Policy Research Working Paper 9661

Diamonds in the Rough?

Repurposing Multi-Topic Surveys to Estimate Individual-Level Consumption Poverty

Theophiline Bose-Duker
Isis Gaddis
Talip Kilic
Valérie Lechene
Krishna Pendakur

WORLD BANK GROUP
Development Economics
Development Data Group
May 2021

Policy Research Working Paper 9661

Abstract

Traditional per capita measures of poverty assign the same poverty status to individuals living in the same household and overlook differences in living standards within households. There has been a long-standing need for a tool that enables poverty measurement at the individual level, while avoiding overly complex estimation techniques and, if possible, using readily available household survey data. An ordinary least squares–based strategy was recently introduced to estimate individual resource shares. This paper presents the theory behind this approach in an accessible fashion for those interested in individual-level consumption poverty measurement using existing household survey data. The strategy's assumptions are compared with the assumptions of the prevailing per capita approach to deriving poverty estimates. The empirical analysis presents competing individual-level poverty estimates in four diverse countries under the individual resource shares strategy versus the per capita approach. The results suggest that poverty is underestimated under the per capita approach. There is further evidence that women may be poorer than men, and that children and the elderly are disproportionately affected by poverty. However, the pursuit of the individual resource shares approach reveals cross-country heterogeneity in the extent of increase in headcount poverty estimates, and in the direction of change in headcount poverty estimates for men and women. The paper concludes with suggestions for further methodological research in this area.

This paper is a product of the Development Data Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at igaddis@worldbank.org or tkilic@worldbank.org.

Diamonds in the Rough?
Repurposing Multi-Topic Surveys to Estimate Individual-Level Consumption Poverty

Theophiline Bose-Duker[1], Isis Gaddis[2], Talip Kilic[3], Valérie Lechene[4], and Krishna Pendakur*[5]

[1]World Bank
[2]World Bank and Institute of Labor Economics (IZA)
[3]World Bank
[4]University College London and Institute for Fiscal Studies (IFS)
[5]Simon Fraser University

JEL Codes: C83, D13, I32, O15

Keywords: Individual poverty, intrahousehold allocation, gender, lifecycle

*The authors gratefully acknowledge the comments from participants at the "Estimating Resource Allocation within Households" workshop at the World Bank on November 5, 2019, where the results in this paper were first presented. In addition, we would like to thank various colleagues, who provided comments on earlier drafts of this paper. This study received funding from the Knowledge for Change Program (KCP). Alexander Wolf contributed to this research project during his time as a post-doctoral research fellow at the Institute for Fiscal Studies (IFS). The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. The authors may be contacted at igaddis@worldbank.org or tkilic@worldbank.org.

1 Introduction

Most monetary measures of poverty, such as the World Bank's global estimates of poverty, classify an individual as poor if s/he lives in a household whose consumption or income falls below a poverty line. Such methods cannot provide insights into differences in poverty within households, even though empirical evidence of many (non-monetary) dimensions of welfare – education, health, freedom from violence – routinely show that substantive gaps between household members may exist and that women and children may be disproportionately represented among the poor (e.g. Vijaya et al., 2014; Espinoza-Delgado and Klasen, 2018; Alkire et al., 2019; Klasen and Lahoti, forthcoming). Concerns over women's disadvantaged position in many domains of welfare and economic opportunities are also embedded in the Sustainable Development Goals (SDGs), especially goal 5 on gender equality and empowerment of all women and girls.

The inability of the global poverty monitoring system to track the poverty of men, women and children separately has been widely criticized (e.g. Grown, 2014) and was highlighted as a "significant concern" in the report of the Commission on Global Poverty (World Bank, 2017). Indeed, being able to correctly identify poor and non-poor individuals is crucial for policy makers if certain groups tend to experience poverty more than others. For instance, if women are systematically getting less than a per capita measure would suggest, then policies designed to alleviate poverty for women might miss their target. Likewise, it might be that the incidence of child poverty is greater in single parent households than in two parent households, something that would be important to know from a targeting perspective. Or it might be that investments in the education and health of children are related with individual resources in consumption, suggesting that improvements in the latter would benefit the former. The list of questions requiring correctly labeling individuals' poverty status is endless.

There are, of course, explanations as to why monetary poverty estimates often do not distinguish among individuals living in the same household. Monetary poverty measures are typically based on consumption and most household surveys collect consumption data for the household as a whole, rather than for individual household members. Measuring differences in consumption between men, women and children living in the same household is not an easy task. First, it is very expensive and difficult to collect person-level spending on private goods. While we can relatively easily observe household purchases, it is costly and complicated to measure individual consumption. Think about the stereotypical bottle of milk. While it is straightforward to collect information on the household's expenditure on milk, it is not only expensive, but also not necessarily informative, to post an enumerator next to the refrigerator to measure each individual's milk consumption, since people might change their behavior due to being observed (i.e. the Hawthorne effect). For most of the purposes for which household expenditure data is collected, measuring individual consumption is not necessary, so that collecting information on individual consumption is a question which has not been much pursued until now. Second, expenditure may not equal consumption. For example, if shelter is completely shareable, then two people can each spend $500 on shelter, but may each experience a consumption flow of $1,000. The link between spending in a household and the experienced consumption flow is scale economies. Unfortunately, the degree of scale economies in the consumption of each good is not typically observed. These two factors make it difficult, if not impossible, to directly observe (or measure through household surveys) the total consumption flow to individuals within households.

The lack of individual-level consumption data has spawned a growing literature that estimates how resources are allocated within households by developing structural models of household decision-making. An important contribution to this literature is the workhorse model by Dunbar, Lewbel, and Pendakur (2013) denoted hence forth as DLP. A growing academic literature uses the DLP model to answer policy-relevant questions – e.g. to show that intrahousehold inequality in resource allocation can explain mortality rates of older women in India (Calvi, 2020) or to explore inequality between foster and non-foster children in Malawi (Penglase, 2021).

Lechene, Pendakur, and Wolf (2020) propose a linear reframing of the DLP model, denoted as L-DLP (linear DLP), which allows for the estimation of the share of household consumption expenditure for each household member, which we refer to as the *resource share*, using existing household survey data and ordinary least squares (OLS) estimation of Engel curves.

Similar to DLP, L-DLP is theory consistent, which means it imposes restrictions on observed behavior, identifying assumptions can be spelled out, and it is possible to recover structural parameters from OLS estimation. It also incorporates a conceptually small, but empirically crucial extension of DLP, since it allows for multiple men and women. Previous models only accommodate nuclear households (one man, one woman, any number of children), which are only a small fraction of households in many developing countries. Finally, and helpfully, L-DLP comes with a pre-test, which enables the researcher to find out immediately whether the method could work or not on a given data set.

This paper borrows from Lechene, Pendakur, and Wolf (2020) but extends the analysis in three directions. First, we present the theory behind L-DLP in a way that is easily accessible to a broad audience of poverty experts. Second, we illustrate the application of L-DLP graphically and show the Stata code that is necessary to estimate the model. Third, we present novel empirical results. Specifically, we compare L-DLP-based poverty estimates for men, women and children - on the whole and by age group - to those that are obtained with the prevailing approach to derive individual-level poverty estimates, namely the per capita approach, which assumes equal sharing of resources within the household.

Overall, we argue that L-DLP is a useful tool, which should have a place in the toolkit of economists interested in the measurement of poverty at the individual level. In both DLP and L-DLP, the object of interest is the resource share of each individual in a household, defined as the fraction of total household expenditure that is enjoyed by that individual. The resource share is closely related to the level of individual expenditures, which is equal to the resource share times total household consumption. Although both of these objects are of vital welfare importance, they are not directly observable from household behavior. Thus, the structural model of household behavior is what allows us to connect the dots between observed household behavior and unobserved resource shares and individual expenditure levels. The methodology outlined in this paper shows how to identify resource shares from typically available data, and how to use these resource shares in a way that respects the existence of scale economies. Resource shares are important to welfare analysis, and poverty measurement, for at least three reasons. First, resource shares are proportional to individual expenditure and consumption across the people in a household. They therefore provide an indicator of material well-being comparable across household members and can speak to within-household inequality.[1] Second, resource shares multiply household expenditure to give person-level expenditure, which may be comparable across households. Third, in conjunction with a poverty line, these person-level expenditures can be used to identify an individual's poverty status and compute individual-level poverty rates, which can be compared to standard per-capita poverty rates. However, since poverty is experienced at the individual level, standard per-capita poverty measures may lead us astray and mismeasure the true individual poverty rate if there is inequality within households. Further, if there is any inequality inside households, we are more likely to mischaracterize individuals as poor or non-poor if they belong to a household which is close to the poverty line.

The paper is structured as follows. Section 2 discusses the problems inherent to measuring individual consumption and poverty. Section 3 presents the theory behind L-DLP in a fashion accessible to economists and practitioners interested in measuring individual poverty using off-the-shelf household budget data and OLS. Our ambition is that L-LDP joins the other tools used by experts in poverty measurement. To be convincing, we have to be very open about the assumptions of the method. We compare L-DLP and per capita measures so as to make a clear case about the identifying assumptions of both methods. Section 4 discusses results obtained using L-DLP to measure individual poverty using standard household survey data for four developing countries, and compares poverty rates obtained with L-DLP with those obtained from the per capita measure. We show further how L-DLP estimates of individual poverty can be used to examine questions otherwise unanswerable, by exploring gender and lifecycle differences in poverty. Section 5 concludes with a

[1] This assumes that there are no differences in needs between household members. If needs differ, for example between adults and children, then resource shares need to be normalized before one can draw inference on differences in material well-being within the household.

set of recommendations for future research.

2 Problems inherent to measuring individual consumption poverty

In this section, we contrast dream data, the data which would ideally be available for measuring individual resources, with real data, in its form most often available to researchers (section 2.1), so as to illustrate the nature of the problems inherent to measuring individual poverty. We then examine what has been done before to try to overcome these problems, both in theory and in practice (section 2.2).

2.1 Dream data versus real data

An easy way to understand the problems inherent to measuring the amount of consumption enjoyed by each individual in a household is to start by thinking about the data which would contain all the necessary information. Such dream data would look like Table 1a.

Table 1a: Dream Data

	Expenditure				Scale
	Man	Woman	Child	Hhld	Econ
Food	400	300	200	900	1
Clothing	50	75	25	150	1
Shelter	200	200	200	600	3
Transport	125	62.5	62.5	250	2
Other	45	37.5	37.5	120	1
Total	820	675	525	2020	

In these dream data, you can see, for a nuclear household composed of a man, a woman and a child, *person-level* annual expenditures on food, clothing, shelter, transport and other goods. Food and clothing are not shared goods, and so are straightforward to analyze. For instance, for food, we observe that out of the $900 the household spends on food, $400 is spent on the man, $300 on the woman and $200 on the child. Food is not shareable (in the sense defined in the introduction), so that the scale economy, given in the rightmost column, equals 1, telling us that each person's food consumption is equal to 1 times their spending on food. In this way, the scale economy for the good links spending to consumption. The household spends $400 on food for the man, yielding

$400 worth of food consumption. This is not surprising given that food is not shareable—if one person eats a unit of food, it cannot be eaten by another person.

Shelter and transport are shared to some extent, so that we need to distinguish between consumption and expenditure. We will define (somewhat sloppily for now) the *consumption* level of a good to be the amount a single individual (not living in a household) would have to spend to get the same amount. For these shared goods, consumption equals spending times the scale economy. Suppose shelter is entirely shared; since the household's expenditure on shelter is $600, it means that each individual consumes $600 worth of shelter. This means that the scale economy for shelter in this household is equal to 3. Thus, for example, it is as though the man spends $200 on shelter, but enjoys shelter consumption equal to $600 (equals 3 times 200).

Transport, on the other hand, is not entirely shared. Suppose that transportation expenditures are on a motorcycle, and that the man uses the motorcycle every day, half the time riding with the woman, and half the time riding with the child. This means that the motorcycle carries 2 people all the time, and so the scale economy is 2. Thus, the $125 spent by the man yields a consumption level of $250 (equals 2 times 125).

The dream data do not face the two key problems that we typically encounter in the real world, lack of individual-level data, and lack of knowledge of scale economies. First, in the dream data, we can directly see the expenditure of each person: the man gets $820, the woman gets $675 and the child gets $525. In terms of resource shares, this corresponds respectively to 41%, 33% and 26% of the household resources going to the man, the woman and the child.

The international poverty line of $1.90 per person per day (Ferreira et al., 2016) is the most commonly used poverty line in the analysis of poverty in developing countries. This poverty line does not account for scale economies, effectively assuming that all the scale economies equal 1.[2] For a household with 3 members, the per-capita expenditure poverty line is household spending of $2,081 per year ($1.90 a day per person), so we would conclude on this basis that the household is poor and count all 3 of its members as poor.

With dream data, and holding on to the assumption that scale economies are all equal to 1, we can compare the expenditure levels for the man, woman and child to the poverty line of $1.90 per day—or, $694 per year—without making any adjustment for scale economies. This would lead us to conclude that the woman and the child are poor but the man is not.

Second, the dream data tell us the scale economies enjoyed for each good, so that we can speak additionally to consumption distinctly from expenditure. Scale economies account for sharing of goods, and may vary across goods. Essentially, scale economies expand the amount of consumption that the individuals in households can enjoy. As a consequence, shareable goods (those with scale

[2] This is a simplified assumption to impose comparability across countries that use different equivalence scales in their national poverty estimations.

economies in their consumption) feel cheap within the household. Alternatively put, shareable goods have shadow prices that are lower than their market prices. Consequently, scale economies affect the demands for goods within households.

Knowledge of scale economies is relevant to poverty analysis. For example, if scale economies are large, then the poverty line for a household should be adjusted downwards to take account of this fact. This is akin to poverty measurement strategies like the OECD standard approach, which accounts for scale economies through an equivalence scale (see, for example, OECD, 2013).

In this paper, we focus on how to identify resource shares in a context where scale economies are present. However, we do not try to identify scale economies themselves. That task remains for new research. In practice, we will use data to reveal resource shares and draw on auxilliary data for scale economies.

