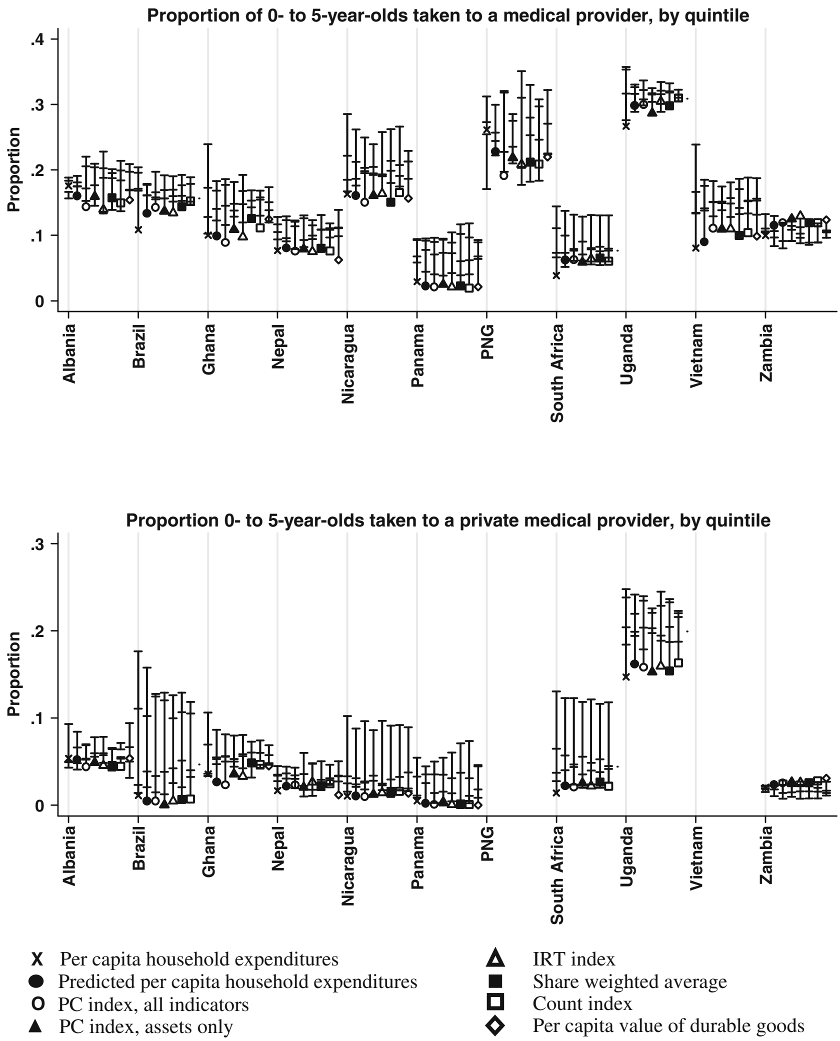

Fig. 2 Differences in child medical provider usage by quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile after controlling for dummy variables for age and gender. PNG refers to Papua New Guinea

people—as measured by the asset index—are more likely to have been reported ill (the share is roughly equal across quintiles when per capita expenditures are used). Therefore, even though fewer seek care conditional on illness, they are more likely to have sought care when one does not condition on illness.

The results for seeking private care are qualitatively similar. In most cases, the different measures yield the same conclusion about the importance of economic status for medical care–seeking behavior—and in only one case (Zambia) is the size of the rich-poor differential not statistically significantly different from zero. For care-seeking behavior among adults, the magnitudes of the gaps are typically smaller using the asset index, but the results would not be misleading about the statistical

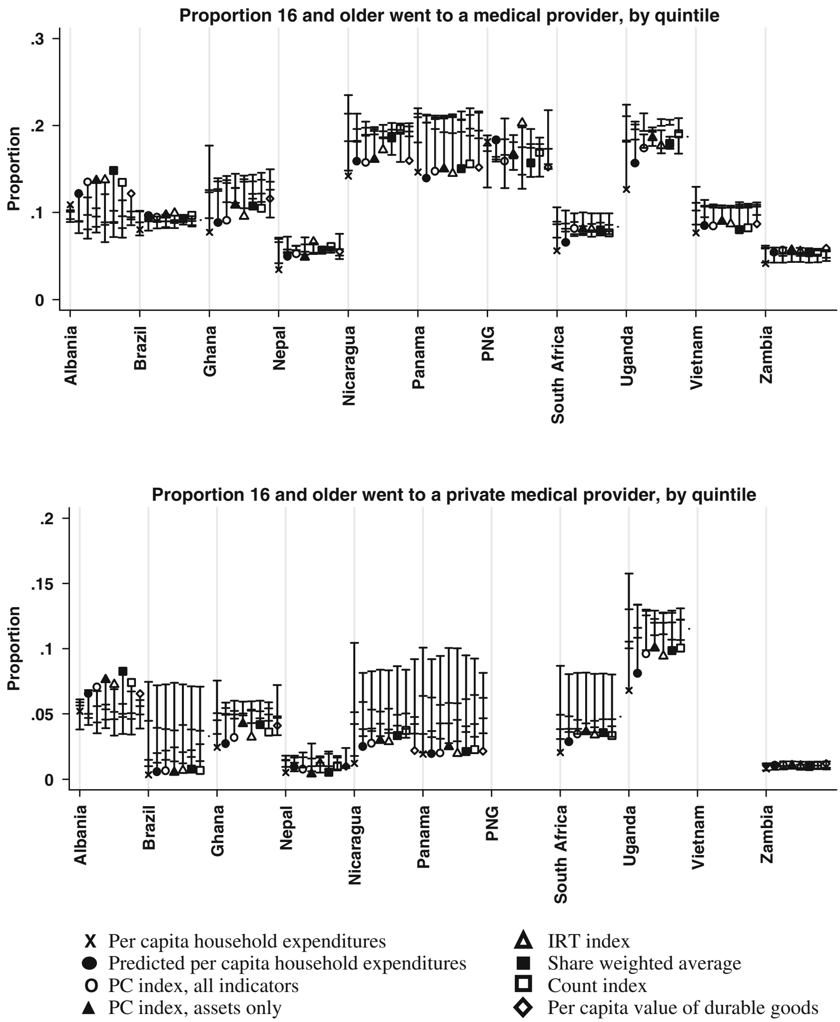

Fig. 3 Differences in adult medical provider usage by quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile after controlling for dummy variables for age and gender. PNG refers to Papua New Guinea

significance of economic status as a correlate of behavior (again, with the exception of Zambia).

