

Children's Resources in Collective Households: Identification, Estimation and an Application to Child Poverty in Malawi

Geoffrey Dunbar, Arthur Lewbel and Krishna Pendakur
Simon Fraser University, Boston College, Simon Fraser University

September 12, 2011

- Children's resources matter.
 - Much social and economic policy is aimed at improving the material lives of children.
- But, children's resources are hard to identify, because children live in households.
- Collective household models allow us to think about individuals who live in households.
- But, they're a bit shabby when it comes to children:
 - they ignore them, or treat them as attributes of adults or women.
- We propose a collective household model that takes children seriously:
 - they are people with well-being;
 - their resource shares in households can be measured.

Our Contributions

- A collective household model with children who are economic agents.
 - Dauphin et al (2009) and Cherchye et al (2008) also do this, but they test the collective model, rather than estimate its parameters. Cherchye et al (2010) can bound parameters. Bargain and Donni (2010) are similar to us (more later)
- We identify children's resources using private assignable goods.
 - *private* goods do not have scale economies. *assignable* goods are consumed by a known person.
 - Chiappori and Ekelund (2008) give high-level identification conditions.
- We show that the resource shares of children in a given household type are identified if
 - resource shares don't vary with household expenditure; and
 - preferences are *similar across people*, or *similar across types*.
- We don't need data on singles or price data. We do need data on private assignables.

Our Contributions

Unlike many previous contributions

- We identify the level (rather than just the slope) of the resource share of each household member, including those of children.
- We allow for complex scale economies, rather than just allowing for purely private or purely public goods.
- We don't assume that single people have the same preferences as people in families, and so don't use data on singles (e.g., single children).
- Our models are pretty easy to implement.

Our Findings

- We use Malawian data household-level consumption data, essentially regressing clothing budget shares (for each person's clothing) on total expenditure.
- Empirically, we implement using **(clothing+footwear)** as a private assignable good.
- We identify shares of total expenditure on all goods.
- We find that:
 - men get bigger shares of household resources than women, and that men's shares do not really decline with the number of children (women's shares do decline).
 - if wives are more educated, men get less and women and children get more.
 - if the children are girls, women get more and the children get less.

Our Findings

- We find that men have larger resource shares than women.
- This is **not** because men have bigger clothing shares than women. In fact, men's average clothing budget shares are lower than women's.
- **Levels** of budget shares mix together the effects of (shadow) prices, preferences and resources.
- We provide identifying restrictions that parse these out.
- In our preferred empirical model,
 - *levels* of budget shares mix everything together
 - *slopes* of budget shares with respect to the log of total expenditure only depend on either (resource shares and prices) or (resource shares and preferences).

Collective Household Models

- Becker (1965, 1981) and Apps and Rees (eg., 1988) got us thinking about households as **collections of individuals with utility**.
- Chiappori and friends spurred recent *collective household* models which don't fully specify the household decision-making process, but rather ask what efficiency of that decision process implies. (Chiappori (1988, 1992), Bourguignon and Chiappori (1994), Browning, Bourguignon, Chiappori, and Lechene (1994), Browning and Chiappori (1998), Vermeulen (2002), Browning, Chiappori and Lewbel (2008), Lise and Seitz (2004; 2008), and Cherchye, L., B. De Rock, and F. Vermeulen (2008; 2010); Chiappori and Ekelund (2008); Lewbel and Pendakur (2008); Bargain and Donni (2010))
- These more recent models have some commonalities—the household reaches the pareto frontier; each person:
 - faces a shadow budget constraint.
 - faces a common shadow price vector.
 - gets a share of household expenditure. This is our object of interest, the **Resource Share** (aka: "Pareto Weight", "Sharing Rule")