Dream data are wonderful in principle but in practice hard to come by. Data that are relatively close to such dream data have been used by Cherchye et al. (2017), and by Bargain et al. (2018). However, they have data only on the within-household allocation of spending, and not on scale economies. They found substantial evidence of within-household inequality and argue that the within-household distribution of spending is critically important to our understanding of poverty and inequality.

Real data are like dream data, with most of the data missing. Historically, real data, such as that collected in household surveys, looked like Table 1b. For each household, the only information collected would be total household expenditure (or income).

For the purposes of poverty measurement, these data are insufficient. So, assumptions were added: first, expenditure was assumed to be divided equally between individuals in the household, yielding the individual-level expenditure in the bottom row of Table 1c in italics. Second, the scale economies were assumed to be 1 for each good, so that these individual-level expenditures would be comparable across different types of households, and comparable between people living in households and people living alone. These two assumptions are sufficient to deliver the per-capita methodology for poverty measurement.

Table 1b: Real Data, traditional, no assumptions

	Expenditure				Scale
	Man	Wom	Child	Hhld	Econ
Food				900	
Clothing				150	
Shelter				600	
Transport				250	
Other				120	
Total				2020	

Table 1c: Real Data, traditional, with assumptions

	Expenditure				Scale
	Man	Wom	Child	Hhld	Econ
Food				900	*1*
Clothing				150	*1*
Shelter				600	*1*
Transport				250	*1*
Other				120	*1*
Total	*673*	*673*	*673*	2020	

However, in some cases, we have real data with a crucial additional piece of information. In particular, in many existing data sets, the person-level expenditures on at least some goods are available. Table 1d shows what such real data look like, with clothing expenditure data collected at the person-level.

Table 1d: Real Data, modern, no assumptions

	Expenditure				Scale
	Man	Wom	Child	Hhld	Econ
Food				900	
Clothing	50	75	25	150	
Shelter				600	
Transport				250	
Other				120	
Total				2020	

Table 1e: Real Data, modern, with assumptions

	Expenditure				Scale
	Man	Wom	Child	Hhld	Econ
Food				900	?
Clothing	50	75	25	150	*1*
Shelter				600	?
Transport				250	?
Other				120	?
Total	*820*	*675*	*525*	2020	

For the same nuclear household as in the dream data, we observe again the household's expenditures on food, clothing, shelter, transport and other. Contrarily to the dream data, we observe individual expenditure only on clothing. Further, we do not observe anything about scale economies.

Because we still face missing data relative to the dream data in Table 1a, we still do not have enough information to directly engage in individual-level poverty analysis. However, the methods outlined in this paper show how to add assumptions (similar to those linking Tables 1b and 1c) to generate individual-level expenditures as in the bottom row of Table 1e. These person-level expenditures are similar in spirit to those in the bottom row of Table 1c, but they allow for inequality in the intra-household distribution of expenditure (and consumption).

However, the methods we develop here do not identify the scale economies enjoyed by household members.[3] But, instead of assuming those scale economies are *all* equal to 1, we assume that they equal to 1 only for the assignable expenditure of clothing. For all other goods, scale economies are unrestricted. This means that we can assume their values (as in the OECD standard practice), which is the approach pursued in this paper, or estimate them via other means. The estimated individual-level expenditures are robust to any values for those scale economies.

The contribution of the model is substantial in this case. With real data and no model, there is no path to consider within household inequality, and with standard tools, one would conclude that every member of the household is poor. However, with dream data, we observe that there is

[3] A few papers have investigated the identification of scale economies: Lewbel and Pendakur (2008b); Lewbel and Pendakur (2021); and Calvi et al. (2021). However, none of these papers uses price variation to identify shadow prices. They instead reveal the value of low shadow prices within households indirectly, via income effects.

intra-household inequality and we conclude that the woman and the child are poor, while the man is not poor. The combination of real data and the household model give us a light to shine inside the household, to reveal the inequality within, provided the assumptions underlying the model are reasonable.

The per capita measures, widely used in practice, are one model of how resources are shared inside households.[4] DLP (and L-DLP) are another model. We will explain both models in section 3, but first we examine what has been done before.

2.2 What has been done before: A non technical review of theory and practice

We first review, in a non technical way, what has been done in theory to lead to implementable methods to estimate individual resources from household consumption. We then examine the current practice of individual poverty measurement.

2.2.1 In theory

Going back to the origins of formal micro-economic theory, households were assumed to have utility functions or representative utilities so that consumption choices could be represented as resulting from the maximization of a household utility function subject to a household budget constraint. (e.g. Becker, 1965, 1981; Jorgenson and Slesnick, 1984; Blackorby and Donaldson, 1993; Pendakur, 1999). In this representation, household level choices are related to market prices and household income. Statements about poverty can be made at the level of the household, or at the level of individuals under the assumption of equal sharing of resources, using per capita measures.

Structural models of household behavior borrowing from game theory appeared in the 1980s, with McElroy and Horney (1981), Apps and Rees (1988) and Apps and Savage (1989). These models allow for individual preferences and fully specify how resources are shared. But, they turned out to be quite conditional in their implementation, as they required cardinalization of preferences for instance. If you changed preferences, or changed the bargaining model, the resulting estimates changed. For these reasons, these models were not extensively used for individual poverty measurement.

The seminal work of Chiappori (1988, 1991) introduces the collective model, an alternative representation of the household, as a collection of people (with utility functions) living together, who reach the Pareto frontier. This is a semi-structural model in that the process by which choices are made is not specified, only that they are Pareto efficient. Consequently, one need not specify the

[4] Note that to go from resource shares to poverty rates, one needs to take a stand on an unobserved needs correction. We discuss this in the empirical implementation and in the appendix.

exact bargaining or choice model used by household members. Rather, one need only assume that they reach an efficient outcome. The model is tested and extended in Browning et al. (1994) and Blundell et al. (2005). Further, the model has a nonparametric characterization, so that individual utility functions and preferences need not be specified. Its identification is studied in Chiappori and Ekeland (2009).

Pareto efficiency is appealing not only because it does not specify the unobservable process by which individuals reach decisions, but also because the First theorem of Welfare Economics tells us that Pareto efficient decisions can be decentralized. This is extremely useful for the purpose of measuring individual poverty. Indeed, decentralization means that the efficient choices of agents characterized by their own preferences can be represented equivalently as resulting from the maximization of a weighted sum of the individual utility functions subject to a household budget constraint or as the maximization of each individual utility function, subject to an individual shadow budget constraint. The shadow budgets reflect the sharing of resources in the household. The next question is to establish restrictions on behavior under which the shadow budgets can be estimated using information on household choices, household income and their environment.

Browning, Chiappori, and Lewbel (2013), denoted hence forth as BCL, and DLP extend the collective model to allow for good specific economies of scale, a desirable extension for a household model. They also give identification results showing how data can reveal model parameters. BCL show nonparametric identification of a very general model using data on the preferences of single individuals and the demand functions of households in a context with both price and budget variation (see also Lewbel and Lin, 2020). DLP show semiparametric identification of a less general (because partly specified) model using data on just the demand functions of households in a context with just budget variation.

A number of theoretical contributions develop different aspects of the collective model: Lewbel and Pendakur (2008b) and DLP recast BCL so as to dispense with the need for price variation and estimate the structural model with nonlinear Engel curves; Dunbar et al. (2019) allow for randomness in the resource shares; Sokollu and Valente (2019) and Brown et al. (2021) explore different identifying assumptions.

2.2.2 In practice

Among the papers listed above, BCL and DLP theoretically offer a way to estimate poverty at the individual level. Both papers contain empirical applications. Yet, despite a small, but growing, academic literature, these models are not used for routine poverty estimation and analysis, which is, at least in parts, owed to the complexity of estimating these models. This complexity can also undermine the transparency of the results, which is of paramount importance when advising policy makers. In practice, the per capita measure, with its shortcomings (detailed in section 3.7), still dominates.

BCL is demanding in terms of data since it requires observed price variation and observed preferences for single individuals. In the BCL model, the scale economy parameters are identified (in part) from price variation. But, in many contexts, observed price variation is either/both very small and/or endogenous. In the BCL model, the within household allocation of expenditure is identified (in part) by comparing individual preferences to household demand curves. In many countries, especially in the developing world, the density of single individuals (who do not live in households comprised of multiple people) is very low, and may be close to zero for some types of individuals, e.g., children, adult women, old and infirm people. Consequently, observing the preferences of single individuals may be a big lift. A final difficulty with BCL as written is that it requires the estimation of many high-dimensional nonlinear functions, which makes it computationally burdensome. A consequence of all this is that only two papers have implemented BCL in its unrestricted form: BCL and Pendakur (2018).

DLP tried to develop a do-able version of BCL, by making it easier in both dimensions. It is identified from the Engel curves of households (and not singles), so that there is no need to observe price variation or the preferences of single individuals. However, it is still a high-dimensional nonlinear model that may be computationally difficult to implement. The hurdles to estimating DLP will be apparent in section (3.2). More researchers have implemented DLP than have implemented BCL. See, e.g. Bargain et al. (2014) in Côte d'Ivoire; Bargain et al. (2018) in Bangladesh; Brown et al. (2021) in Bangladesh; Bose-Duker (2019) in Ghana; Bose-Duker et al. (2020) in Jamaica and Khadan et al. (2020) in Suriname.

The empirical relevance of these methods goes way beyond the measurement of individual poverty. Calvi (2020) shows that in India, women are poorer than men, and older women even more so, and that this is reflected in higher mortality rate for older women. Penglase (2021) examines the existence of intra-household inequality using data on foster children in Malawi.

All in all, in practice, poverty measurement is still most often done by measuring consumption at the household level, dividing by the number of household members and comparing against a per capita poverty line, thus eliminating a priori the possibility of intra household inequality.

3 Theory

3.1 Notation and definitions

Let t index types of people that live in households. We let the types be $t = m, f, c$ for male adults, female adults, and children. But these could equally be men, women, female children and male children, or any other categorization, as long as we observe some expenditure at the level of each type. For instance, if the data contains information on expenditure on men's clothing, women's clothing and children's clothing, the types are male, female and children, and if the data contains information on expenditure on male clothing, female clothing, male children clothing and female children clothing, the types are now male, female, male children and female children.

A household consists of N^t individuals of each type t; and let the total number of individuals in a household be $N = \sum_t N^t$. The observed household budget is denoted y. Let Q be the observed vector of quantities purchased by the household. Let q^t be the quantity of consumption enjoyed by members of type t. The market price vector is p. These last two may or may not be observed.

BCL provide a very general model of the household, and show how to identify that model with data. Their model has a few key assumptions. First, they assume that households reach a Pareto efficient allocation by some unspecified means, which implies that the household's demands can be represented as the sum of individual demands. Second, they assume that the household scale economies are embodied in a consumption technology that expands the consumption possibilities of the household, as described below, and defines a shadow price vector for within household consumption. Third, they assume that each individual has a shadow budget. These three assumptions (together with some regularity conditions) imply that the household purchases the sum of what each individual would purchase if they faced their shadow budget constraint.

The BCL model has two important features that together characterize the shadow budget constraints of individuals—scale economies and resource shares. Let a diagonal matrix A characterize *scale economies*. A has one element for each good. An element of A equals 1 for a good that is not shareable, and is less than 1 for a good that is shareable. The numbers shown in the dream data Table 1a are the reciprocals of these numbers.

Scale economies determine how expenditures relate to consumption flows, and (therefore) determine the shadow prices of consumption within the household. For a good that is not shareable, the household must purchase an amount equal to the sum of what each of the individuals consumes. In contrast, for a good that is shareable, the household purchases less than the sum of what each individual consumes. Specifically, BCL (when A is diagonal) has that the household must purchase $Q = A\left(\sum_t q^t\right)$. Since, for shareable goods, the relevant element of A is less than 1, scale economies *expand* the amount of consumption that may be enjoyed for a given level of household purchase.[5]

Scale economies also affect the shadow prices of consumption in the household. In comparison to when living alone, shareable goods feel cheap when living in a household. BCL show that **the shadow price of consumption, $\widetilde{p}$,** (when A is diagonal) within the household is $\widetilde{p} = Ap$. So, for

[5]BCL in fact allow for an arbitrary function relating Q_h to q_h^t of the form $Q_h = Z\left(\sum_t q_h^t\right)$ where Z is a vector-valued function of the vector $\sum_t q_h^t$. But, when Z is just a diagonal matrix, the model simplifies to the version we discuss here.

shareable goods, the shadow price of consumption within the household is less than the market price. In contrast the shadow price of consumption for single individuals equals the market price—singles cannot take advantage of scale economies in consumption.

Going back to the example of the dream data, we suppose that shelter is entirely shared. Here, the element of A equals 1/3 so that the scale economy is 3. This means that in Table 1a, each individual spends \$200, but actually gets to consume \$600 worth of shelter. Spending within the household is done at within household shadow prices Ap. This means that the \$200 spent by each individual is spent at the much cheaper price $\frac{1}{3}p_{shelter}$, so that this spending within the household is comparable to \$600 (equals $200/\left(\frac{1}{3}p_{shelter}\right)$). So, it is important to keep in mind that the bottom row of Table 1a (and Table 1e) measures spending (not consumption).

In the example of the dream data, we knew the household expenditure on the goods as well as the shadow individual consumption, from which we could deduce the shadow price and the economies of scale. With real data, we allow for scale economies, but we do not estimate them. We come to this when we explain the identification of the resource shares in this model, in section (3.2).

The *resource share*, denoted η^t, is the fraction of the household budget going to type t. The sum of the resource shares is 1, $\sum_t \eta^t = 1$. We assume that all members of the same type get an equal part of that type's resource share.[6] Thus, a type's shadow budget is $\widetilde{y}^t = \eta^t y$; and, **a person's shadow budget** is $\widetilde{y}^t/N^t = \eta^t y/N^t$.