Figure 4 shows results for the number of children ever born to women currently aged 20 to 35 (top panel) and for the proportion of those children who are no longer alive (bottom panel). Differences in (and levels of) the number of births born to women are very consistent, regardless of the economic status measure used. Nepal is the only country for which the measure used makes a big difference: the gap between the richest and poorest quintiles in the average number of children born is slightly more than 1 child using per capita expenditures, but it is closer to half a child when the asset index is used (although both of these gaps are statistically significantly different from zero). In general, however, the asset indices all produce

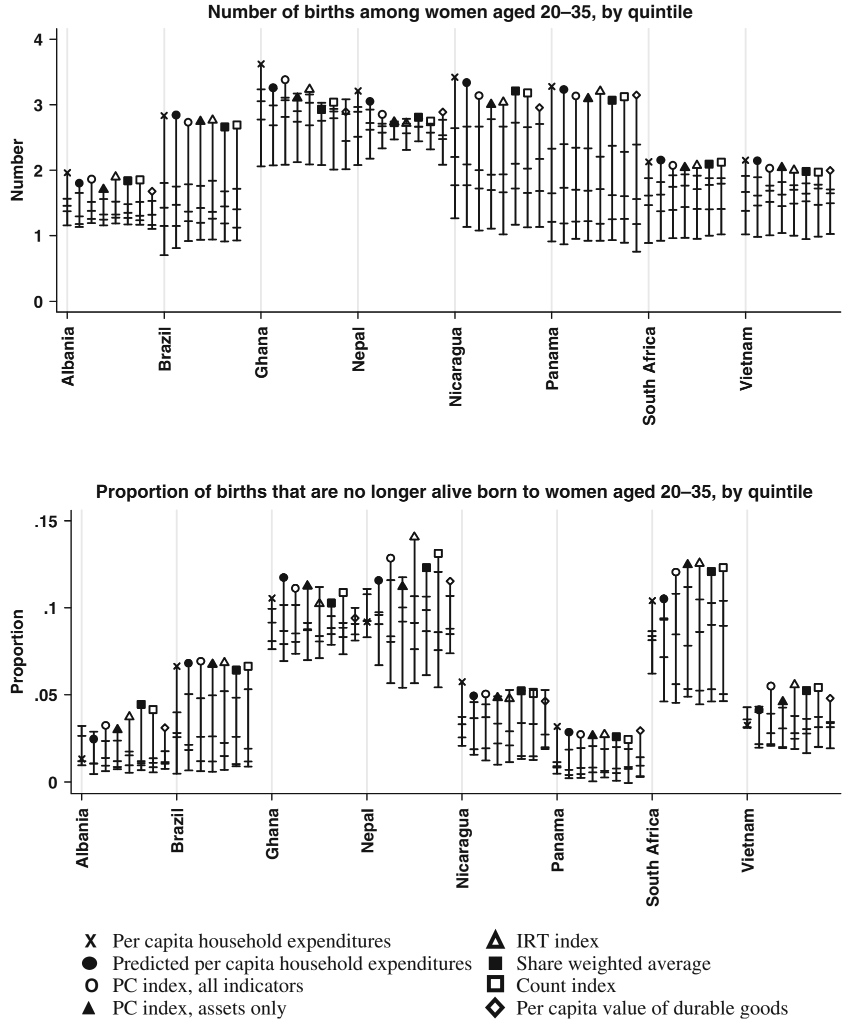

Fig. 4 Differences in fertility and child mortality quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile after controlling for dummy variables for women's age

similar gaps across quintiles. In some cases, per capita expenditure quintiles yield smaller differences between child mortality in rich and poor households (the difference-in-differences is statistically significant in Albania, Nepal, South Africa, and Vietnam). In Albania, Nepal, and Vietnam, the highest level of mortality is not in the poorest quintile when per capita expenditures are used. On the other hand, in all countries, all of the asset indices (including predicted per capita expenditures) suggest that the highest level of mortality is in the poorest (or next-to-poorest) quintile.

Figure 5 shows results for female labor participation and for the overall (male and female) proportion of the labor force that is self-employed. Once again, the rich-poor gap is fairly insensitive to the economic status measure used. Per capita expenditure quintiles tend to suggest flatter rich-poor gradients in several countries, especially for