Identification in Collective Household Models

- These models allow the researcher to identify how resource shares respond to covariates that don't affect preferences or shadow prices, sometimes called *distribution factors*.
- Some further allow the identification of the level of resource shares (Browning, Chiappori and Lewbel (2008); Cherchye et al (2010); Chiappori and Ekelund (2008)).
 - Browning, Chiappori and Lewbel (2008) and Lewbel and Pendakur (2008) don't have a place for kids;
 - Bargain and Donni (2010) have a place for kids, but identify from the assumption that singles have the same preferences as parents.
 - Cherchye, L., B. De Rock, and F. Vermeulen (2010) offer only set-identification;
 - Cherchye, L., B. De Rock, and F. Vermeulen (2010) and Chiappori and Ekelund (2008) allow only pure public or pure private goods.

We extend Browning Chiappori and Lewbel (2008 BCL) to allow for the presence of children as agents with utility. In their model:

- households act as if individuals within households face an unobserved shadow budget constraint (decentralization result);
- the shadow constraint is characterised by *shadow prices* and a shadow budget equal to the *resource share* times the household expenditure;
 - shadow prices can be any function of market prices, not just equal to market prices (pure private) or market prices per capita (pure public);
 - the **level** of the resource share is identified (unlike earlier collective household approaches);
- the shadow constraint is identified from household-level behaviour combined with behaviour of single individuals.

Consumption Technology and Shadow Prices

- The shadow price vector is not equal to the market price vector.
- The household exploits a *consumption technology* which converts market purchases of goods into within-household private good equivalents.
 - It determines the slope of the shadow budget constraint.
 - It is different in different types/sizes of households. Let s give the number of children in a household, $s = 1, 2, 3, \dots$
 - Let the shadow price K -vector be given by

$$A'_s p,$$

where A_s is a $K \times K$ matrix.

- The consumption technology A_s is the same for all household members. Within a household, people face the shadow prices $A'_s p$.

- Private goods have 1 on the diagonal and 0 off the diagonal. If a private good is assignable, you know who gets to consume it.
- Public goods have $1/(s + 2)$ on the diagonal and 0 off the diagonal and an equal share going to everyone.
- The bulk of the literature has only pure public and pure private goods.
- We allow for much more general consumption technologies (i.e., partially public and partially complementary goods).
- But, we need a private assignable good to exist for each person. So, there has to be a sorted version of A that has a block that is 1's on the diagonal and 0's off it.

Resource Shares

- The resource share gives the extent of the shadow budget constraint. This is different for different household members.
- Let t index people in the household, where $t = m, f, c$. Let η_{ts} be the resource share of person t in a household with s children.
- Let y be total expenditure in the household: the male gets to spend $\eta_{ms}y$, the female gets to spend $\eta_{fs}y$ and the children together get to spend $s\eta_{cs}y$.
 - Children get an equal share η_{cs} each. This can be relaxed if we have more assignable goods.
- Resource shares add up to 1.
- Resource shares may depend on the household budget constraint (p and y), and attributes of the household and of people in the household.

Demand System

- Let W_{ts} be the **household's** budget share function for person t 's assignable good in a household with s children (s indexes household types).
- Let w_t be **person t 's** budget share function for their assignable if they were living alone (i.e., facing market prices and getting to spend y).
- BCL show that W_{ts} is given by

$$\begin{aligned}W_{cs}(y, p) &= s\eta_{cs}(p, y)w_c(\eta_{cs}(p, y)y, A'_s p) \\W_{ms}(y, p) &= \eta_{ms}(p, y)w_m(\eta_{ms}(p, y)y, A'_s p) \\W_{fs}(y, p) &= \eta_{fs}(p, y)w_f(\eta_{fs}(p, y)y, A'_s p)\end{aligned}\tag{1}$$

- With S household sizes, you have $3S$ observable functions W_{ts} .
- Too many functions to identify: since A'_s is not observed, it is like an s index on $w_t(\cdot)$, so it's like having both η_{ts} and w_{ts} as unobserved functions.