Individuals are assumed to live in efficient collective households, which are collections of people (with utility functions) living together, who reach the Pareto frontier. Thanks to the First Theorem of Welfare Economics, this means that the household problem reduces to a set of individual problems, in which it is as if each person spends their shadow budget, $\widetilde{y}^t/N^t$, at the within-household shadow prices, Ap. The household purchases enough to satisfy everyone's demands at these budget constraints. Consequently, household demands are a mix of individual demands.

3.2 Identification

Formally, BCL demands are given by

$$Q^t(p,y) = A\left(\sum_t N^t q^t\left(\widetilde{p}, \widetilde{y}^t/N^t\right)\right) = A\left(\sum_t N^t q^t\left(Ap, \eta^t y/N^t\right)\right)$$

[6] Of course, this is a simplifying assumption. It is entirely possible that there is inequality within person types, in addition to inequality between person types. However, we argue that capturing between-type inequality is already a significant advancement over the prevailing per capita approach, which does not allow for any intra-household inequality.

BCL show that the model parameters A and η^t (which may be functions of p, y) are identified if the functions Q^t and q^t are observed. Even in this case, estimation may be difficult, for at least three reasons: first, q^t may not be observed (as with children, where we do not observe children living alone); second, there may not be observed price variation in the data, frustrating our ability to identify A; and, third, Q^t is a compound function of q^t and A, η^t, so the problem may be computationally difficult.

DLP address all three of these problems, by focusing on *assignable goods.* These are defined as nonshareable goods known (by the researcher) to be consumed only by one type of individual in the household. In the real data in Table 1d, clothing is such a good. Since assignable goods are private, there are no scale economies in consumption of these goods; their shadow price is equal to their market price and the relevant element of the matrix A is 1. Since they are assignable, only one type of household member wants any of the good, and we have that the household demand for the assignable good of a type equals the demand for that good for that type, evaluated at their shadow budget constraint:

$$Q^t = q^t\left(\widetilde{p}, \widetilde{y}^t/N^t\right) = q^t\left(Ap, \eta^t y/N^t\right) \tag{1}$$

Demand functions accounting for price variation may be troublesome to work with if prices are unobserved. DLP provide household-level Engel curves—which hold prices constant— for assignable goods. Let $W^t(y)$ denote the *observed* household Engel curve function for type t's assignable good; that is the fraction of household expenditure commanded by that good at the household budget y, holding constant prices p at the market price vector. If p^t gives the price of that good, $W^t(y) = p^t Q^t(y)/y$. Let $\widetilde{w}^t(\widetilde{y}^t)$ denote the *unobserved* individual Engel curve function for type t. It gives the fraction of expenditure commanded by the assignable good for type t at shadow prices $\widetilde{p} = Ap$ and shadow budget $\widetilde{y}^t$.

DLP show that household Engel curves for assignable goods are given by[7]

$$W^t(y) = \eta^t(y)\, \widetilde{w}^t\left(\widetilde{y}^t/N^t\right) = \eta^t(y)\, \widetilde{w}^t\left(\eta^t(y)y/N^t\right) \tag{2}$$

Here, the parameter η^t is written as a function of y. Because we are holding p constant, we do not write it as depending on p.

Here, we relate an observed object, the household Engel curve for the assignable good of type t individuals, to two unknown objects: the individual Engel curve for the assignable good of type t individuals and the resource share of type t individuals. The latter is the holy grail. DLP next specify a minimal set of assumptions about the right hand side of the equation above so as to be

[7] The jump from quantities to Engel curves may be obscure. Recall that for assignable goods, $Q_h^t = q_h^t\left(\widetilde{p}, \widetilde{y}_h^t\right)$ and that $\widetilde{y}_h^t = \eta_h^t y_h$. Substituting $\eta_h^t y_h$ for $\widetilde{y}_h$ on the RHS and replacing $W^t(y) = p^t Q^t(y)/y$ and rearranging yields the budget share form.

able to identify the resource shares from the households' Engel curves.

DLP impose three assumptions to identify resource shares from household Engel curves in the absence of price variation. First, they assume that resource shares do not depend on the household budget so that $\eta^t(y) = \eta^t$. This means that whatever the level of total household expenditure y, the way in which it is shared between the types of individuals is fixed (with respect to total expenditure). This is a strong assumption, but recall that the point of comparison is the per capita measure, which similarly assumes that total expenditure is shared in a fixed way but additionally imposes that there is no inequality within households.

Second, they assume that individual Engel curve functions are given by the Almost Ideal demand system of Deaton and Muellbauer (1980): $w^t(y) = \alpha^t + \beta^t \ln y$. This is the most popular demand specification in use, and so perhaps reasonable.

Third, they assume a condition they call Similarity across People (SAP), which, given the Almost Ideal structure above, implies that the slopes of the (unobserved) Engel curves are equal to the same value for all household members: $\beta^t = \beta$.

Substituting these restrictions into (2) yields:

$$W^t(y) = \eta^t \left(\alpha^t + \beta \left(\ln y + \ln \eta^t - \ln N^t\right)\right) \tag{3}$$

If there are three types of individuals in households, men, women and children, and three assignable goods, for example men's clothing, women's clothing and children's clothing, you have:

$$\begin{aligned} W^m(y) &= \eta^m \left(\alpha^m + \beta \left(\ln y + \ln \eta^m - \ln N^m\right)\right) \\ W^f(y) &= \eta^f \left(\alpha^f + \beta \left(\ln y + \ln \eta^f - \ln N^f\right)\right) \\ W^c(y) &= \eta^c \left(\alpha^c + \beta \left(\ln y + \ln \eta^c - \ln N^c\right)\right) \end{aligned} \tag{4}$$

There are: four unknown parameters, β, η^m, η^f and η^c; three Engel curves and the fact that the sum of the resource shares is equal to one. Hence, under the assumption of Similarity across People (SAP), the resource shares can be identified.

In practice, identification of this model has proven troublesome for several reasons. First, the model is nonlinear in parameters, since we need to estimate the products of the resource shares by the slope of the Engel curves, $\eta^t\beta$. Second, the resource shares have to be strictly positive, since they enter as $\ln \eta^t$. Estimation is therefore a nonlinear optimization subject to bounding restrictions on parameters. This can be difficult to estimate if the algorithm ventures in regions of negative resource shares. A further practical difficulty arises if resource shares are allowed to depend on characteristics, in which case a function has to be bounded at all values of the characteristics. If for a value of the characteristics, the resource shares take a negative value, the optimizer will crash.

Similarity across types (SAT) is the assumption that preferences are similar for individuals of the same type between different households. Showing identification under SAT is somewhat more involved than under SAP. Given that L-DLP is based on SAP, rather than SAT, we will leave interested readers to look at DLP if they want to learn about identification under SAT.

3.3 Linear DLP

The linearization of DLP that we propose is a re-framing of DLP. It is exact and theory consistent.

Let $h = 1, ..., H$ index households. Let ε_h^t be an error term, added to each of the Engel curve equations in (3). Index all data (W^t, y and N^t) with the subscript h. Then, we have

$$W^t(y_h) = \eta^t \left(\alpha^t + \beta \left(\ln y_h + \ln \eta^t - \ln N_h^t\right)\right) + \varepsilon_h^t.$$

Re-write equation (4) for type t in household h as

$$W^t = a_h^t + b^t \ln y_h + \varepsilon_h^t \tag{5}$$

where

$$a_h^t = \eta^t \alpha^t + \eta^t \beta \ln \eta^t - \eta^t \beta \ln N_h^t,$$

and

$$b^t = \eta^t \beta.$$

Let $W_h = \sum_t W_h^t$ be the household budget-share for all assignables:

$$W_h = a_h + b \ln y_h + \varepsilon_h \tag{6}$$

where,

$$a_h = \sum_t a_h^t$$

and

$$b = \sum b^t = \beta.$$

Notice that the resource share η^t appears in both a_h^t and b^t. But it appears in a very simple way in b^t, allowing us to express resource shares solely in terms of b^t:

$$\eta^t = b^t / b.$$

Since equations (5) and (6) take the form of linear regression equations, we may regress W_h^t and

W_h on $\ln y_h$, collect estimated coefficients on $\ln y_h$, $\widehat{b}^t$ and $\widehat{b}$, and construct estimates of the resource shares as[8]:

$$\widehat{\eta}^t = \widehat{b}^t \,/\, \widehat{b}$$

Note that the linearity of these regressions implies $\widehat{b} = \sum \widehat{b}_t$. Consequently, one could alternatively just regress W_h^t on $\ln y_h$, and construct $\widehat{\eta}^t = \widehat{b}^t \,/\, \sum_t \widehat{b}^t$, which would be numerically identical.[9]

DLP note that $\beta \neq 0$ is an identifying restriction of the model. This corresponds to the fact that if $\widehat{b}$ is close to zero, the estimator behaves "wildly". We use this fact below in our discussion of the pre-test of the model.

Finally, note that one could also include N_h^t as a regressor in these linear regressions (as it shows up in the terms a_h^t). We come to this, and the inclusion of other covariates, in a later subsection.

3.4 Graphical representation of linear DLP

Below, we show household-level micro-data on food expenditures from the 2015 Bangladesh Integrated Household Survey (described in detail in section 4.1), which is one of the few surveys that collects food consumption at the individual level. In Figure 1 we show, for all nuclear households with one male adult, one female adult and one child, the fraction of household expenditure spent on food for the adult male, W_h^m (on the left), and the fraction of household expenditure spent on food for all people, W_h (on the right), as functions of household expenditure y (in taka, the local currency).

The model of DLP relates Engel curves to the natural logarithm of household expenditure $\ln y$. So, in Figure 2, we transform the horizontal axis correspondingly.

Finally, the model of DLP posits a linear relationship between Engel curves and the log household expenditure. In Figure 3, we show univariate (aka: simple) linear regressions of W_h^m and W_h on $\ln y$, running through the data, and give the slope coefficients, b^m and b, in each graph.

We are now in a position to calculate the man's resource share. It is the ratio of the slope coefficient in the Men's Food Engel Curve to the slope coefficient in the All Food Engel Curve: $\eta^m = -0.065/-0.145 = 0.448$, or 44.8 percent. This means that the man's share of total household expenditure is about 45 percent.

It is important to note that this is not in general equal to the man's share of food in the

[8]In Stata, we could implement this via, e.g., the following code:

```
sureg (W_male lny) (W_all lny)
nlcom eta_male:  [W_male]lny / [W_male]all
```

[9]In Stata, we could implement this alternative expression using the code:

```
sureg (W_male lny) (W_female lny) (W_children lny)
nlcom (eta_male:  [W_male]lny/([W_male]lny+[W_female]lny+[W_children]lny)
```

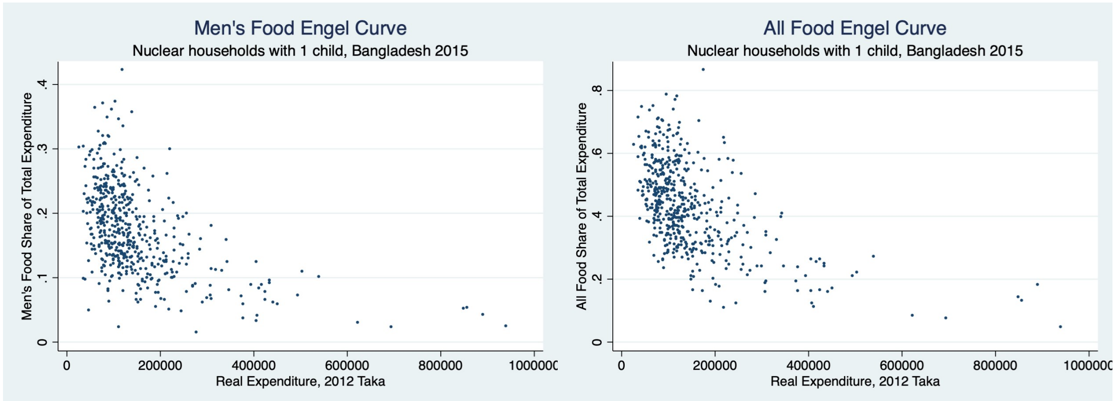

Figure 1: Food Engel curves (real expenditure)

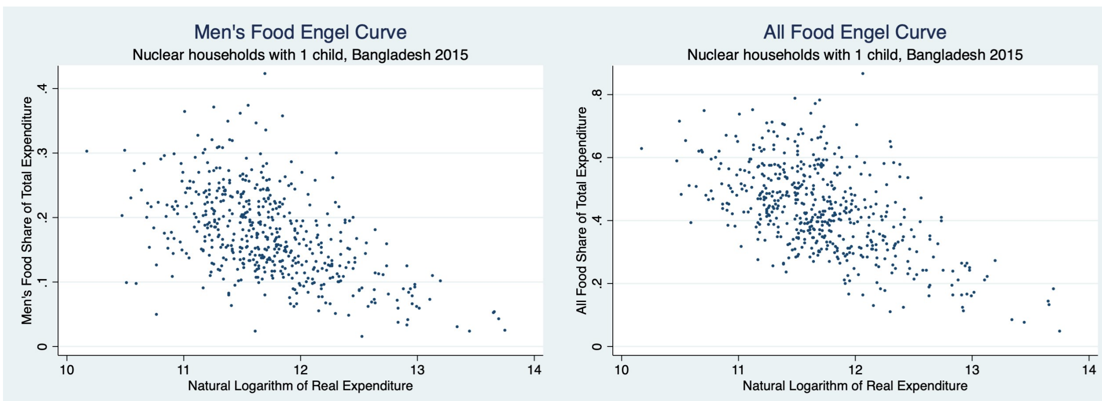

Figure 2: Food Engel curves (Ln(real expenditure))

household. For example, in these data, the average of $\ln y$ is 11.7. For households with $\ln y = 11.7$, the regression suggests that households spend 17 percent of expenditure on men's food, and 43 percent of expenditure on food altogether. The ratio of these is 40 percent, which is less than the man's resource share.