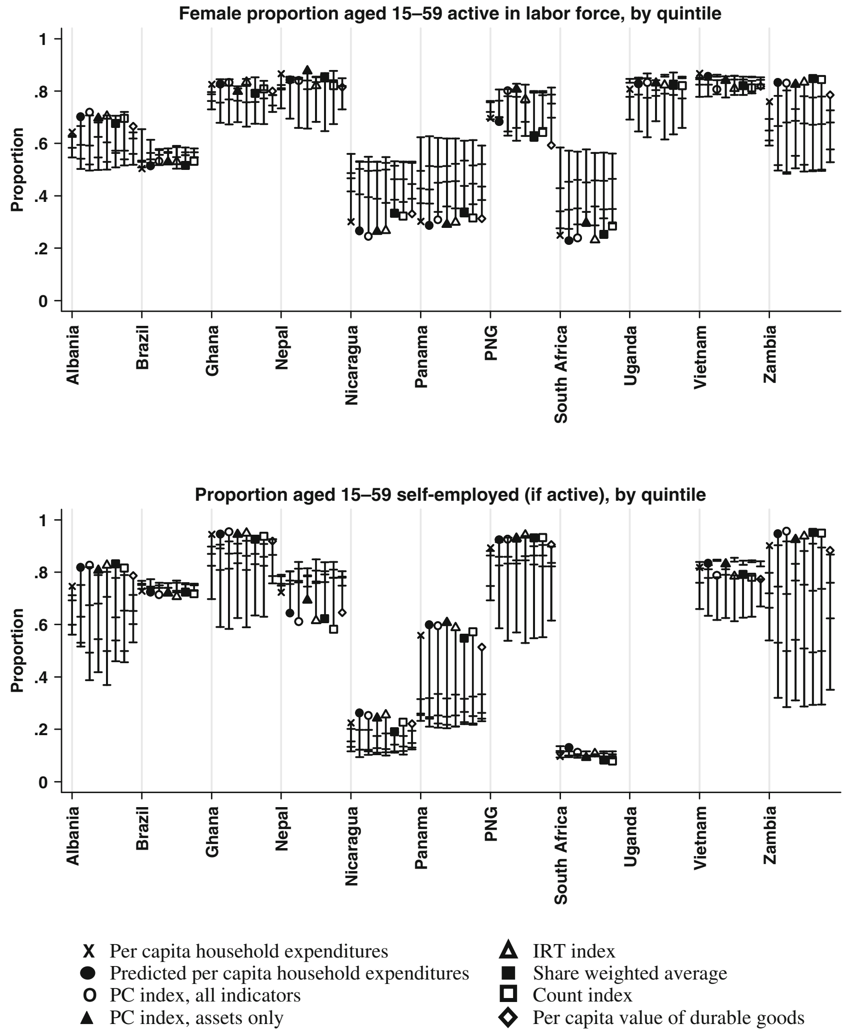

Fig. 5 Differences in labor force outcomes by quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile after controlling for dummy variables for age and, in the bottom panel, gender. PNG refers to Papua New Guinea

self-employment. The difference-in-differences (comparing the principal components index to per capita expenditures) is statistically significant in seven of the countries for labor force participation and in six of the countries for self-employment. But conclusions about the statistical significance of the importance of economic status as a correlate of labor outcomes are the same regardless of whether per capita expenditures or asset indices are used to derive quintiles.

Household Location, Size, and Composition

The results so far suggest that despite household re-rankings, conclusions about inequalities across quintiles in education outcomes, health care–seeking behavior, fertility, and child mortality, as well as labor market outcomes, are not very sensitive to the particular economic status measure used to classify households. Two indicators are potentially more sensitive. First, Lindelow (2006) argued that an asset index in Mozambique is more likely than per capita household expenditures to identify rich households as being urban, suggesting that urban/rural residence might differ systematically across economic status measures. Second, per capita expenditures is, by construction, scaled by household size, whereas the asset indices incorporate no such adjustment; thus, household size (and, as discussed below, household composition) may differ systematically as well.

The top panel of Fig. 6 shows the proportion of the population that is urban for each country, economic status measure, and quintile.[22] The difference in urbanization between the poorest and richest quintiles is indeed always statistically significantly larger when the principal components asset index is used than when per capita expenditures are used. The largest difference in the rich-poor gap in urbanization is in Albania, where it is 75 percentage points by the principal components index but only 22 percentage points by per capita expenditures—or a difference-in-differences of more than 53 percentage points. The difference-in-differences is 50 percentage points in Zambia, on the order of 20 percentage points in Ghana and Nicaragua, and smaller in the other countries.

Rich-poor differences in household composition are also substantively different when the different economic status measures are used. The bottom panel of Fig. 6 shows that differences in household size are much larger when per capita expenditures are used. Moreover, the poorest quintile has the largest household size in all countries when per capita expenditures are used. The difference relative to the richest quintile can be quite large: up to almost 4.5 household members in South Africa. On the other hand, the principal components index typically yields a smaller rich-poor gap that never exceeds 1.6 household members (also South Africa). The difference-in-differences (comparing the principal components index to per capita expenditures) is statistically significantly different from zero in all the countries and ranges from 1.5 (Vietnam) to almost 5 (Zambia). Importantly, rankings by asset indices do not always imply that the poorest households are the largest. In Nepal, Uganda, Vietnam, and Zambia, the asset indices suggest that the poorest households have the fewest household members.

Figure 7 shows differences across quintiles and economic status measures of two variables characterizing household composition: female headship (top panel) and the dependency ratio (bottom panel).[23] It is hard to discern a pattern across countries or indices in the extent of female headship. The rich-poor gap tends to be larger for the asset indices than for expenditures, and this happens both in places where female-headed households are concentrated in the poorest (e.g., Nicaragua) and the richest (e.g., Zambia) quintiles. On the other hand, the dependency ratio is

[22] The definition of *urban* differs across countries. For the purpose of this analysis, we use the definition as described in the context of each data set.

[23] The dependency ratio is defined here as the ratio of the number of household members less than 16 years old plus those aged 60 or older, divided by total household size.