Engel Curve Identification

- Assume that $\eta_{tf}(p, y)$ is independent of y .
 - Samuelson (1954) shows that $\eta_{tf}(p, y)$ has to depend on p .
 - But it may be independent of y —this condition is implied by plausible models of household decision making, e.g., PIGL utility plus weighted S-Gini household decision functions.
 - PIGL includes PIGLOG (includes Almost Ideal); weighted S-Gini includes utilitarian (possibly with price-dependent weights).
- Assume either
 - that preferences *similar across people* (SAP); or
 - that, for a person, preferences are *similar across types* (SAT).
- Theorems 1 and 2 shows conditions under which the resource shares of all household members are identified from Engel curve data.

Engel Curves

- Abusing the notation slightly, we have household Engel curves for person t 's private assignable:

$$\begin{aligned}W_{cs}(y) &= s\eta_{cs}w_{cs}(\eta_{cs}y) \\W_{ms}(y) &= \eta_{ms}w_{ms}(\eta_{ms}y) \\W_{fs}(y) &= \eta_{fs}w_{fs}(\eta_{fs}y).\end{aligned}\tag{2}$$

- Here, the *Engel curve* function w_{ts} gives the demand function for person t when facing the price vector $A'_s p$ for one particular value of p , so that, e.g., $w_{cs}(\eta_{cs}y) = w_c(\eta_{cs}(p)y, A'_s p)$ for that p .
- The resource share η_{ts} does not depend on y by assumption, and its dependence on p is suppressed in the Engel curve $w_{cs}(\eta_{cs}y)$ because prices are held constant.
- Here, η_{ts} are not identified, but, you could pick up something that affected η_{ts} but not w_{ts} (a "distribution factor").

- Here it is again:

$$W_{cs}(y) = s\eta_{cs} w_{cs}(\eta_{cs}y)$$

$$W_{ms}(y) = \eta_{ms} w_{ms}(\eta_{ms}y)$$

$$W_{fs}(y) = \eta_{fs} w_{fs}(\eta_{fs}y).$$

- You need to add something. Too many ts subscripts.
- Could add w_{ts} observed, but where do you get them? (Bargain and Donni (2010): singles)
 - And, where do you observe children's w_{cs} ?
- Could add preferences identical across people, $w_{ts} = w_s$.
- Could add preferences identical across prices, $w_{ts} = w_t$.
- You don't need identical-ness—you can use similarity, a separable piece of preferences that is either the same across people (subscript t), or the same across price vectors A_s (subscripts s).

Similarity Intuition

- Let the latent budget share functions w_{ts} be additive in a few known functions of expenditure. For example, a K 'th order polynomial in y :

$$w_{ts}(y) = a_{ts}^0 + a_{ts}^1 \ln y + a_{ts}^2 (\ln y)^2 \dots + a_{ts}^K (\ln y)^K.$$

- Let one of these coefficients be the same across people, e.g., $a_{ts}^2 = a_s^2$.
- Then, we get to drop the t subscript on that term:

$$W_{cs}(y) = s\eta_{cs} w_{cs}(\eta_{cs}y) = s\eta_{cs} a_{cs}^0 + s(\eta_{cs})^2 a_{cs}^1 y + s(\eta_{cs})^3 a_s^2 y^2 \dots$$

$$W_{ms}(y) = \eta_{ms} w_{ms}(\eta_{ms}y) = \eta_{ms} a_{ms}^0 + (\eta_{ms})^2 a_{ms}^1 y + (\eta_{ms})^3 a_s^2 y^2 \dots$$

$$W_{fs}(y) = \eta_{fs} w_{fs}(\eta_{fs}y) = \eta_{fs} a_{fs}^0 + (\eta_{fs})^2 a_{fs}^1 y + (\eta_{fs})^3 a_s^2 y^2 \dots$$

- Here, for any household size s , the 3 coefficients on the y^2 term identify the 3 unknown parameters: η_{ms} , η_{fs} and a_s^2 .
- A similar argument works if we drop an s subscript on any term.
- Our theorems give conditions on utility functions that allow identification of this sort.