The bottom line here is that resource shares are identified by the budget response of Engel curves (the slopes), and not by the levels of Engel curves. This has two implications that practitioners should keep in mind. First, a resource share gives the fraction of **total household expenditure** enjoyed by an individual household member. The allocation of that expenditure across goods is a matter of the preferences of that individual. They may demand more of some goods than other household members, and less of other goods. Second, the identification of the resource share of each household member comes from the slopes of Engel curves. Household members whose assignable good responds more to an increase in household income command a greater resource share within the household than those whose assignable good responds less.

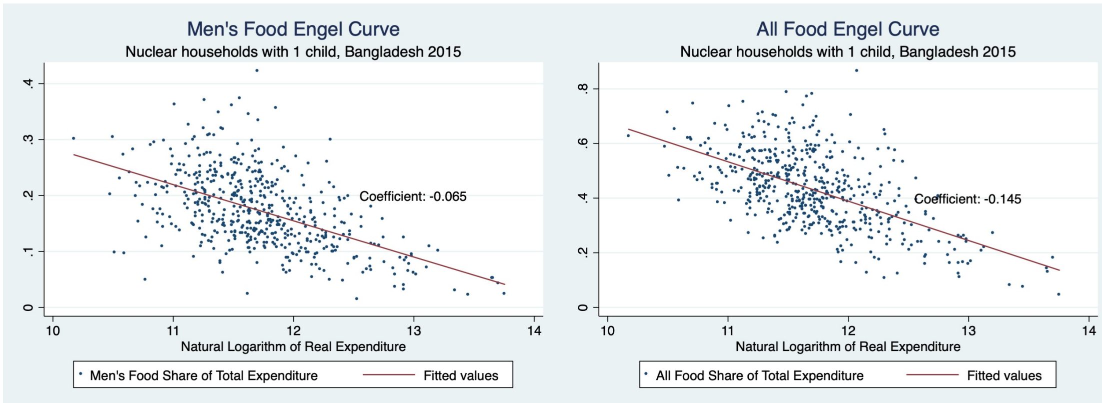

Figure 3: Food Engel curves (fitted values)

3.5 Including covariates

Now, assume there are a set of covariates $\widetilde{z}_h$ upon which we want to condition all the elements of the model, including resource shares η^t and preference parameters α^t and β. Note that the number of household members also affects resource shares and preferences. So, define z_h to be the vector comprised of logs of the numbers of household members and $\widetilde{z}_h$: $z_h = [\ln N_h^m \ \ln N_h^m \ \ln N_h^m \ \widetilde{z}_h]$. Let $z = 0$ denote a reference household type, with a meaningful definition. For example, its first three elements are zero for nuclear households with 1 child. If $\widetilde{z}$ includes education variables, we could let them equal zero for the modal education level.

In this case,

$$W^t(y_h, z_h) = \eta^t(z_h)\left(\alpha^t(z_h) + \beta(z_h)\left(\ln y_h + \ln \eta^t(z_h) - \ln N_h^t\right)\right) + \varepsilon_h^t.$$

Re-write equation (4) for type t in household h as

$$W^t = a_h^t + b_h^t \ln y_h + \varepsilon_h^t \tag{7}$$

where

$$a_h^t = \eta^t(z_h)\,\alpha^t(z_h) + \eta^t(z_h)\,\beta(z_h)\ln \eta^t(z_h) - \eta^t(z_h)\,\beta(z_h)\ln N_h^t, \tag{8}$$

and

$$b_h^t = \eta^t(z_h)\,\beta(z_h)\,. \tag{9}$$

Let $W_h = \sum_t W_h^t$ be the household budget-share for all assignables:

$$W_h = a_h + b_h \ln y_h + \varepsilon_h \tag{10}$$

where,

$$a_h = \sum_t a_h^t$$

and

$$b_h = \sum b_h^t = \beta\left(z_h\right).$$

The key difference between these expressions and those in the model without covariates is that b_h^t is subscripted due to its dependence on z_h. However, the resource shares $\eta^t(z_h)$ are still given by the simple ratio

$$\eta^t(z_h) = b_h^t / b_h.$$

Lechene, Pendakur, and Wolf (2020) suggest approximating this model with linear regressions that accommodate the fact that both a_h^t and b_h^t depend on z_h. The easiest approximation is to add z_h as regressors, and to interact $\ln y_h$ with z_h. This makes both a_h^t and b_h^t linear in z_h. This model can be implemented by regressing W_h^t and W_h on $z_h, \ln y_h$ and $z_h * \ln y_h$. This amounts to specifying linear forms for a_h^t and b_h^t as follows

$$a_h^t = a_0^t + a_N^{t\prime} \ln N_h + a_{\widetilde{z}}^{t\prime} \widetilde{z}_h = a_0^t + a_z^{t\prime} z_h, \tag{11}$$

and

$$b_h^t = b_0^t + b_N^{t\prime} \ln N_h + b_{\widetilde{z}}^{t\prime} \widetilde{z}_h = b_0^t + b_z^{t\prime} z_h. \tag{12}$$

Because these are linear, a_h and b_h, their sums over t, are defined analogously:

$$a_h = \sum_t a_h^t = a_0 + a_N' \ln N_h + a_{\widetilde{z}}' \widetilde{z}_h = a_0 + a_z' z_h, \tag{13}$$

and

$$b_h = \sum b_h^t = b_0 + b_N' \ln N_h + b_{\widetilde{z}}' \widetilde{z}_h = b_0 + b_z' z_h, \tag{14}$$

for suitably defined coefficients a_0, a_z, b_0, b_z.[10]

[10] In Stata, for example, we would first specify a list of covariates z_h, and then the list of its interactions with $\ln y$. Then, since $z = 0$ for the reference type, we have that b_h^t for the reference type equals the coefficient on $\ln y$. Supposing there were three covariates, we can compute the estimated value of the men's resource share in the reference household using the following Stata code:

```
global z ‘‘lnNm lnNf lnNc z1 z2 z3’’
global z_lny ‘‘lnNm_lny lnNf_lny lnNc_lny z1_lny z2_lny z3_lny’’
sureg (W_male $z lny $z_lny) (W_all $z lny $z_lny)
nlcom eta_male:  [W_male]lny / [W_male]all
```

To estimate the value of a resource share for other values of the covariates z, we would adjust the numerator and denominator accordingly.

3.6 Pre-test

Note that if the denominator $\hat{b} = \sum \widehat{b}_h^t$ is close to zero, the method does not work, and depending on the software you are using, you will get meaningless results, as you are trying to divide by zero. But given that the resource shares are constructed post-estimation, this does not cause issues with the estimation, contrarily to what happens when using a nonlinear optimization routine. This is in part the basis of the pre-test we present below.

Lechene, Pendakur, and Wolf (2020) suggest two pre-tests, both based on the model (10) using the approximating terms (13) and (14). This is a linear regression of W_h on $z_h, \ln y_h$ and $z_h * \ln y_h$. The first test assesses whether or not the estimate of b_h is statistically significantly different from 0 for a household with a fixed value of z_h, for example the reference household (or the mean value of z_h). Since b_h equals the coefficient on $\ln y$ for such a household, this is very simple.[11]

The second test they propose assesses whether or not the distribution of b_h is very far from zero. Here, for every observation in the data, they test whether or not $\widehat{b}_h = \widehat{b}_0 + \widehat{\boldsymbol{b}}' \boldsymbol{z}_h$ is statistically significantly different from zero, and report the fraction of households for which it is statistically significant. They argue that a "large" fraction of households should have an estimated overall Engel curve that is either upward or downward sloping, where "large" is taken to be 75 percent of the sample (other cutoffs could be used).

3.7 L-DLP versus per capita

You can test the per capita model within L-DLP. We note that this functional form for resource shares allows for the possibility that the resource shares of person types equal their per-capita share. In particular, if $b_0^t = 0$ for all t, $\boldsymbol{b}_{\tilde{z}}^t = \boldsymbol{0}$ for all t, $b_{N^{t'}}^t = 0$ for all $t' \neq t$ and $b_{N^t}^t = \kappa$ for all t, then we get per-capita resource shares, $\eta^t(\boldsymbol{z}_h) = N^t\kappa / \sum_t N^t\kappa = N^t / \sum_t N^t$.[12]

4 Empirical implementation

4.1 Data sources and selection

This paper draws on household survey data for four countries – the 2008 Albania Living Standards Measurement Survey, the 2015 Bangladesh Integrated Household Survey, the 2003 Bulgaria Multi-topic Household Survey and the 2010-11 Malawi Third Integrated Household Survey. The countries

[11] For example, in Stata, we check the $t-$statistic on `lny` in the following regression:

```
regress (W_all $z lny $z_lny)
```

[12] One could additionally restrict $\sum_t \boldsymbol{b}_N^t = \boldsymbol{0}$, implying that $\widehat{\eta}^t(\boldsymbol{z}_h) = b_h^t / \left(\sum_t b_0^t\right)$. This further simplifies the denominator, but at the cost of not nesting the per-capita model.

and data sets were selected as follows.[13]

In a first step, we identified household surveys for developing and transition countries from the World Bank's database of standardized consumption data sets, which satisfied the following two conditions: first, the full set of microdata and data documentation had to be accessible to the research team, and second, clothing expenditure had to be disaggregated by type of individual (i.e. men, women and children).[14]

In a second step, the team excluded several data sets on the grounds that they did not pass basic data quality and data documentation requirements. A common data quality concern, for example, was that in some data sets even childless households reported significant expenditure on children's clothing.[15] This suggests that either households were purchasing clothing for children residing in other households, or that some household members (i.e. children) were not properly enumerated in the household roster. In terms of documentation, several surveys did not provide any information about the age cut-offs used to distinguish between children's and adults' clothing in the expenditure module, which rendered them unsuitable for the analysis in this paper. Based on these criteria the team identified candidate data sets for 12 countries – Albania, Bangladesh, Bulgaria, Ethiopia, Ghana, Iraq, Malawi, Nigeria, Tajikistan, Tanzania, Timor-Leste and Uganda.

In a third step, Engel curves for clothing were estimated for each of the 12 countries. In the case of the 2015 Bangladesh Integrated Household Survey, which in addition to clothing also collected food consumption data assignable to individual household members, Engel curves were estimated separately for food and for clothing. As described in section 3.6, a useful pre-test to guide the decision about whether the L-DLP-method could be applied to a given data set, is to check that Engel curve estimations for the assignable good yield a slope parameter significantly different from zero. In our case, five of the 12 country data sets (Albania, Bangladesh, Bulgaria, Iraq and Malawi) passed this pre-test, with Bangladesh passing the pre-test for both food and clothing, which rendered them candidate data sets for the analysis in this paper. However, Iraq was ultimately excluded from the analysis because the poverty estimates derived from the 2006-07 Iraq Household Socioeconomic Survey were extremely low (at conventional poverty lines), which rendered the data unsuitable for the analysis of age and gender profiles of poverty.[16] We now turn to provide a brief description of each of the four data sets used in this paper.

[13] For more information, see https://www.worldbank.org/en/programs/lsms

[14] Many data sets were not fully accessible to the study team. This is a well-known conundrum with household survey data sets conducted by national statistical offices, which are sometimes only accessible at a significant cost or not available for public use at all (see Demombynes and Sandefur, 2014; Serajuddin et al., 2015; Beegle et al., 2016).

[15] To assess this systematically, the team computed the ratio of the mean budget shares on children's clothing for household with children (i.e. youngest household member <14 years) and households without young children (i.e. youngest household member $>=18$ years). A data set was flagged as potentially problematic if the ratio was below 10.

[16] Aggregate results for Iraq, however, are presented in Lechene, Pendakur, and Wolf (2020).

The 2008 Albania Living Standards Measurement Survey (LSMS) is a nationally representative multi-topic household survey conducted by the Albanian Institute of Statistics (INSTAT).[17] The survey had a target sample size of approximately 3,600 households, which were selected using a two-stage clustered sampling design (see Memushi, 2014 for details). The data set has been widely used to analyze poverty trends in Albania (see INSTAT, UNDP and World Bank, 2009).

The 2015 Bangladesh Integrated Household Survey (BIHS) is the second survey of a panel of three BIHS conducted in 2011-12, 2015 and 2017-18. The data were collected by the International Food Policy Research Institute (IFPRI) and the Policy Research and Strategy Support Program for Food Security and Agricultural Development (funded by the United States Agency for International Development). The BHIS data consist of two subsamples – one that is nationally representative for rural Bangladesh, and another one that is representative for rural "Feed the Future" zones, which are areas targeted by a US government-supported anti-poverty program. In this paper, we use the two subsamples together to estimate resource shares (to take advantage of the larger sample size) but restrict the analysis to the subsample representative for rural Bangladesh for estimating poverty in order to ensure that poverty estimates are representative for rural Bangladesh at large. The survey had a sample size of 6,500 households (of which 5,500 are in the nationally representative subsample), which were selected using a two-stage clustered sampling design drawing on a sampling frame developed from the 2001 Bangladesh population census (Ahmed, 2016).[18]

We exploit a feature of the BIHS that is rare for household surveys, that is the fact that the survey collected detailed information on food consumption of individual household members. To this end, the survey interviewed a woman in the household in charge of cooking, supervising and serving food to provide detailed information (recipe, ingredients, weights of raw and cooked ingredients) on foods consumed in the household during the previous day. Subsequently, the respondent was asked to report on the amounts of each meal consumed by the different household members, consumed by guests, given away or left over. The BIHS series has been widely used to estimate individual dietary intake, quality and diversity, which is a testimony to the high quality and granularity of nutritional information available in the surveys (Islam et al., 2018; Karageorgou et al., 2018; Sraboni and Quisumbing, 2018; D'Souza and Tandon, 2019). We aggregate individual level food consumption to consumption at the person-type-level to mimic the information that is available for clothing.