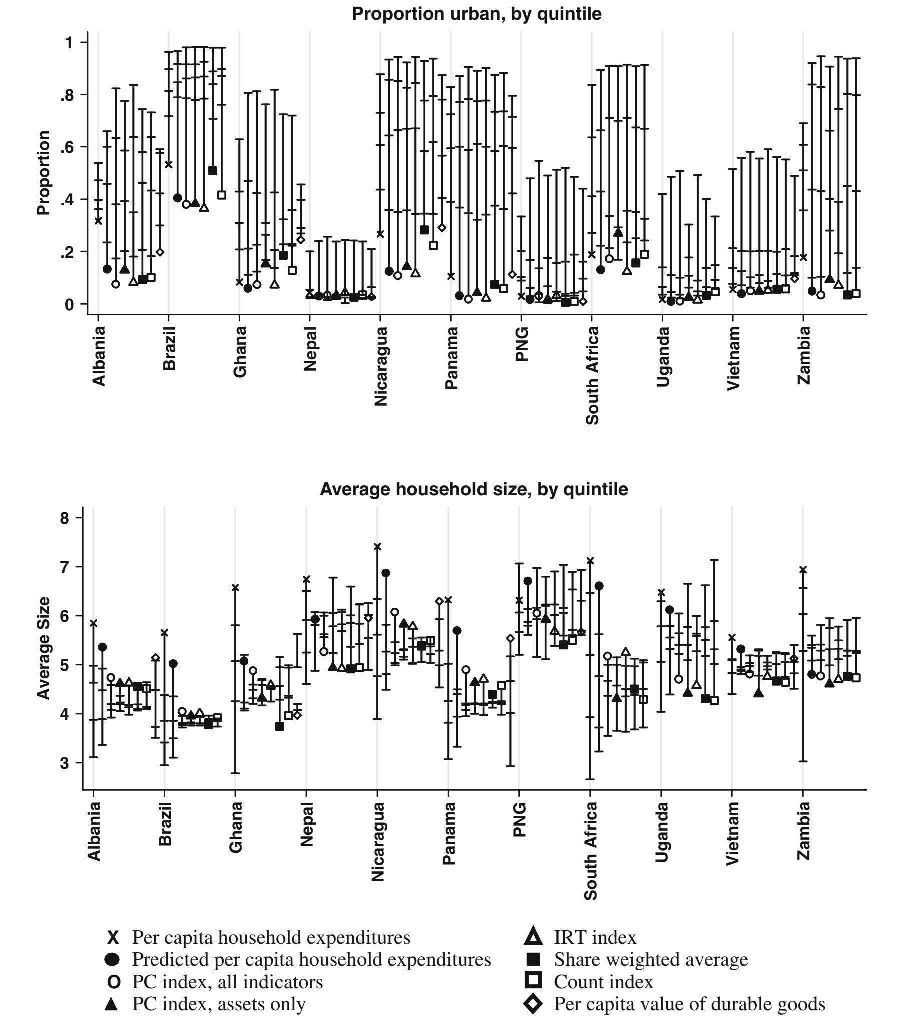

Fig. 6 Differences in urban location and in household size by quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile. PNG refers to Papua New Guinea

always larger in the poorest households, regardless of the economic status measure used. The rich-poor gap in the dependency ratio is virtually always larger when per capita expenditures are used than when the asset indices are used (with the difference-in-differences being statistically significantly different from zero in 9 of the 11 countries).

In sum, while the gradients in human development outcomes are largely consistent across the different economic status measures, gaps in urbanization and household demographic composition are substantially different. In particular, the poor according to asset indices are more likely to be in rural areas than the poor according to expenditures. At the same time, while the poor according to

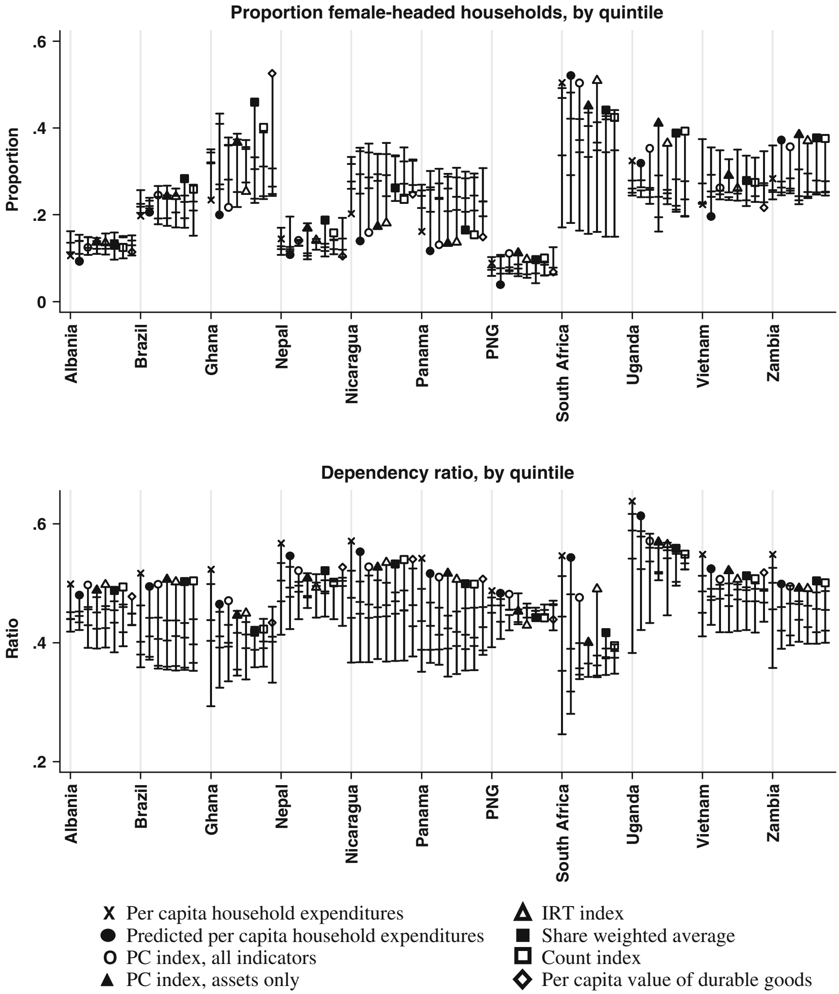

Fig. 7 Differences in female headship and the dependency ratio by quintile using various welfare measures. Symbols indicate the poorest quintile. Each marking shows the predicted gap from the previous quintile. PNG refers to Papua New Guinea

expenditures are systematically in larger households, the rich-poor gap in household size is much less pronounced when an asset index is used.

Congruence and Divergence in Rankings

The results so far suggest that inferences about the association between welfare measures and outcomes are quite robust to the measure used. At the same time, expenditures and asset indices do not always identify the same households as poor. In this section, we investigate factors that might explain congruence in household rankings across different approaches; that is, we seek to address the question of when the alternative approaches are most likely to be different. We focus on two main potential factors that are associated with congruence household rankings: the predictability of expenditures and the treatment of economies of scale within households.[24] Because the various asset indices yielded extremely similar rankings, we focus in this section on the correlation in rankings by expenditures by the principal components index.