Identification via Preferences Similar Across People (SAP)

- Assume that people's preferences satisfy SAP:

$$w_t(y, p) = d_t(p) + g\left(\frac{y}{G_t(p)}, p\right) \quad \text{for } y \leq y^*(p). \quad (3)$$

- People have budget-share functions for their private assignable that, at low expenditure levels, have the *same shape* (given by g).
- Typically, the restriction is imposed on **all goods** and at **all expenditure levels**.
 - Equivalence-Scale Exactness implies this. A big empirical literature finds it to be roughly true.
- Here, we impose it on **one good** at **low expenditure levels**.
- Thm 1 shows that if preferences satisfy (3), and demands are 'a bit' nonlinear, then resource shares are identified from Engel curve data.

Example: PIGLOG Demands

- Let indirect utility be PIGLOG (includes the massively popular Almost Ideal demand system) for each person t :

$$\begin{aligned}V_t(p, y) &= b_t(p) [\ln y - \ln a_t(p)], \\w_t(y, p) &= d_t(p) + \beta_t(p) \ln y,\end{aligned}$$

where d_t and $\beta(p)$ are functions of $a_t(p)$ and $b(p)$.

- SAP implies $b_t(p) = b(p)$.
- Then, household Engel curves are given by

$$\begin{aligned}W_{cs}(y) &= s\eta_{cs}(\delta_{cs} + \beta_s \ln \eta_{cs}) + s\eta_{cs}\beta_s \ln y, \\W_{ms}(y) &= \eta_{ms}(\delta_{ms} + \beta_s \ln \eta_{ms}) + \eta_{ms}\beta_s \ln y, \\W_{fs}(y) &= \eta_{fs}(\delta_{fs} + \beta_s \ln \eta_{fs}) + \eta_{fs}\beta_s \ln y,\end{aligned}\tag{4}$$

for any household size s , and where $\delta_{ts} = d_t(A'_s p)$ and $\beta_s = \beta(A'_s p)$.

- For any household size, there are 3 slopes wrt to $\ln y$ revealed by the data, and 3 unknown parameters: β_s , η_{ms} and η_{fs} .

- Given PIGLOG preferences and SAP, we have

$$\begin{aligned}W_{cs}(y) &= s\eta_{cs}(\delta_{cs} + \beta_s \ln \eta_{cs}) + s\eta_{cs}\beta_s \ln y, \\W_{ms}(y) &= \eta_{ms}(\delta_{ms} + \beta_s \ln \eta_{ms}) + \eta_{ms}\beta_s \ln y, \\W_{fs}(y) &= \eta_{fs}(\delta_{fs} + \beta_s \ln \eta_{fs}) + \eta_{fs}\beta_s \ln y,\end{aligned}\tag{5}$$

- The level of the private assignable budget share doesn't tell you much: it mixes preference effects (the t part of δ_{ts}), shadow price effects (the s part of δ_{ts}) and resource share effects (η_{ts}).
- We identify off of the total expenditure response of the budget share.
- In Malawi, men's clothing budget shares are smaller than women's, but their resource shares are larger.

Identification via Preferences Similar Across Types (SAT)

- Let $p = [\bar{p}, \hat{p}]$: \bar{p} is for purely private goods (\bar{p} contains p_t , the private assignable price for person t); \hat{p} is for other goods. Shadow price of private goods is \bar{p} , but that of other goods is $\hat{A}_s \hat{p}$.
- For private goods, budget shares vary across household sizes due to 2 factors only: resource shares, and *cross-price* demand responses.
- Assume SAT:

$$w_t(y, p) = g_t \left(\frac{y}{G_t(p)}, \bar{p} \right) \quad \text{for } y \leq y^*(p). \quad (6)$$

- A bit like Lewbel and Pendakur (2008). Cross-price effects load onto an income deflator.
- Lewbel and Pendakur (and Bargain and Donni) apply this restriction to **all price effects** for **all goods** and at **all expenditure levels**.
- Here, we only restrict the **cross-price effects** of **non-private goods** on the **private assignable goods**, only at **low expenditure levels**.
- Thm 2 shows that if preferences satisfy (6), and demands are 'a bit' nonlinear, then resource shares are identified from Engel curve data.