The 2003 Bulgaria Multi-topic Household Survey (MHS) is a nationally representative household survey conducted by the Bulgaria National Statistical Institute (NSI).[19] The survey had a planned sample size of around 3,700 households but due to non-response the final sample size was 3,023. Unlike the other surveys used in this paper, the Bulgaria MHS was designed to be self-weighting;

[17] https://microdata.worldbank.org/index.php/catalog/1933/related-materials
[18] https://dataverse.harvard.edu/data set.xhtml?persistentId=doi:10.7910/DVN/BXSYEL
[19] https://microdata.worldbank.org/index.php/catalog/2270/related_materials/

hence no sampling weights are used in the analysis (Hertz, 2009).

The 2010-11 Malawi Third Integrated Household Survey (IHS) is a nationally representative survey, which was conducted by the Malawi National Statistical Office (NSO) with technical assistance provided by the World Bank.[20] The survey used a two-stage clustered sampling approach based on listing data from the 2008 Malawi Population and Housing Census for a target sample size of just under 12,300 households. The IHS series is one of the main instruments implemented by the Government of Malawi to monitor and evaluate the living conditions of Malawian households (see, for example, Republic of Malawi, 2012).

4.2 Descriptive statistics

Table 2 shows descriptive statistics (means and standard deviations) for the five analysis samples used in this paper. For Bangladesh, we distinguish between the sample used with clothing as the assignable good (for ease of reference, simply referred to as Bangladesh), and the sample used with food as the assignable good (referred to as Bangladesh – food). Since data on individual food intake were not available for some households in the Bangladesh data set, the sample size is somewhat smaller for the latter than the former (5,465 vs 5,950 households).

The first panel of Table 2 shows the average age of men, women and children in the five samples. Adults are youngest in Malawi (36/35 years for men/women) and oldest in Bulgaria (49/51 years for men/women). The average age of children is between 7 (Malawi) and 9 years (Albania). The second panel presents information on years of schooling. Education levels are lowest in the Bangladesh sample, where the average adult benefited from approximately 4 years of schooling. Education levels in the Malawi sample are similar to Bangladesh for women, but significantly higher for men (at close to 6 years). Education levels are much higher in the two Eastern European samples but also show gender gaps, with approximately 10 (men) / 9 (women) years of schooling in Albania and 11 (men) / 10 (women) years in Bulgaria. As discussed in section 5.1, the Bangladesh data are representative for rural Bangladesh while the other data sets are nationally representative, with between 16 percent (Bulgaria) and 55 percent (Albania) of the sample being urban (third panel). Therefore, any difference between Bangladesh and the other three countries partly reflects the different geographic coverage of the data.

The fourth panel shows household budget shares for the assignable good (i.e. clothing in all samples except for Bangladesh-food). Budget shares for men's clothing vary between 0.6 percent in Malawi and 1.5 percent in Albania and Bangladesh. In all samples, households spend slightly more of their budget on women's clothing – between 0.9 percent in Malawi and 1.6 percent in Albania and Bangladesh. Budget shares for clothing of children are similar across countries, varying between 0.6

[20] https://microdata.worldbank.org/index.php/catalog/1003

Table 2: **Descriptive statistics of the five data sets**

Variable		Albania	Bangladesh	Bulgaria	Malawi	Bangladesh - food
			Age			
Men	Mean	44.8	41.7	48.9	35.8	41.8
	Std dev	*13.4*	*13.2*	*16.4*	*13.7*	*13.2*
Women	Mean	45.2	38.6	51.3	35.3	38.8
	Std dev	*13.5*	*11.0*	*17.0*	*14.7*	*11.0*
Children	Mean	9.1	8.0	8.4	6.7	8.0
	Std dev	*4.1*	*3.8*	*4.5*	*3.6*	*3.8*
			Years of schooling			
Men	Mean	9.67	4.18	10.63	5.71	4.22
	Std dev	*3.39*	*3.93*	*3.69*	*3.73*	*3.93*
Women	Mean	8.88	3.80	10.18	4.01	3.79
	Std dev	*3.42*	*3.26*	*4.08*	*3.53*	*3.27*
			General household characteristics			
Urban household	Mean	0.55	0.00	0.16	0.23	0.00
	Std dev	*0.50*	*0.00*	*0.36*	*0.42*	*0.00*
			Household budget shares of the assignable good			
Men's share	Mean	0.015	0.015	0.012	0.006	0.194
	Std dev	*0.022*	*0.013*	*0.020*	*0.016*	*0.127*
Women's share	Mean	0.016	0.016	0.013	0.009	0.213
	Std dev	*0.023*	*0.012*	*0.022*	*0.017*	*0.118*
Children's share	Mean	0.009	0.008	0.006	0.009	0.159
	Std dev	*0.016*	*0.009*	*0.016*	*0.018*	*0.131*
Total share	Mean	0.040	0.039	0.031	0.024	0.566
	Std dev	*0.042*	*0.021*	*0.038*	*0.036*	*0.152*
N		3,518	5,950	2,864	11,898	5,465

percent in Bulgaria and 0.9 percent in Albania and Malawi. In total, households spend between 2.4 (Malawi) and 4 (Albania) percent of their budget on clothing. As to be expected, budget shares are considerably higher for food, with 19.4 percent of the household budget devoted to men's food, 21.3 percent to women's food and 15.9 percent on children's food in the Bangladesh-food sample, for a combined food budget share of 56.6 percent.

4.3 Test of identification

The test of identification is a test of significance of the slope of the Engel curve for the assignable good for the household. In Table 3 below, for the four countries that we analyze, we have indicated the sample size, which varies from 2,099 for Bulgaria to 10,873 for Malawi; followed by the budget share of the assignable good and its standard deviation. Small shares are obtained for clothing, whose values are between 2.5 and 4.1 percent of the budget, and on the last row, we have the budget share of assignable food, considerably larger, at almost 57 percent. The standard deviations of the budget shares are large relative to the means, indicating that there is considerable dispersion of the clothing shares in all countries. Clothing is found to be a luxury in Albania, Bulgaria and Malawi, and a necessity in Bangladesh. Food is found to be a necessity in Bangladesh as it is generally expected, according to Engel's law. The slope, evaluated at the mean of the covariates, is always significantly different from zero, which means that the data from these countries pass the first part of the identification test, and the resource shares can be estimated. We then report the percentage of observations in the sample for which the slope is significantly different from zero, and here again, if we (arbitrarily) chose a threshold of 75 percent, then we see that the data from all countries pass the second part of the identification test.

Table 3: Test of Identification

Country	sample N	budget share	std dev	slope at $\overline{z}$	t-test of slope	% of sample significant
Albania	3,279	0.041	0.042	0.014	4.7	84
Bangladesh	6,120	0.039	0.021	-0.016	-21.4	100
Bulgaria	2,099	0.036	0.040	0.014	5.2	90
Malawi	10,873	0.025	0.036	0.009	10.0	98
Bangladesh–Food	5,604	0.568	0.150	-0.120	-17.2	100

Note: Single person households are excluded from this table. The results in this table are common to this paper and Lechene, Pendakur, and Wolf (2020).

4.4 Resource shares

In Table 4, we present the values of the resource shares (per person) estimated using our method, on data from the countries that pass the identification test. We show the resource shares for men, women, and children, evaluated at the mean value of the covariates and the mean of the resource shares, evaluated at all values of the covariates. These two objects are different since the resource share is a non linear combination of the parameters of the Engel curves. For the former, we give the standard error and for the latter, the standard deviation.

Men's resource shares are greater than women's resource shares in every country, except Bulgaria. Children's resource shares are considerably smaller than adults' resource shares. Below the estimated resource shares, we indicate their standard errors. Note that here, a test of whether a resource share is significantly different from zero is irrelevant. The column after the resource shares indicates the fraction of values of the estimated shares that are outside of [0,1]. These are very small, except for Bulgaria (at almost 8 percent) and Albania (just above 6 percent).

The last column of table 4 tests our method against the resource share used most widely for poverty analysis, the per capita share. We report the value of the Wald test statistic, degrees of freedom and associated p-value. We cannot reject the per capita model for Albania and Bulgaria, and we reject it for Bangladesh and Malawi. Note that the sample sizes for Albania and Bulgaria are about half the sample sizes for Bangladesh and Malawi, suggesting that larger sample sizes are needed to estimate these models.

Table 4: Predicted Resource Shares

Country	sample size	Evaluated at $\overline{\boldsymbol{z}}$ men est *std err*	women est *std err*	children est *std err*	Evaluated at all $\boldsymbol{z}_h$ men mean *std dev*	women mean *std dev*	children mean *std dev*	η outside [0,1]	per cap test Wald, df *p-value*
Albania	3,279	0.282	0.247	0.134	0.28	0.256	0.126	0.062	45, 35
		0.032	*0.033*	*0.030*	*0.369*	*0.340*	*0.166*		*0.129*
Bangladesh	6,120	0.312	0.286	0.120	0.311	0.284	0.122	0	387, 41
		0.011	*0.014*	*0.010*	*0.114*	*0.118*	*0.059*		*0.000*
Bulgaria	2,099	0.304	0.372	0.188	0.292	0.387	0.173	0.079	49, 35
		0.038	*0.041*	*0.061*	*0.14*	*0.218*	*0.214*		*0.058*
Malawi	10,873	0.312	0.274	0.124	0.31	0.267	0.127	0.015	267, 45
		0.028	*0.03*	*0.011*	*0.179*	*0.154*	*0.089*		*0.000*
Bangladesh	4,990	0.325	0.290	0.132	0.322	0.290	0.135	0.002	
Clothing		*0.013*	*0.017*	*0.012*	*0.109*	*0.118*	*0.064*		
Bangladesh	4,990	0.309	0.256	0.174	0.313	0.250	0.176	0.042	232, 41
Food		*0.014*	*0.015*	*0.011*	*0.110*	*0.114*	*0.082*		*0.000*
Difference		0.016	0.034	-0.043					
Clothing-Food		*0.019*	*0.022*	*0.016*					

Note: Single person households are excluded from this table. The results in this table are common to this paper and Lechene, Pendakur, and Wolf (2020).

The bottom rows of Table 4 show resource share estimates for Bangladesh using clothing vs food as the assignable good, estimated on a common sample of 4,990 households, and tests whether the shares are significantly different from each other for the two assignable goods.[21] For men and women, the difference between resource shares (at mean values of covariates) depending upon whether food or clothing are used as the assignable good is not statistically significant. Since the model allows, in principle, to use any assignable good to obtain resource shares, this is good news, because the estimates should not differ as per the choice of the assignable good.

For children, however, the resource shares are different: 13.2 percent (per child) with clothing, compared to 17.4 percent (per child) with food. This is a nontrivial difference, which – as shown in section 4.7 – matters for the assessment whether children are poorer than adults in rural Bangladesh.

[21]This sample restriction ensures that the estimates are not affected by differences in sample composition. Restricting the sample only has a marginal effect on the estimated resource shares (as can be seen by comparing the resource share estimates for clothing in the upper part of Table 4 with those further below).

The fact that children's resource shares are different for the two assignable goods is concerning and points to a rejection of some aspect of the model with regards to one or both assignable goods. One hypothesis is that clothing may be more shareable between children than between adults, e.g. because children wear hand-me-downs from their siblings and/or discarded clothing items from their parents. If this is the case, scale economies would be larger and shadow prices smaller for children than for adults, which could explain the results we find here (see Lechene, Pendakur, and Wolf, 2020 for further discussion). Considering this sensitivity of children's resource share estimates to the choice of the assignable good, the concluding section of this paper outlines an agenda for further methodological work to further validate estimates of intra-household resource shares and the resulting headcount poverty rates, with a focus on a comparison of alternative assignable goods and how to best measure individual consumption of these goods in household surveys. However, it is important to bear in mind that the per-capita model also requires a strong assumption – that resources are shared equally between household members – which rarely finds empirical support (Lewbel and Pendakur, 2008b; Lise and Seitz, 2011).

4.5 Testing the per capita model with poverty rates

In a next step we use the estimated resource shares to derive poverty rates for men, women and children in each of the four countries. Our first objective, pursued in this section, is to test whether the resulting poverty rates, which take into consideration unequal sharing within households, are significantly different from the conventional poverty estimates, which assume that resources are shared equally within households.

As described in section 2, poverty estimates always incorporate implicit assumption about scale economies.A related issue are differential needs of children relative to adults, an argument that is typically motivated by the observation that children, especially young children, have lower caloric needs than adults (see FAO, 2008). Such information is typically summarized by equivalence scales, which express the cost of living of a household of a given size and demographic composition in relation to that of a reference household (for example, a single adult), when both households attain the same level of utility or living standard (Lewbel and Pendakur, 2008a). While the calibration of equivalence scales remains a long-standing research topic and raises complex identification issues, this paper uses a widely used equivalence scale, the so-called modified OECD scale, which was first proposed by Hagenaars et al. (1994). This scale assigns an equivalence value of 1.0 to the first adult, of 0.5 to the second and each subsequent adult, and of 0.3 to each child (OECD, 2013).[22] This

[22]The modified OECD scale is used, for example in Batana et al. (2013) to measure global poverty of children, adults and the elderly – it is also the standard equivalence scale used by the statistical office of the European Union. Other examples from the academic literature include Madden (2011), Peichl et al. (2012), Akay et al. (2016) and Borah et al. (2019). While the age cut-offs used to distinguish between adults and children slightly vary between

scale, which is further described in Appendix A, accounts for economies of scale in consumption and incorporates the assumption that children require 60 percent of the resources needed by an adult (0.3/0.5). For consistency purposes, the scale is applied to both sets of poverty estimates – those assuming equal sharing and those assuming unequal sharing.

In addition to equivalence scales, the computation of poverty rates requires specifying a poverty line as a threshold to distinguish the poor and non-poor. A commonly used threshold is the well-known international poverty line of $1.90 per person per day, which is used to measure global extreme poverty (Ferreira et al., 2016; World Bank, 2018). However, this poverty line, which is based on the cost of living in the poorest countries in the world, is not well suited for measuring poverty in middle income countries. Therefore, we follow the approach outlined in World Bank (2018) and use higher poverty lines for middle income countries. More specifically, we use a poverty line of $1.90 for Malawi (a low-income country), a poverty line of $3.20 for Bangladesh (a lower middle-income country) and a poverty line of $5.50 for Albania and Bulgaria (upper middle-income countries).[23] All three poverty lines are expressed in 2011 purchasing power parities (PPPs) and translated to local currency units using the 2011 PPPs combined with national Consumer Price Indices (CPIs) to adjust for inflation between 2011 and the year in which the survey was conducted.