The Predictability of Expenditures

There is a mildly positive association between the variability of per capita expenditures and the rank correlation between per capita expenditures and the asset index. Across the 11 countries, the correlation between the congruence (i.e., the rank correlation of per capita expenditures and the principal components asset index) and the standard deviation of log per capita expenditures is .110 (column 2 of Table 4). The result is somewhat intuitive: when there is more inequality in a society, this manifests itself similarly in the expenditure and asset dimensions. However, this association is weak.

There is a much stronger association with the extent to which the variation in per capita expenditures is *explained* by observed household characteristics. This result was predicted by Montgomery et al. (2000), who showed that asset indicators and asset indices will be better proxies for per capita expenditures the higher the *R*-squared of the regression of expenditures on the indicators. Indeed, in this set of 11 countries, the congruence is higher when the *R*-squared of the regression is higher (column 3 of Table 4). This result is quite intuitive: rankings derived from the two approaches will be most similar when assets and expenditures "move together," and therefore assets are able to explain the variation in expenditures.

But it is not just when the explanatory power of the asset indicators themselves is high that there is congruence: the correlation between expenditures and asset index rankings is also higher when the explanatory power of an alternative non-overlapping set of variables is higher. Column 4 of Table 4 reports the share of the variation in per capita expenditures explained by a set of household and cluster social and demographic characteristics that excludes the asset indicators. The approach follows that of the first stage of the "poverty mapping" methodology, described in Elbers et al. (2002, 2003) and Alderman et al. (2002), in which the per capita expenditures measure is regressed, administrative region by administrative region in each country, on urban location, age and sex of the head of household, employment indicators of the head of the household, highest education attained by male and female household members, demographic composition of household, and cluster means of all these variables.[25] The share of the variation explained by these models is similar, or

[24] We also explored the relationships with other potential country and data set characteristics that one might expect to be associated with congruence: the number of assets and the share of their covariance explained by the first principal component; overall poverty in the country; and whether or not education or health expenditures are included in expenditure aggregate. While poverty is weakly negatively related to congruence and the share explained by the first component is weakly positively related to congruence, none of these are significant correlates of congruence. The results are described in Online Resource 4.

[25] The share reported in Table 4 is the total sum of squares explained in these regressions divided by the overall sum of squares. Clusters are the lowest sampling unit used in the survey: they are typically the primary sampling unit (PSU) from which 15–30 households are randomly selected.

Table 4 Correlates of congruence between per capita expenditures and asset index rankings

	Congruence (rank correlation between PCE and PC index, all indicators) (1)	Standard Deviation of Log PCE (2)	Proportion of Variation in ln(PCE) Explained by Indicators (R^2) (3)	Proportion of Variation in ln(PCE) Explained by non-indicators (4)	Share of Food in Total Household Expenditures (5)	Proportion of Variation in ln(nonfood PCE) Explained by Indicators (R^2) (6)	Proportion of Variation in ln(nonfood PCE) Explained by Non-indicators (7)
Albania	.47	0.52	.41	.40	.64	.48	.35
Brazil	.72	0.91	.72	.68	.35	.72	.68
Ghana	.43	0.74	.25	.50	.60	.37	.49
Nepal	.48	0.70	.43	.49	.69	.50	.47
Nicaragua	.71	0.76	.64	.54	—	—	—
Panama	.70	0.96	.63	.57	.56	.68	.56
Papua New Guinea	.47	0.87	.36	.56	.64	.41	.61
South Africa	.67	1.09	.65	.69	.44	.66	.70
Uganda	.55	0.72	.49	.45	.55	.50	.43
Vietnam	.61	0.59	.57	.48	.57	.60	.49
Zambia	.39	1.17	.19	.43	.69	.46	.45
Correlation With Column 1	1	.110	.970	.694	–.837	.945	.643

Notes: Column 1 repeats the third column of Table 1; column 2 is the standard deviation of ln(PCE); column 3 is the *R*-squared of the regression of ln(PCE) on all the variables that make up the "all indicators asset index"; column 4 is the explained divided by total sum of squares in region-by-region regressions of ln(PCE) on a set of explanatory variables (urban location; age and sex of the head of household; employment indicators of the head of the household; highest education attained by male and female household members; and demographic composition of household) and their cluster means; column 5 is the number of asset indicators used in the construction of the all indicators asset index; column 6 repeats column 3 but with the nonfood share of expenditure only; and column 7 repeats column 4 but with the nonfood share of expenditures only. A dash indicates that data are not available.

higher, than that in the models that simply include indicators. This share is highly correlated with the congruence between the asset index and per capita expenditures—with a correlation of .694 across data sets.[26]

The intuition for this result is somewhat less clear. One possible explanation is that a high explanatory power, either by the asset indices or by the alternative set of household and cluster characteristics, indicates less measurement error in reported expenditures. By this logic, when measurement error is low, per capita expenditures and an asset index yield similar rankings and *vice versa*. This is consistent with arguments from some researchers that one advantage of an asset index is less measurement error in identifying the long-run "wealth" or "income" that is associated with inequalities in education (Filmer and Pritchett 2001) or child nutritional outcomes (Sahn and Stifel 2003). Those researchers argued, on the basis of results consistent with attenuation bias as well as instrumental variables regressions, that the evidence is consistent with more measurement error in per capita expenditures than in an asset index. The results here are typically consistent with attenuation associated with measurement error: in most of the outcomes considered in Figs. 1 through 7, the rich-poor gap is larger when an asset index is used than when per capita expenditures are used.