Example: PIGLOG Demands

- Again, assume that indirect utility is PIGLOG:

$$V_t(p, y) = b_t(p) [\ln y - \ln a_t(p)]$$

SAT holds if $b_t(p) = \bar{b}_t(\bar{p}/p_t)$ and $a_t(p) = \bar{a}_t(\bar{p})$. (PIGLOG identification can be under a weaker restriction.)

- This implies budget-share functions

$$w_t(y, p) = d_t(p) + \beta_t(\bar{p}/p_t) \ln y,$$

where $d_t(p)$ is a function of $\bar{a}_t(\bar{p})$ and $\bar{b}_t(\bar{p}/p_t)$, and

$\beta_t(\bar{p}/p_t) = -\partial \ln \bar{b}_t(\bar{p}/p_t) / \partial \ln p_t$, which is the same for all $A'_s p$.

- Household Engel curves are given by:

$$W_{cs}(y) = s\eta_{cs} (\delta_{cs} + \beta_c \ln \eta_{cs}) + s\eta_{cs}\beta_c \ln y, \quad (7)$$

$$W_{ms}(y) = \eta_{ms} (\delta_{ms} + \beta_m \ln \eta_{ms}) + \eta_{ms}\beta_m \ln y,$$

$$W_{fs}(y) = \eta_{fs} (\delta_{fs} + \beta_f \ln \eta_{fs}) + \eta_{fs}\beta_f \ln y,$$

where $\delta_{ts} = d_t(A'_s p)$ and $\beta_t = \beta_t(\bar{p}/p_t)$.

- With 3 household sizes, there are 9 slopes revealed by the data, and 9 unknown parameters: $\beta_m, \beta_f, \beta_c, \eta_{m1}, \eta_{f1}, \eta_{m2}, \eta_{f2}, \eta_{m3}$ and η_{f3} .

- We implement the model with PIGLOG indirect utility yielding household Engel curves given by:

$$\begin{aligned}W_{cs}(y) &= s\eta_{cs}(\delta_{cs} + \beta_c \ln \eta_{cs}) + s\eta_{cs}\beta_{cs} \ln y, \\W_{ms}(y) &= \eta_{ms}(\delta_{ms} + \beta_m \ln \eta_{ms}) + \eta_{ms}\beta_{ms} \ln y, \\W_{fs}(y) &= \eta_{fs}(\delta_{fs} + \beta_f \ln \eta_{fs}) + \eta_{fs}\beta_{fs} \ln y,\end{aligned}\tag{8}$$

with $\beta_{ts} = \beta_s$ for SAP identification, $\beta_{ts} = \beta_t$ for SAT identification, or $\beta_{ts} = \beta$ for identification using both restrictions for extra efficiency.

- Everything (δ_{ts} , β_{ts} and η_{ts}) can depend arbitrarily on individual and household demographics.

- This model is linear in the variables (a constant and $\ln y$ for each t, s), and so a reduced form could be estimated via OLS, with structural parameters given as nonlinear functions of reduced form parameters.
- We estimate the structural model directly via nonlinear SUR.
- We also account for possible endogeneity via nonlinear GMM.

- We use the Malawi Integrated Household Survey, conducted in 2004-2005:
 - from the National Statistics Office of the Government of Malawi with assistance from the International Food Policy Research Institute and the World Bank, includes roughly 11,000 households.
- The data are of high quality: enumerators were monitored; big cash bonuses were used as an incentive system; about 5 per cent of the original random sample in each years had to be resampled because dwellings were unoccupied; (only) 0.4 per cent of initial respondents refused to answer the survey.
- We use 2794 households comprised of non-urban married couples with 1-4 children aged less than 15.
- Private assignable good is men's, women's and children's clothing (including footwear).