The poverty lines referenced above are defined as per capita poverty lines, derived from national poverty lines that estimate the average cost of living of poor households in per capita terms. If household consumption is expressed in adult equivalent terms, the poverty line ought to be adjusted. If the poverty line is not adjusted but held fixed (as for example in Batana et al., 2013) then, mechanically, poverty rates of all households but single adults decline when transitioning from the per capita approach to the per adult equivalent approach (Deaton and Zaidi, 2002; Ravallion, 2015). This is not a desirable feature since the underlying poverty lines were not derived for single adult households, which are rare in developing countries, but for households whose demographics are broadly representative of the poor population. Here we follow the approach outlined in Ravallion (2015) – implemented in Newhouse et al. (2017), Batana and Cockburn (2018) and Muñoz Boudet et al. (2021) – of rescaling the poverty line by the ratio of the number of household members to the number of adult equivalents in a reference household. The reference household composition is defined as the median number of adults and children among households whose per capita consumption is close to the per capita poverty line in each country.[24] This way, poverty rates of households with

studies (from 14+ to 17+ years) – we use an age cut-off of 15+ years in line with the definitions of the household survey data on which this study is based. For a broader discussion on the challenges of estimating equivalence scales, see Deaton and Zaidi (2002) and Lewbel and Pendakur (2008a).

[23] These lines are based on the median values of national poverty lines in lower and upper middle income countries in about 2011 (Jolliffe and Prydz, 2016).

[24] More precisely, we use households with consumption per capita between 0.9 and 1.1 of the poverty line. This amounts to 4 household members in Albania (3 adults and 1 child), 2 household members in Bulgaria (2 adults and 0 children) and 4 household members in Malawi (2 adults and 2 children). The reference household composition in

'reference' (in other words, typical) demographics among the poor are not strongly affected by the choice of the equivalence scale.

Table 5 shows (headcount) poverty rates of men, women, children and all people combined under the assumptions of equal vs. unequal sharing, and tests for significant differences between the two approaches.[25] In all four countries, and in Bangladesh irrespective of the assignable good, the overall (all people) poverty rate is significantly different if the analysis allows for unequal sharing within households than if equal sharing is imposed. This finding is consistent with the large literature showing that resources are often not equally distributed within households (e.g. Lewbel and Pendakur, 2008b; Lise and Seitz, 2011). Moreover, in all estimations the overall poverty rate is higher if we consider unequal sharing within households, which suggests that standard poverty rates may underestimate the level of poverty in society (see De Vreyer and Lambert, forthcoming, for a similar result for Senegal).[26] The increase in the headcount rates varies between 2.4 percentage points (Bangladesh food) and 10.7 percentage points (Bulgaria). Put differently, using clothing as the privately assignable good, the additional aggregate number of individuals that are identified as poor under unequal sharing of resources is estimated to range from 242,000 (8 percent of the total population) in Albania to 8,372,000 individuals in rural Bangladesh (7 percent of the rural population). The comparable estimates are 835,000 (11 percent of the total population) in Bulgaria and 1,086,000 million (7 percent of the total population) in Malawi (see Table B.1, Appendix).

If we compare poverty rates for men, women and children, it is noticeable that poverty rates of children are always significantly higher if the analysis considers unequal sharing within households. This reflects that the estimated resource shares of children are typically smaller than the estimated resource shares of adults, at least for the sample of countries considered in this paper (see section 4.4). The opposite trend is observed for adult men, for whom poverty rates are lower under the assumption of unequal sharing in situations where the difference is statistically significant (i.e. the two Bangladesh estimations and Malawi). Table B.1 in the Appendix translates this into absolute numbers. Using clothing as the assignable good, the reduction in the aggregate number of poor men under unequal sharing of resources is estimated to range from 612,000 in Malawi (16 percent of the adult male population) to 7,486,000 in rural Bangladesh (23 percent of the rural adult male population). For women, the results are mixed, with significantly lower poverty rates under the

Bangladesh also amounts to 4 household members (2 adults and 2 children) irrespective of which assignable good is used.

[25] Standard errors are bootstrapped because poverty rates are a discontinuous function of resource shares, which are themselves nonlinear functions of estimated OLS coefficients.

[26] If no household has sufficient budget to keep all its members above the poverty line, then inequality will reduce measured poverty and the converse. Therefore if, in some households, the per capita budgets are above the poverty line and in some households, they are below, inequality can lead either to an increase or a decrease in poverty headcount.

Table 5: Poverty Rates of Men, Women and Children Assuming Equal vs Unequal Sharing

Country		Sharing	**Men** Est	*Std err*		**Women** Est	*Std err*		**Children** Est	*Std err*		**All people** Est	*Std err*	
Albania	Poverty rates	Equal	0.306	*0.012*		0.313	*0.012*		0.052	*0.007*		0.251	*0.009*	
		Uneq	0.274	*0.054*		0.390	*0.054*		0.331	*0.086*		0.332	*0.023*	
	Difference		-0.032	*0.056*		0.077	*0.055*		0.279	*0.086*	***	0.080	*0.025*	***
Bangladesh	Poverty rates	Equal	0.527	*0.024*		0.510	*0.021*		0.138	*0.014*		0.377	*0.019*	
		Uneq	0.295	*0.025*		0.384	*0.027*		0.637	*0.044*		0.452	*0.020*	
	Difference		-0.233	*0.023*	***	-0.126	*0.021*	***	0.499	*0.040*	***	0.075	*0.009*	***
Bulgaria	Poverty rates	Equal	0.056	*0.010*		0.066	*0.011*		0.019	*0.008*		0.055	*0.009*	
		Uneq	0.108	*0.044*		0.162	*0.044*		0.319	*0.118*		0.162	*0.029*	
	Difference		0.052	*0.042*		0.096	*0.043*	**	0.299	*0.118*	**	0.107	*0.027*	***
Malawi	Poverty rates	Equal	0.658	*0.008*		0.686	*0.007*		0.422	*0.008*		0.549	*0.007*	
		Uneq	0.493	*0.024*		0.592	*0.032*		0.701	*0.031*		0.622	*0.010*	
	Difference		-0.165	*0.024*	***	-0.094	*0.032*	***	0.279	*0.031*	***	0.073	*0.010*	***
Bangladesh - food	Poverty rates	Equal	0.520	*0.038*		0.500	*0.034*		0.124	*0.019*		0.368	*0.029*	
		Uneq	0.317	*0.042*		0.541	*0.037*		0.309	*0.036*		0.391	*0.028*	
	Difference		-0.203	*0.028*	***	0.040	*0.024*	*	0.185	*0.031*	***	0.024	*0.008*	***

Note: Based on the modified OECD equivalence scale.

* denotes the gender gap is significant at 10%; ** at 5%; *** at 1%.

assumption of unequal sharing in some estimations (i.e. Bangladesh, Malawi) and significantly higher poverty rates in others (Bulgaria, Bangladesh – food). In absolute numbers, the aggregate number of poor women is reduced by 375,000 in Malawi (9 percent of the adult female population) and 4,857,000 million in rural Bangladesh (13 percent of the rural adult female population) if we move from equal to unequal sharing of resources and use clothing as the assignable good. Conversely, the aggregate number of poor women increases by 328,000 in Bulgaria (10 percent of the adult female population) and 86,000 in Albania (though not statistically significant – corresponding to 8 percent of the adult female population). Finally, in rural Bangladesh specifically, the estimates for headcount poverty and number of poor people under unequal sharing of resources – on the whole and separately for women and children – are sensitive to the assignable good. In particular, if the estimations are based on food, as opposed to clothing, the overall headcount poverty rate under unequal sharing decreases by 6 percentage points, while the headcount poverty rate among women increases by 16 percentage points.

Table 5 also shows how women's poverty rates are in part attributable to the distribution of women across households and in part to unequal sharing inside households. In Albania, Bulgaria and Malawi, women's poverty rates under equal sharing are higher than the men's poverty rates, reflecting the fact that women tend to live in households that are poorer overall. However, the differences in poverty rates by gender are small, especially when compared with the differences in poverty rates by gender under the assumption of unequal sharing. When we were looking at differences of one percentage point in poverty rates under equal sharing, we are now looking at differences of up to 23 percentage points when we allow for the fact that resources might be shared unequally between members of the same household. These results illustrate in a striking way how important it is to account in a credible manner for intra-household allocation of resources.

4.6 Age and gender differences in poverty among adults

We now turn to explore what the individual poverty estimates can reveal about age and gender differences in poverty among adults. We distinguish between three age groups – 16 to 39 years (core reproductive years), 40 to 59 years (advanced and post-reproductive years) and 60+ (seniors).[27] The definition of age groups is guided by the desire to delineate groups that have a meaningful interpretation in terms of stages in the lifecycle as well as sample size considerations, which requires defining groups that are not overly narrow.

Table 6 shows the (headcount) poverty rates for each age group and for all adults combined. The results are further disaggregated by sex and we test if the male-female difference is statistically

[27] Our 'core' reproductive age group is slightly narrower than the reproductive age definition in Demographic and Health Surveys, which typically consider 15-49 as reproductive years for women (https://www.dhsprogram.com/Methodology/Survey-Types/DHS-Questionnaires.cfm).

Table 6: Poverty Rates of Male and Female Adults by Age

Country			16-39			40-59			60plus			All adults (16plus)		
			Est	*Std err*		Est	*Std err*		Est	*Std err*		Est	*Std err*	
Albania	Poverty rates	men	0.311	*0.065*		0.237	*0.056*		0.256	*0.073*		0.274	*0.054*	
		women	0.361	*0.060*		0.314	*0.067*		0.575	*0.076*		0.390	*0.054*	
		total	0.336	*0.041*		0.276	*0.034*		0.420	*0.044*		0.332	*0.032*	
	Gender gap		0.049	*0.095*		0.076	*0.102*		0.319	*0.120*	***	0.116	*0.087*	
Bangladesh	Poverty rates	men	0.294	*0.029*		0.257	*0.029*		0.372	*0.030*		0.295	*0.025*	
		women	0.348	*0.031*		0.409	*0.030*		0.507	*0.033*		0.384	*0.027*	
		total	0.325	*0.024*		0.337	*0.020*		0.436	*0.024*		0.344	*0.020*	
	Gender gap		0.053	*0.038*		0.152	*0.043*	***	0.134	*0.041*	***	0.090	*0.034*	***
Bulgaria	Poverty rates	men	0.134	*0.056*		0.116	*0.050*		0.062	*0.046*		0.108	*0.044*	
		women	0.153	*0.048*		0.137	*0.041*		0.197	*0.065*		0.162	*0.044*	
		total	0.143	*0.040*		0.127	*0.032*		0.137	*0.036*		0.136	*0.031*	
	Gender gap		0.019	*0.068*		0.022	*0.065*		0.135	*0.089*		0.054	*0.063*	
Malawi	Poverty rates	men	0.457	*0.027*		0.500	*0.029*		0.731	*0.038*		0.493	*0.024*	
		women	0.581	*0.038*		0.591	*0.038*		0.658	*0.034*		0.592	*0.032*	
		total	0.522	*0.019*		0.545	*0.021*		0.690	*0.025*		0.545	*0.017*	
	Gender gap		0.124	*0.054*	**	0.091	*0.052*	*	-0.072	*0.053*		0.099	*0.046*	**
Bangladesh - food	Poverty rates	men	0.272	*0.044*		0.337	*0.047*		0.417	*0.047*		0.317	*0.042*	
		women	0.525	*0.041*		0.560	*0.038*		0.569	*0.044*		0.541	*0.037*	
		total	0.419	*0.036*		0.455	*0.035*		0.489	*0.034*		0.440	*0.034*	
	Gender gap		0.253	*0.044*	***	0.223	*0.048*	***	0.152	*0.061*	**	0.224	*0.040*	***

Note: Based on the modified OECD equivalence scale.

* denotes the gender gap is significant at 10%; ** at 5%; *** at 1%.

significant. In terms of lifecycle effects, there is evidence from all four countries that the elderly may be disproportionately affected by poverty. Poverty rates for the age group 60+ are often higher than for the two other age groups. However, in the two Eastern European countries (Albania and Bulgaria), poverty rates are only higher among elderly women. In Bangladesh and Malawi, both elderly men and elderly women show higher poverty rates than younger age groups.[28] Poverty rates for the core reproductive vs. advanced and post-reproductive age groups are surprisingly similar, possibly with the exception of Bangladesh, where poverty rates of women aged 40 to 59 years are somewhat higher than for women aged 16 to 39 years, especially if clothing as used as the assignable good.

In terms of gender gaps, our results suggest that women may be poorer than men. Point estimates of the poverty rate are always higher for women than for men (with one exception, the age group 60+ in Malawi). However, these gender gaps are only significant in Bangladesh (for all age groups) and in Albania for the elderly. It is further reassuring that, in the case of Bangladesh, the finding that women are poorer than men is qualitatively supported irrespective of whether food or clothing is used as the assignable good. This is consistent with Lechene, Pendakur, and Wolf (2020). However, there are some noticeable differences. If food is used as the assignable good, gender gaps in poverty are much larger, especially among the younger age groups, while the increase in poverty among the elderly is more muted, than if clothing is used as the assignable good.

The estimates reported so far are based on the modified OECD equivalence scale. As a robustness check we assess the sensitivity of our results to alternative commonly used equivalence scales – the per capita scale and the square root of household size equivalence scale (see Appendix B.1). Unlike the modified OECD equivalence scale, these scales do not account for differences in needs between children and adults. However, while the per capita scale also assumes that there are no economies of scale, the square root of household size scale accounts for economies of scale in consumption. The results in Appendix Tables B.2 and B.3 show that the broad lifecycle and gender patterns described in this section are generally robust to the choice of equivalence scale.