Per capita expenditures are certainly measured with error. The literature suggests that the level of aggregation at which consumption and expenditure data are collected affects accuracy (Hentschel and Lanjouw 1996; for an overview, see Deaton and Grosh 2000). It is also hypothesized that the reference periods, use of diaries instead of recall, item and unit nonresponse, and even the assumptions made in the construction of the expenditures aggregate are all potential sources of measurement errors—although there is less evidence on these issues. But the high explanatory power of observed characteristics also potentially indicates a country with a lower share of transitory shocks in expenditures. In such a situation, asset indicators and per capita expenditures are both closely related to the concept of permanent income and therefore are highly related. Indeed, if the research question is the impact of shocks (e.g., health shocks or weather shocks) on human development outcomes, then asset indices would clearly fall short in their ability to shed light on the issue.

While measurement error and transitory shocks are conceptually very different, it is virtually impossible to distinguish between them in a cross-sectional data set (or even a panel data set) without additional assumptions. Therefore, resolving which of these is a better explanation for congruence is probably infeasible based on our data. But one (modest) conclusion consistent with these findings is that when household expenditures are more predictable (because of either to low measurement error or low transitory shocks), then an asset index and per capita expenditures will yield a more similar household rankings.

Adult Equivalence and Economies of Scale Within Households

The fact that expenditures and asset indices yield vastly different economic gradients in household composition (Figs. 6 and 7) suggests an additional explanation for

[26] When asset indicators are included in the set of household characteristics, the share of variance in each country increases by a small amount, but the association with the rank correlation between the assets index and expenditures is similar: the correlation coefficient is .710.

divergence in rankings: per capita expenditures adjust for household size, whereas asset indices do not. In most welfare analyses, expenditures are scaled by the total number of household members before poverty profiles are derived. Deaton and Zaidi (2002) described this as the best benchmark, but they also described various approaches to adjust for household composition and size in order to account for the age of household members as well as for economies of scale within households.

Adjusting for "adult equivalence" attempts to address the issue that children's needs are lower (e.g., their daily caloric requirements are lower than those of adults) and therefore can achieve equivalent levels of welfare at lower levels of consumption. Adjusting for household "economies of scale" attempts to address the issue that household members may benefit from each other's consumption, or because the existence of household public goods (such as a good roof) means that each household member can consume the good (achieving higher welfare) without facing the tradeoff of another member having to consume less (Deaton 1997). A household public good enables higher levels of overall household welfare than an equivalently priced individually consumed good.

Since there is limited theoretical basis for setting the parameters characterizing the equivalence between children and adults and the extent of economies of scale within households, we follow what Deaton and Zaidi described as the *ad hoc* approach by varying these parameters and assess the sensitivity of our results. Specifically, we calculate

$$\text{Adj. expenditures} = (\text{Total expenditures})/(\alpha \times \text{No. of children} + \text{No. of adults})^{\theta}, \quad (8)$$

where α is the equivalence between children and adults, and θ accounts for economies of scale.[27] We then estimate the congruence in rankings at different values of α and θ. Using values of α and θ both equal to 1 is equivalent to scaling by total household size and yields per capita household expenditures; α equal to 1 and θ equal to zero yields total household expenditures.

Figure 8 plots, for each country, congruence (the rank correlation between per capita expenditures and the principal components index) against the economies of scale parameter θ at four different values of the adult equivalence parameter α (e.g., the top-left panel sets α equal to 1, the top-right panel sets α equal to .75). Adult equivalence does not generally affect the results. There is an appreciable difference in the congruence between per capita expenditures and the asset index as α changes in Albania, but in all the other countries, treating children differently from adults barely affects the rank correlation between expenditures and the asset index.[28]

The congruence is, however, affected by the economies-of-scale parameter. The general pattern is that of an inverse-U shape with low rank correlations when the scaling parameter is equal to 0 or 1, and higher correlations in between those values. In most cases, the lowest-ranked correlation is when θ equals 1. The highest degree of congruence is at a scaling parameter of 0.7 or higher in two countries (Albania and Vietnam); between 0.5 and 0.4 in most countries; and at 0.3 or lower in two

[27] In our application, children are defined as household members aged 15 years or younger, and adults are defined as household members aged 16 and older.

[28] Drèze and Srinivasan (1997) similarly found that poverty rankings across groups of households (e.g., male-headed, female-headed, single widow) are not substantively affected by adjusting for equivalence scales.