Table 1: Data Means, Malawian micro-data

	couples with				all
	1 kid	2 kids	3 kids	4 kids	
Number of Observations	845	825	667	457	2794
clothing plus men	1.46	1.34	1.21	1.00	1.29
footwear women	2.10	1.92	1.61	1.52	1.84
(in per cent) children	1.06	1.50	1.69	1.89	1.48
log-total-expenditure	-0.13	-0.06	0.01	0.11	-0.04

Engel Curve Specification

- Recall, eqs look like

$$W_{ms}(y) = \eta_{ms} (\delta_{ms} + \beta_m \ln \eta_{ms}) + \eta_{ms} \beta_{ms} \ln y.$$

- Let s denote 4 household size dummies (1-4 children). the s index above will be absorbed by these dummies.
- Let z denote 14 demographic variables:
 - region of residence (non-urban North and non-urban Central with non-urban South as the left-out category);
 - the average age of children less 5; the minimum age of children less 5; and the proportion of children who are girls;
 - the age of the man less 28 and the age of the woman less 22 (the average ages of men and women in the sample);
 - the education levels of the household head and spouse (ranging from -2 to 4, where 0 is the model education level);
 - the log of the distance of the village to a road and to a daily market; a dummy indicating that the 3 month recall period for consumption occurred over the dry season;
 - and dummy variables indicating that the household is christian or muslim (with animist/other as the left-out category).

- Recall, eqs look like

$$W_{ms}(y) = \eta_{ms} (\delta_{ms} + \beta_m \ln \eta_{ms}) + \eta_{ms} \beta_{ms} \ln y.$$

- s is 4 household size dummies (1-4 children); z is 14 demographic variables.
- Let δ_{ts} and η_{ts} be linear in s, z for each person t .
- Given SAP, let β_s be linear in s, z ; Given SAT, let β_t be linear in a constant and z for each person t ; Given both SAP&SAT, let β be linear in a constant and z .
- Estimation is via nonlinear SUR or GMM.

Table 2a: Estimated Levels of Resource Shares

		SAP		SAT		SAP&SAT	
		Est	<i>Std Err</i>	Est	<i>Std Err</i>	Est	<i>StdErr</i>
1 kid	man	0.443	<i>0.048</i>	0.378	<i>0.076</i>	0.400	0.045
	woman	0.308	<i>0.041</i>	0.368	<i>0.062</i>	0.373	0.042
	kids	0.249	<i>0.037</i>	0.254	<i>0.072</i>	0.227	0.036
	each kid	0.249	<i>0.037</i>	0.254	<i>0.072</i>	0.227	0.036
2 kids	man	0.423	<i>0.051</i>	0.436	<i>0.090</i>	0.462	0.051
	woman	0.222	<i>0.042</i>	0.212	<i>0.056</i>	0.221	0.043
	kids	0.355	<i>0.045</i>	0.352	<i>0.100</i>	0.317	0.045
	each kid	0.177	<i>0.022</i>	0.176	<i>0.050</i>	0.158	0.023
3 kids	man	0.427	<i>0.057</i>	0.437	<i>0.099</i>	0.466	0.053
	woman	0.185	<i>0.046</i>	0.166	<i>0.054</i>	0.176	0.044
	kids	0.388	<i>0.050</i>	0.397	<i>0.114</i>	0.358	0.050
	each kid	0.129	<i>0.017</i>	0.132	<i>0.038</i>	0.119	0.017
4 kids	man	0.318	<i>0.070</i>	0.352	<i>0.112</i>	0.384	0.063
	woman	0.214	<i>0.054</i>	0.168	<i>0.062</i>	0.182	0.052
	kids	0.468	<i>0.061</i>	0.479	<i>0.133</i>	0.434	0.059
	each kid	0.117	<i>0.015</i>	0.120	<i>0.033</i>	0.109	0.015