4.7 Adult versus child poverty

This section turns to the comparison of poverty between children and adults. Since expenditure on children is often not further disaggregated by sex in expenditure modules of household surveys, we cannot estimate differences in poverty between boys and girls but focus on the comparison between children and adults. It is well known that child poverty rates can be very sensitive to the choice of equivalence scales (see, for example, Newhouse et al., 2017). We therefore compare, already in the main text, child and adult poverty rates for three different equivalence scales – the modified OECD

[28] In Bangladesh, if the analysis is based on food, there is no discernible increase in poverty for elderly women.

Table 7: Poverty Rates of Children and Adults under Different Equivalence Scales

		Adults		Children		Children vs adults		
Country	Eq Scale	Pov est	*Std err*	Pov est	*Std err*	Pov est	*Std err*	Sig level
Albania	OECD	0.332	*0.032*	0.331	*0.086*	-0.002	*0.106*	
	RootN	0.309	*0.034*	0.644	*0.077*	0.335	*0.102*	***
	Per cap.	0.314	*0.034*	0.700	*0.075*	0.386	*0.100*	***
Bangladesh	OECD	0.344	*0.020*	0.637	*0.044*	0.293	*0.048*	***
	RootN	0.269	*0.035*	0.834	*0.024*	0.565	*0.033*	***
	Per cap.	0.300	*0.014*	0.855	*0.019*	0.555	*0.030*	***
Bulgaria	OECD	0.136	*0.031*	0.319	*0.118*	0.183	*0.126*	
	RootN	0.113	*0.034*	0.420	*0.108*	0.307	*0.116*	***
	Per cap.	0.173	*0.030*	0.516	*0.100*	0.343	*0.113*	***
Malawi	OECD	0.545	*0.017*	0.701	*0.031*	0.156	*0.046*	***
	RootN	0.513	*0.018*	0.853	*0.019*	0.340	*0.036*	***
	Per cap.	0.537	*0.017*	0.888	*0.014*	0.350	*0.030*	***
Bangladesh - food	OECD	0.440	*0.034*	0.309	*0.036*	-0.131	*0.044*	***
	RootN	0.367	*0.045*	0.628	*0.043*	0.261	*0.039*	***
	Per cap.	0.397	*0.016*	0.691	*0.025*	0.294	*0.037*	***

Note: RootN depicts the square root of household size equivalence scale.
* denotes the child-adult gap is significant at 10%; ** at 5%; *** at 1%.

scale, the per capita scale and the square root of household size scale.

Table 7 shows estimated headcount poverty rates for adults and children under three different assumptions about equivalence scales, and tests whether the gap between children and adults is statistically significant. The results provide support to the notion that children are poorer than adults, but also highlight again the importance of equivalence scale adjustments for the assessment of child poverty. If the analysis is based on the modified OECD equivalence scale, child poverty rates are considerably higher than adult poverty rates in Bulgaria and Malawi, though the difference is statistically significant only in Malawi. In Albania, the child-adult gap is not significant, while in Bangladesh children are poorer than adults if clothing is used as the assignable good, but less poor if food is used as the assignable good. Conversely, for the two other equivalence scales, child poverty rates are always larger than adult poverty rates and the difference between child and adult poverty is statistically significant.

The difference in results between the modified OECD scale on the one hand and the square root of household size and per capita scales on the other hand, reflects that the former assumes that children require less resources than adults (60 percent), while the two others assume there is no differences in needs between children and adults. It is therefore intuitive that the OECD scale shows lower rates of child poverty, compared to the two other scales.

5 Conclusion

Despite the growing empirical evidence on unequal sharing of resources within households, monetary poverty estimates are still mostly based on household-level measures of resources and poor individuals are identified based on the poverty status of their households and under the assumption of equal sharing of resources – regardless of potential intra-household differences among men, women and children in access to and use of resources. The disconnect is in part due to lack of cost-effective survey methods that can collect individual-disaggregated consumption data as part of national household consumption and expenditure surveys.

Our paper is the latest contribution to a surging strand of microeconomic research that develops structural models that are applied to existing household survey data to derive intra-household resource shares that in turn underlie gender- and age-differentiated poverty estimates. These models require household survey data that allows for the computation of a comprehensive consumption aggregate in which at least part of consumption can be assigned to household members (e.g. clothing expenditures that are disaggregated for men, women, and children that are part of the same household).

The analysis leverages a new model that that has been developed by Lechene, Pendakur, and Wolf (2020) and that estimates the share of household consumption of each household member. The model is a theory-consistent, linearized, and easier-to-implement version of the model originally proposed by Dunbar, Lewbel, and Pendakur (2013). Augmenting this model, we present a test that can be used to verify the suitability of existing household survey data sets for model estimation and make available fully documented syntax files that allow for replication elsewhere. The model is in turn applied to existing multi-topic household survey data from Albania, Bulgaria, Bangladesh, and Malawi.

In each country, the analysis demonstrates substantial within-household consumption inequality among men, women and children based on our estimated intra-household resource shares – in other words, under the assumption of unequal sharing of resources. There is cross-country consistent and statistically significant evidence on underestimation in headcount poverty among all people, and particularly among children, under the business-as-usual assumption of equal sharing of resources. The pronounced increase in poverty among children is due to the fact that their estimated resource shares are significantly smaller than those for men and women in each country of interest. Moving away from the assumption of equal sharing to unequal sharing of resources, there is, however, considerable cross-country heterogeneity in (i) the extent to which headcount poverty increases among the population as a whole, (ii) the direction of change in poverty among men and among women, and (iii) the magnitude of the gender difference in poverty among adults. Exploring the heterogeneity in headcount poverty estimates within different adult age categories under the assumption of unequal sharing of resources, there is cross-country evidence that the elderly (i.e. adults that are 60+) may be disproportionately affected by poverty. Finally, in the specific case of Bangladesh, we compare poverty estimates for men, women, and children for two alternative assignable goods (clothing versus food). The sensitivity of women's and children's headcount poverty estimates to the choice of the assignable good provides motivation for future research that should seek to validate modelled estimates of intra-household resource shares and resulting headcount poverty rates (e.g. along the lines of Bargain et al., 2018). The model validation is likely best pursued in randomized survey experiments that can be implemented in diverse geographic contexts.

An example of such a survey experiment would assign sampled households to one of several treatment arms. The first treatment arm, denoted here as the non-scalable gold standard, would collect intrahousehold, individual-specific consumption data to compute observed resource shares and poverty rates. In addition, by only using a subset of the available individual-specific consumption data, this treatment arm could also be used to compute predicted resource shares using the L-DLP and potentially other methods. Additional treatment arms could implement second-best survey methods that could build off of the prevailing approaches in existing household surveys and that would allow for the estimation of resource shares based on data collection methods that are more easily scalable in household surveys. Such a set up would allow to compare predicted and observed measures of intra-household resource shares and poverty rates for subsamples of household drawn randomly from the same population. Therefore, any difference between the observed and predicted measures in the first subsample would be attributable to the modeling exercise itself, while any differences between predicted measures in the first and second subsamples would be attributable to the approach used to collect assignable consumption data (i.e. the non-scalable gold standard vs scalable data collection methods). Such experimentation would be key to providing more conclusive guidance on the design of future household consumption and expenditure surveys and enabling national statistical offices and the international development community to adopt more gender-sensitive approaches to consumption data collection and analysis.

References

Ahmed, A. (2016). Description of the Bangladesh Integrated Household Survey. International Food Policy Research Institute (IFPRI), Washington, DC.

Akay, A., O. B. Bargain, C. Giulietti, J. D. Robalino, and K. F. Zimmermann (2016). Remittances and relative concerns in rural China. *China Economic Review 37*, 191–207. Special Issue on Human Capital, Labor Markets, and Migration.

Alkire, S., R. Ul Haq, and A. Alim (2019). The state of multidimensional child poverty in South Asia: a contextual and gendered view. OPHI Working Paper 127, Oxford Poverty and Human Development Initiative (OPHI), Oxford.

Apps, P. and E. Savage (1989). Labour supply, welfare rankings and the measurement of inequality. *Journal of Public Economics 39*(3), 335–364.

Apps, P. F. and R. Rees (1988). Taxation and the household. *Journal of Public Economics 35*(3), 355–369.

Bargain, O., O. Donni, and P. Kwenda (2014). Intrahousehold distribution and poverty: Evidence from Côte d'Ivoire. *Journal of Development Economics 107*, 262–276.

Bargain, O., G. LaCroix, and L. Tiberti (2018). Validating the collective model of household consumption using direct evidence on sharing. IZA Discussion Papers 11653, Institute of Labor Economics (IZA), Bonn.

Batana, Y., M. Bussolo, and J. Cockburn (2013). Global extreme poverty rates for children, adults and the elderly. *Economics Letters 120*(3), 405–407.

Batana, Y. and J. Cockburn (2018). Do demographics matter for African child poverty? World Bank Policy Research Working Paper 8426, World Bank, Washington DC.

Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal 75*(299), 493 – 517.

Becker, G. S. (1981). *A Treatise on the Family*. Cambridge: Harvard University Press.

Beegle, K., L. Christiaensen, A. Dabalen, and I. Gaddis (2016). Poverty in a rising Africa. World Bank, Washington, DC.

Blackorby, C. and D. Donaldson (1993). Household equivalence scales and welfare comparisons: A comment. *Journal of Public Economics 50*(1), 143–146.

Blundell, R., P. Chiappori, and C. Meghir (2005). Collective labor supply with children. *Journal of Political Economy 113*(6), 1277–1306.

Borah, M., C. Keldenich, and A. Knabe (2019). Reference income effects in the determination of equivalence scales using income satisfaction data. *Review of Income and Wealth 65*(4), 736–770.

Bose-Duker, T. (2019). Intra-household resource allocation and poverty: The Ghanaian case. Unpublished manuscript.

Bose-Duker, T., M. Henry, and E. Strobl (2020). Children's resource shares: Male versus female-headed households. *Journal of Family and Economic Issues*, 1–13.

Brown, C., R. Calvi, and J. Penglase (2021). Sharing the pie: An analysis of undernutrition and individual consumption in Bangladesh. CEPR Discussion Paper 15925, Centre for Economic Policy Research, London.

Browning, M., F. Bourguignon, P.-A. Chiappori, and V. Lechene (1994). Income and outcomes: A structural model of intrahousehold allocation. *Journal of Political Economy 102*(6), 1067–1096.

Browning, M., P.-A. Chiappori, and A. Lewbel (2013). Estimating consumption economies of scale, adult equivalence scales, and household bargaining power. *Review of Economic Studies 80*(4), 1267–1303.

Calvi, R. (2020). Why are older women missing in India? The age profile of bargaining power and poverty. *Journal of Political Economy 128*(7), 2453–2501.

Calvi, R., J. Penglase, D. Tommasi, and A. Wolf (2021). The more the poorer? Resource sharing and scale economies in large families. CEPR Discussion Paper 15924, Centre for Economic Policy Research, London.

Cherchye, L., T. Demuynck, B. De Rock, and F. Vermeulen (2017). Household consumption when the marriage is stable. *American Economic Review 107*(6), 1507–34.

Chiappori, P.-A. (1988). Rational household labor supply. *Econometrica 56*(1), 63–90.

Chiappori, P.-A. (1991). Nash-bargained household decisions: A rejoinder. *International Economic Review 32*(3), 761–762.

Chiappori, P.-A. and I. Ekeland (2009). The microeconomics of efficient group behavior: Identification. *Econometrica 77*(3), 763–799.

De Vreyer, P. and S. Lambert (forthcoming). Inequality, poverty, and the intra-household allocation of consumption in Senegal. *World Bank Economic Review*.

Deaton, A. and J. Muellbauer (1980). An almost ideal demand system. *American Economic Review 70*(3), 312–326.

Deaton, A. and S. Zaidi (2002). Guidelines for constructing consumption aggregates for welfare analysis. Living Standards Measurement Study Working Paper 135, World Bank, Washington DC.

Demombynes, G. and J. Sandefur (2014). Costing a data revolution. CGD Working Paper 383, Centre for Global Development, Washington DC.

D'Souza, A. and S. Tandon (2019). Intrahousehold nutritional inequities in rural Bangladesh. *Economic Development and Cultural Change 67*(3), 625–657.

Dunbar, G. R., A. Lewbel, and K. Pendakur (2013). Children's resources in collective households: Identification, estimation, and an application to child poverty in Malawi. *American Economic Review 103*(1), 438–471.

Dunbar, G. R., A. Lewbel, and K. Pendakur (2019). Identification of random resource shares in collective households without preference similarity restrictions. *Journal of Business & Economic Statistics 39*(2), 402–421.

Espinoza-Delgado, J. and S. Klasen (2018). Gender and multidimensional poverty in Nicaragua: An individual based approach. *World Development 110*, 466–491.

FAO (2008). Fao methodology for the measurement of food deprivation: Updating the minimum dietary energy requirements. Food and Agriculture Organization, Rome.

Ferreira, F. H. G., S. Chen, A. Dabalen, Y. Dikhanov, N. Hamadeh, D. Jolliffe, A. Narayan, E. B. Prydz, A. Revenga, P. Sangraula, U. Serajuddin, and N. Yosh (2016). A global count of the extreme poor in 2012: data issues, methodology and initial results. *The Journal of Economic Inequality 14*(2), 141–172.

Grown, C. (2014). Missing women: Gender and the extreme poverty debate. Learning Lab, United States Agency for International Development, Washington, DC.

Hagenaars, A., K. de Vos, and M. A. Zaidi (1994). Poverty statistics in the late 1980s: Research based on micro-data. Office for Official Publications of the European Communities, Luxembourg.

Hertz, T. (2009). The effect of nonfarm income on investment in Bulgarian family farming. *Agricultural Economics 40*(2), 161–176.

INSTAT, UNDP and World Bank (2009). Albania: Trends in poverty 2002-2005-2008. World Bank Microdata Library (Albania LSMS 2008), Washington DC, World Bank.