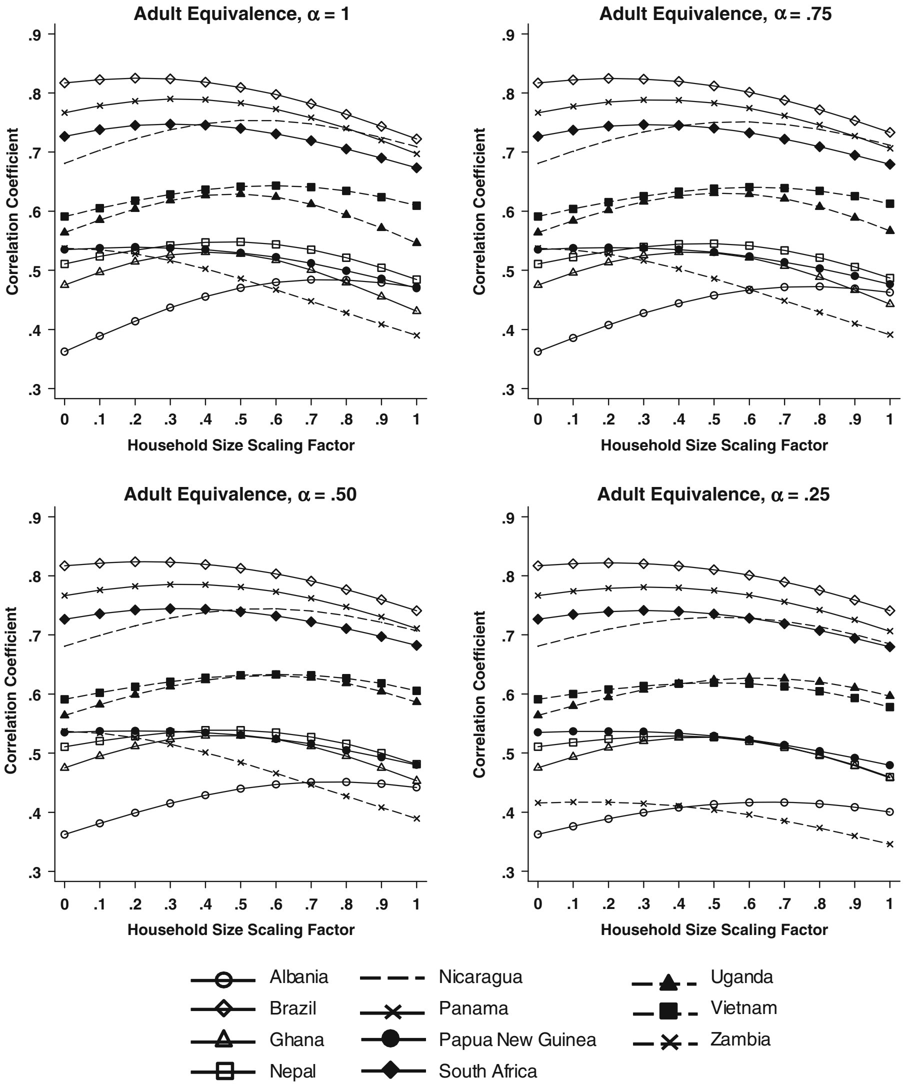

Fig. 8 Rank correlation between asset index using all indicators and household expenditures per adjusted household size, with various scaling factors used for adjustment and adult equivalence values. Adult equivalence is parameter α and scaling factor is parameter θ in the following adjustment to household expenditures: (Household expenditures) / (α × Number of children + Number of adults)$^{\theta}$. When α = 1 and θ = 1, this is just per capita household expenditures; when α = 1 and θ = 0, this is total household expenditures

countries (Papua New Guinea and Zambia). This suggests that part of the divergence in rankings is indeed due to different degrees of accounting for economies of scale, and that the asset index ranking is typically closer to that of expenditures when the latter is adjusted for economies of scale than when it is not.

Based on their analysis of the relationship between the food budget share and household size in Pakistan, Lanjouw and Ravallion (1995) argued that a value of 0.6 for θ might be defensible. They note, however, that this value implies a relatively high share of public goods in household consumption (on the order of 20%). Drèze and Srinivasan (1997) argued that in a household of only adults, the economies-of-scale parameter should, theoretically, equal the share of private goods in household expenditures. In their analysis of rural India, they found that this implies a value of around 0.85 for θ. In their empirical analysis, they found that poverty comparisons using per capita expenditures do not suggest that widows are an especially poor group in India. However, rankings are reversed at a value of 0.8 and, at that economies-of-scale parameter, widows are identified as an especially poor group—in line with the authors' prior research based on sociological and anthropological research. Similarly, Lanjouw et al. (2004) showed how estimates of the incidence of poverty in different groups in transition economies in the early 1990s are sensitive to assumptions about θ. For example, in Bulgaria, they found that the elderly are better off than households with many children when economic status is assessed on the basis of per capita expenditures; but for any value of θ less than 0.9, the elderly are worse off.[29] All of this research suggests that some adjustment to expenditures for economies of scale is in order, which would bring the asset index and expenditure-based rankings in closer alignment, although there is little agreement on what the appropriate value of θ is.

Although the theoretical discussion of economies of scale is framed in terms of public and private goods, empirical analyses typically single out food as the quintessential private good (see the discussion in Deaton and Paxson 1998).[30] Our data strongly support the notion that asset indices are more closely associated with the nonfood component of expenditures. First, in countries where the average share of food in total expenditures is high, the correlation between per capita expenditures and the principal components asset index is low: the correlation is –.84 across the 10 countries with available data (column 5 of Table 4). Second, the rank correlation of the asset index and per capita food expenditures within countries is substantially lower than that of the asset index and per capita nonfood expenditures: the former averages .38 across the countries, while the latter averages .66 (columns 4 and 5 of the bottom panel of Table 5). If nonfood expenditures are not adjusted for household size, the rank correlation increases further and in four countries exceeds .75 (Brazil, Panama, South Africa, and Zambia).

Asset indices, as they are typically implemented, consist almost entirely of household public goods: consumer durables, such as radios or televisions; housing quality, such as type of flooring; or the availability of electricity. Household expenditures, on the other hand, are typically dominated by expenditures on private goods, with food making up a substantial share of expenditures in the data from the developing countries we analyze. Therefore, it should perhaps not come as a surprise

[29] Other studies use subjectively reported measures of welfare to document the existence of economies of scale (Pradhan and Ravallion 2000). However, as discussed in Deaton and Zaidi (2002), a formal comparison of measured and subjective welfare often yields unbelievably small values of θ.

[30] Deaton and Paxson (1998) showed how one would expect that, holding per capita total expenditures constant, larger household size should be associated with higher per capita food expenditures. This is because households would be able to exploit the economies-of-scale aspect of the public-goods (i.e., nonfood) portion of expenditures, which would effectively leave more money per person to be allocated to food. If true, this would allow estimation of the economies-of-scale parameter. However, they found exactly the opposite result: larger households are associated with lower per capita spending on food, a puzzle that they were unable to resolve.