Islam, A. H. M. S., J. Braun, A. L. Thorne-Lyman, and A. U. Ahmed (2018, June). Farm diversification and food and nutrition security in Bangladesh: Empirical evidence from nationally representative household panel data. *Food Security 10*(3), 701–720.

Jolliffe, D. and E. B. Prydz (2016). Estimating international poverty lines from comparable national thresholds. *The Journal of Economic Inequality 14*(2), 185–198.

Jorgenson, D. and D. Slesnick (1984). Inequality in the distribution of individual welfare. In R. L. Basmann and G. F. Rhodes (Eds.), *Advances in Econometrics*, pp. 67–130. Greenwich: JAI Press.

Karageorgou, D., F. Imamura, J. Zhang, P. Shi, D. Mozaffarian, and R. Micha (2018). Assessing dietary intakes from household budget surveys: A national analysis in Bangladesh. *PLoS ONE 13*(8), 1–22.

Khadan, J., E. Strobl, and T. Tuffour (2020). Poverty and intra-household resource allocation in Surinamese households. IDB Working Paper 1045, Inter-American Development Bank, Washington DC.

Klasen, S. and R. Lahoti (forthcoming). How serious is the neglect of intra-household inequality in multi-dimensional poverty and inequality analyses? Evidence from India. *Review of Income and Wealth*.

Lechene, V., K. Pendakur, and A. Wolf (2020). OLS estimation of the intra-household distribution of expenditure. IFS Working Paper W20/06, Institute for Fiscal Studies, London.

Lewbel, A. and X. Lin (2020). Identification of semiparametric model coefficients. With an application to collective models. Unpublished manuscript.

Lewbel, A. and K. Pendakur (2008a). Equivalence scales. In S. Durlauf and L. Blume (Eds.), *New Palgrave Dictionary of Economics* (2nd ed.). Basingstoke, New York, NY: Palgrave Macmillan.

Lewbel, A. and K. Pendakur (2008b). Estimation of collective household models with Engel curves. *Journal of Econometrics 147*(2), 350 – 358.

Lewbel, A. and K. Pendakur (2021). Inefficient collective households: Cooperation and consumption. Unpublished manuscript.

Lise, J. and S. Seitz (2011). Consumption inequality and intra-household allocations. *The Review of Economic Studies 78*(1), 328–355.

Madden, D. (2011). Health and income poverty in Ireland, 2003-2006. *Journal of Economic Inequality 9*, 23–33.

McElroy, M. B. and M. J. Horney (1981). Nash-bargained household decisions: Toward a generalization of the theory of demand. *International Economic Review 22*(2), 333–349.

Memushi, A. (2014). Conspicuous consumption and Albanians: Determinant factors. *South-Eastern Europe Journal of Economics 12*, 65–87.

Muñoz Boudet, A. M., A. Bhatt, G. Azcona, J. Yoo, and K. Beegle (2021). A global view of poverty, gender and household composition. World Bank Policy Research Working Paper 9553, World Bank, Washington DC.

Newhouse, D., P. Suárez Becerra, and M. Evans (2017). New global estimates of child poverty and their sensitivity to alternative equivalence scales. *Economics Letters 157*, 125–128.

OECD (2013). Framework for integrated analysis. In *Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*. Paris: OECD Publishing.

Peichl, A., N. Pestel, and H. Schneider (2012). Does size matter? The impact of changes in household structure on income distribution in Germany. *Review of Income and Wealth 58*(1), 118–141.

Pendakur, K. (1999). Semiparametric estimates and tests of base-independent equivalence scales. *Journal of Econometrics 88*(1), 1–40.

Pendakur, K. (2018). Welfare analysis when people are different. *Canadian Journal of Economics 51*(2), 321–360.

Penglase, J. (2021). Consumption Inequality Among Children: Evidence from Child Fostering in Malawi. *The Economic Journal 131*(634), 1000–1025.

Ravallion, M. (2015). On testing the scale sensitivity of poverty measures. *Economics Letters 137*, 88–90.

Republic of Malawi (2012). Integrated household survey 2010-11. Household socio-economic characteristics report. National Statistical Office, Zomba.

Serajuddin, U., H. Uematsu, C. Wieser, N. Yoshida, and A. Dabalen (2015). Data deprivation: Another deprivation to end. World Bank Policy Research Working Paper 7252, World Bank, Washington DC.

Sokollu, S. and C. Valente (2019). Individual consumption in collective households: Identification using panel data with an application to PROGRESA. Unpublished manuscript.

Sraboni, E. and A. Quisumbing (2018). Women's empowerment in agriculture and dietary quality across the life course: Evidence from Bangladesh. *Food Policy 81*, 21–36.

Vijaya, R. M., R. Lahoti, and H. Swaminathan (2014). Moving from the household to the individual: Multidimensional poverty analysis. *World Development 59*, 70–81.

World Bank (2017). Monitoring global poverty. Report of the Commission on Global Poverty. World Bank, Washington DC.

World Bank (2018). Poverty and shared prosperity 2018: Piecing together the poverty puzzle. World Bank, Washington, DC.

Appendix A Equivalence scales

This paper uses three different equivalence scales: (1) the modified OECD scale, (2) the square root scale and the (3) per capita scale.

(1) The modified OECD scale assigns a value of 1 to the first adult household member, and 0.5 to each additional adult member and 0.3 to each child:

$$AE = 1 + 0.5(N_a - 1) + 0.3N_c$$

where AE is the number of adult equivalents, N_a is the number of adults in the household and N_c the number of children. This parameterization assumes that children require 60 percent of adult resources ($0.3/0.5 = 0.6$).

The two other scales are variants of the following general formula:

$$AE = (N_a + \alpha N_c)^\theta$$

where α measures the cost of a child relative to an adult, and θ is a parameter that captures economies of scale.

(2) For $\alpha = 1$ and $\theta = 0.5$, this scale becomes the square root scale:

$$AE = (N_a + N_c)^{0.5}$$

(3) For $\alpha = \theta = 1$, this scale becomes the per capita scale:

$$AE = (N_a + N_c)$$

Appendix B Tables

Table B.1: Poverty rates and the estimated number of poor men women and children assuming equal vs unequal sharing

Country		Sharing	Men			Women			Children			All people		
			Pov.est	Population (000s)		Pov.est	Population (000s)		Pov.est	Population (000s)		Pov.est	Population (000s)	
				Poor	Total		Poor	Total		Poor	Total		Poor	Total
Albania	Pov.rates	=	0.3061	337		0.3133	352		0.0517	40		0.2514	755	
		≠	0.2741	302	1,100	0.3899	438	1,124	0.3306	257	778	0.3319	997	3,003
	≠ vs =	Gap	-0.0320	-35		0.0766	86		0.2789	217		0.0805	242	
Bangladesh	Pov.rates	=	0.5271	16,970		0.5098	19,699		0.1383	5,676		0.3773	42,214	
		≠	0.2946	9,484	32,196	0.3841	14,842	38,638	0.6369	26,141	41,046	0.4521	50,586	111,880
	≠ vs =	Gap	-0.2325	-7,486		-0.1257	-4,857		0.4986	20,465		0.0748	8,372	
Bulgaria	Pov.rates	=	0.0556	176		0.0663	226		0.0195	24		0.0551	430	
		≠	0.1080	343	3,172	0.1624	554	3,411	0.3188	389	1,221	0.1621	1,265	7,804
	≠ vs =	Gap	0.0524	166		0.0961	328		0.2994	365		0.1070	835	
Malawi	Pov.rates	=	0.6580	2,444		0.6862	2,727		0.4218	3,068		0.5491	8,215	
		≠	0.4933	1,833	3,715	0.5919	2,352	3,974	0.7006	5,096	7,273	0.6217	9,301	14,962
	≠ vs =	Gap	-0.1647	-612		-0.0942	-375		0.2788	2,028		0.0726	1,086	
Bangladesh food	Pov.rates	=	0.5199	16,740		0.5004	19,336		0.1239	5,085		0.3678	41,147	
		≠	0.3165	10,190	32,196	0.5408	20,896	38,638	0.3086	12,666	41,046	0.3914	43,794	111,880
	≠ vs =	Gap	-0.2034	-6,549		0.0404	1,560		0.1847	7,581		0.0237	2,647	

Note: Total population estimates are obtained from the UN World Projection Population Estimates at (https://population.un.org/wpp/Download/Standard/Population/) except for Bangladesh.
Estimates of Bangladesh's rural population are obtained using sample weights from the data set which is representative of rural Bangladesh.
Based on the modified OECD equivalence scale (see also Table 5).

Table B.2: Poverty rates of males and females by age - per capita equivalence scale

Country			16-39			40-59			60plus			All adults (16plus)		
			Est	*Std err*		Est	*Std err*		Est	*Std err*		Est	*Std err*	
Albania	Poverty rates	Men	0.300	*0.064*		0.235	*0.055*		0.218	*0.067*		0.261	*0.053*	
		Women	0.377	*0.060*		0.285	*0.065*		0.482	*0.077*		0.367	*0.054*	
		Total	0.339	*0.041*		0.260	*0.035*		0.354	*0.047*		0.314	*0.034*	
	Gender gap		0.077	*0.093*		0.049	*0.098*		0.265	*0.110*	**	0.106	*0.083*	
Bangladesh	Poverty rates	Men	0.262	*0.027*		0.212	*0.029*		0.296	*0.030*		0.251	*0.025*	
		Women	0.323	*0.027*		0.336	*0.025*		0.433	*0.031*		0.340	*0.022*	
		Total	0.297	*0.018*		0.277	*0.016*		0.361	*0.023*		0.300	*0.014*	
	Gender gap		0.062	*0.041*		0.124	*0.044*	***	0.138	*0.041*	***	0.089	*0.037*	**
Bulgaria	Poverty rates	Men	0.201	*0.060*		0.163	*0.054*		0.074	*0.046*		0.153	*0.047*	
		Women	0.207	*0.049*		0.164	*0.040*		0.206	*0.063*		0.192	*0.043*	
		Total	0.204	*0.041*		0.163	*0.032*		0.148	*0.034*		0.173	*0.030*	
	Gender gap		0.005	*0.074*		0.001	*0.070*		0.132	*0.090*		0.039	*0.067*	
Malawi	Poverty rates	Men	0.451	*0.025*		0.499	*0.029*		0.673	*0.040*		0.483	*0.023*	
		Women	0.594	*0.039*		0.574	*0.039*		0.570	*0.036*		0.587	*0.033*	
		Total	0.526	*0.019*		0.536	*0.022*		0.615	*0.025*		0.537	*0.017*	
	Gender gap		0.143	*0.055*	**	0.076	*0.054*		-0.103	*0.057*	*	0.105	*0.047*	**
Bangladesh - food	Poverty rates	Men	0.244	*0.030*		0.291	*0.033*		0.342	*0.044*		0.275	*0.028*	
		Women	0.503	*0.027*		0.489	*0.029*		0.498	*0.038*		0.498	*0.024*	
		Total	0.394	*0.019*		0.395	*0.019*		0.415	*0.025*		0.397	*0.016*	
	Gender gap		0.260	*0.044*	***	0.198	*0.049*	***	0.156	*0.065*	**	0.224	*0.041*	***

Note: Based on the per capita scale. * denotes the gender gap is significant at 10%; ** at 5%; *** at 1%.

Table B.3: Poverty rates of males and females by age - square root equivalence scale

Country			16-39			40-59			60plus			All adults (16plus)		
			Est	*Std err*		Est	*Std err*		Est	*Std err*		Est	*Std err*	
Albania	Poverty rates	Men	0.272	*0.067*		0.217	*0.058*		0.253	*0.074*		0.249	*0.055*	
		Women	0.327	*0.062*		0.295	*0.066*		0.574	*0.075*		0.368	*0.054*	
		Total	0.299	*0.043*		0.256	*0.036*		0.418	*0.044*		0.309	*0.034*	
	Gender gap		0.055	*0.096*		0.078	*0.101*		0.321	*0.121*	***	0.120	*0.086*	
Bangladesh	Poverty rates	Men	0.208	*0.041*		0.190	*0.040*		0.297	*0.038*		0.217	*0.038*	
		Women	0.280	*0.040*		0.331	*0.044*		0.428	*0.040*		0.312	*0.038*	
		Total	0.250	*0.036*		0.264	*0.037*		0.359	*0.034*		0.269	*0.035*	
	Gender gap		0.072	*0.037*	*	0.141	*0.041*	***	0.131	*0.041*	***	0.096	*0.033*	***
Bulgaria	Poverty rates	Men	0.113	*0.055*		0.102	*0.050*		0.059	*0.048*		0.094	*0.045*	
		Women	0.111	*0.049*		0.105	*0.043*		0.178	*0.069*		0.131	*0.046*	
		Total	0.112	*0.041*		0.103	*0.034*		0.125	*0.042*		0.113	*0.034*	
	Gender gap		-0.003	*0.067*		0.004	*0.064*		0.119	*0.088*		0.037	*0.061*	
Malawi	Poverty rates	Men	0.423	*0.027*		0.456	*0.030*		0.692	*0.041*		0.456	*0.025*	
		Women	0.555	*0.039*		0.550	*0.040*		0.646	*0.033*		0.565	*0.034*	
		Total	0.492	*0.020*		0.503	*0.022*		0.666	*0.025*		0.513	*0.018*	
	Gender gap		0.132	*0.055*	**	0.094	*0.057*	*	-0.045	*0.055*		0.108	*0.048*	**
Bangladesh - food	Poverty rates	Men	0.189	*0.052*		0.269	*0.056*		0.335	*0.052*		0.238	*0.050*	
		Women	0.460	*0.051*		0.493	*0.050*		0.493	*0.055*		0.473	*0.049*	
		Total	0.346	*0.047*		0.386	*0.047*		0.410	*0.044*		0.367	*0.045*	
	Gender gap		0.271	*0.042*	***	0.224	*0.048*	***	0.158	*0.059*	***	0.235	*0.039*	***

Note: Based on the square root equivalence scale. * denotes the gender gap is significant at 10%; ** at 5%; *** at 1%.