Table 5 Rank correlation coefficients between welfare indices across households

	Per Capita Household Expend. (1)	PC Index, All Indicators (2)	Per Capita Household Food Expend. (3)	Per Capita Household Nonfood Expend. (4)	Total Household Nonfood Expend. (5)
Correlation with ranking by per capita household expenditures					
Albania	1	.47	.91	.83	.48
Brazil	1	.72	.69	.97	.84
Ghana	1	.43	.92	.88	.44
Nepal	1	.49	.91	.85	.61
Nicaragua	1	.71	—	—	—
Panama	1	.70	.91	.94	.74
Papua New Guinea	1	.47	.91	.84	.70
South Africa	1	.67	.88	.97	.78
Uganda	1	.55	.93	.91	.49
Vietnam	1	.61	.87	.93	.75
Zambia	1	.39	.91	.72	.49
Average	1	.56	.88	.88	.63
Correlation with ranking by principal components index that uses all indicators					
Albania	.47	1	.31	.58	.51
Brazil	.72	1	.42	.75	.84
Ghana	.43	1	.24	.57	.59
Nepal	.49	1	.34	.56	.59
Nicaragua	.71	1	—	—	—
Panama	.70	1	.54	.77	.80
Papua New Guinea	.47	1	.34	.54	.58
South Africa	.67	1	.49	.71	.76
Uganda	.55	1	.46	.57	.56
Vietnam	.61	1	.45	.66	.65
Zambia	.39	1	.16	.67	.75
Average	.56	1	.38	.64	.66

Notes: A dash indicates that data are not available. Cross-country averages are unweighted.

that asset indices are more closely related to nonfood expenditures than to food expenditures, or to economies-of-scale-adjusted expenditures than per capita expenditures. It does suggest, however, that in the poorest settings, where food dominates expenditure aggregates, results derived from asset indices and from expenditures-based measures are likely to differ most.[31]

[31] One might be worried that the results on the predictability of expenditures are also being driven by the share of food in expenditures since both approaches to prediction use nonfood-related variables to predict overall expenditures (columns 3 and 4 of Table 4). However, the results are barely affected if the prediction models are estimated for nonfood expenditures only (columns 6 and 7 of Table 4), indicating that predictability and household public goods are indeed separate issues.

Conclusions

The use of asset indices—instead of per capita expenditures—in welfare analysis in the context of developing countries has been growing in the past few years, especially when data on expenditures are missing or too costly to collect well. Many applications of this alternative approach have derived an asset index on the basis of principal components analysis of a set of asset and housing quality indicators, but some applications have used simpler methods, such as count measures of the number of assets owned, or more sophisticated methods, such as the application of formulae derived from item response theory.

The analysis carried out here has a variety of implications for analysts. The first is that the specific welfare measure used does not appear to strongly affect inferences about the extent to which inequalities in education, health care use, fertility, child mortality, and labor market outcomes are related to economic status. There are two aspects of this. First, within the class of asset indices, results are systematically consistent across aggregation approaches. Therefore, although checking for the robustness of findings across various aggregation methods is probably advisable, the results here suggest that, in most situations, the specific approach used is unlikely to matter much. Second, the economic gradients in outcomes based on asset indices are similar to those based on per capita expenditures. There are some differences, in particular with regard to health care–seeking behavior, but inferences about the importance of economic status are not typically affected. In practice, fielding surveys that include a thorough consumption-and-expenditures module can be substantially more costly and time-consuming than shorter surveys that are limited to collecting data on asset and housing quality indicators. Therefore, if the analytical goal is simply to explore rich-poor gaps, or to "control" for economic status in an analysis of the impact of another variable on outcomes, then an asset-index approach could be a more cost-effective way of approaching the study. Similarly, the lack of a "full" survey that includes expenditures should not preclude welfare analysis if an alternative "light" survey with asset indicators is available.

Despite these similarities, the results suggest that the different measures—but most importantly per capita expenditures versus the class of asset indices—do not yield the same ranking of households. Therefore, targeting a social program to the poorest 20% of the population on the basis of an asset index, for example, would reach an overlapping but different set of households than targeting the poorest 20% on the basis of per capita expenditures. In particular, using an asset index would identify more rural, smaller households with a larger share of working-age members than per capita expenditures would. But the fact that economic status gradients are similar (often steeper) when an asset index is used suggests that these programs would not necessarily be "mistargeted": they might in fact do a better job of identifying the populations with the lowest levels of education, worst health outcomes, or lowest labor force attachment, which may be the appropriate targeting criterion in some cases. Moreover, assets may capture aspects of long-run poverty that might be obscured through household shocks. As such, asset indices may indeed be preferable in some cases, even when expenditures are available. The decision of which approach is more appropriate for targeting will depend *inter alia* on the capability of programs to collect data on the full range of expenditures and consumption; on the extent to which the goal of targeting is to capture those households that are suffering from temporary negative income shocks; and on the desirability of a measure that captures the broader set of factors and behaviors that enter into the determination of expenditures as opposed to factors that are perhaps more narrowly associated with shortfalls in human development outcomes.

Our analysis identifies two important predictors of the congruence of rankings by per capita expenditures and an asset index: (1) the extent to which per capita expenditures can be explained by observed household and community characteristics and (2) the share of household public goods in aggregate expenditures. This suggests that in settings with large transitory shocks to expenditures, or a large amount of measurement error in expenditures, or a large share of private goods—in particular food—in aggregate expenditures, the rankings yielded by expenditures and by an asset index are likely to differ substantially. As analysts consider using an asset-index approach instead of expenditures, they should be mindful that the presence of these factors would limit the ability of drawing implications about expenditures based on results derived from assets.

In sum, using asset indices for targeting is feasible and may be desirable, but it potentially identifies different households as being in the poorest group than expenditures would. Using asset indices to carry out welfare analysis clearly has a place. When per capita expenditure data are missing, the use of an asset index can clearly provide useful guidance to the order of magnitude of rich-poor differentials; however, analysts should be aware that the two approaches are likely to yield similar results in some settings but different results in others.

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Appendix

Table 6 Summary information on countries and data sets in study

	Date of Survey	Number of Households in Analysis	Number of Indicators of Asset Ownership	Number of Indicators of Housing Characteristics
Albania (ALSMS)	2002	3,598	28	12
Brazil (BPPV)	1996/1997	4,940	26	6
Ghana (GLSS)	1991/1992	4,522	27	4
Nepal (NLSS)	1996	3,373	18	6
Nicaragua (EMNV)	2001	4,191	29	9
Panama (PENV)	1997	4,945	28	6
Papua New Guinea (PNGHS)	1996	1,144	20	10
South Africa (SAIHS)	1993	8,791	15	5
Uganda (UNHS)	2000	10,696	13	7
Vietnam (VLSS)	1992/1993	4,800	29	9
Zambia (LCMS)	2004	19,247	62	37

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