Malawi Results: Levels

- Which column is best? Cannot reject that the SAP&SAT is not worse than SAP or SAT. So, focus on SAP&SAT
- Men get a pretty fixed share. Can't reject a nonresponsive men's share.
- Women's shares decline with the number of kids. Can't reject a linear response of 5.5 %age points per child.
- Kids' shares increase with the number of kids.
- Per-kid shares decrease with the number of kids, and are about 11 per cent for the 3rd and 4th kid.
- Looks like kids eat mom's pie.

Table 2b: Estimated Covariate Effects

		SAP		SAT		SAP&SAT	
		Est	<i>Std Err</i>	Est	<i>Std Err</i>	Est	<i>StdErr</i>
min	man	-0.005	<i>0.010</i>	0.007	<i>0.010</i>	0.008	0.009
age	woman	-0.005	<i>0.008</i>	-0.014	<i>0.008</i>	-0.014	0.008
kids	kids	0.010	<i>0.006</i>	0.007	<i>0.007</i>	0.007	0.006
avg	man	0.006	<i>0.010</i>	-0.007	<i>0.010</i>	-0.008	0.009
age	woman	0.006	<i>0.008</i>	0.017	<i>0.008</i>	0.017	0.008
kids	kids	-0.012	<i>0.006</i>	-0.010	<i>0.008</i>	-0.009	0.006
prop	man	0.006	<i>0.029</i>	0.001	<i>0.031</i>	-0.003	0.028
girl	woman	0.053	<i>0.024</i>	0.058	<i>0.027</i>	0.056	0.026
kids	kids	-0.059	<i>0.020</i>	-0.059	<i>0.025</i>	-0.053	0.019
man	man	0.021	<i>0.009</i>	0.008	<i>0.010</i>	0.008	0.010
educ	woman	-0.009	<i>0.008</i>	0.003	<i>0.009</i>	0.002	0.009
	kids	-0.012	<i>0.006</i>	-0.011	<i>0.007</i>	-0.010	0.006
wom.	man	-0.022	<i>0.012</i>	-0.050	<i>0.012</i>	-0.049	0.011
educ	woman	0.007	<i>0.010</i>	0.030	<i>0.012</i>	0.032	0.011
	kids	0.015	<i>0.008</i>	0.020	<i>0.010</i>	0.017	0.008

- kid age matters: if kids are 5 years older, woman gets 9 percentage points more and kids get 5 per cent less; if minimum age is 5 years older, woman gets 7 percentage points less.
- sex of kids matters. All girls: woman gets 5 per cent more, kids get 5 per cent less.
- woman's education matters: if woman is at the 90th percentile of education rather than the median, man gets 10 percentage points less, with 1/3 going to the kids and 2/3 going to the woman.

Testing These Models

- You can test SAT against a less restrictive alternative because with 4 household sizes there is 1 overidentifying restriction. SAT passes this test.
- You can test downwards from SAP or SAT to the combination of SAP&SAT. The combo of SAP&SAT passes both these tests.
- You can test whether or not the levels of people's resource shares depend linearly on the number of kids. SAP&SAT estimates pass this test.
- You can test our general model. If you have 2 assignable goods, you could estimate resource shares on each, and η_{ts} should be the same for both assignables. LR test says it is okay; Wald test says maybe not.

Dealing with Endogeneity

- Some variables are likely endogenous.
 - Total expenditure, for the usual reasons (e.g., purchase infrequency).
 - Number of children, if preference heterogeneity regarding fertility is correlated with preference heterogeneity in consumption choices.
- We have wealth instruments (separated into livestock and durables) for total expenditure, and medical-oriented instruments for number of children: distance to doctor; indicator of whether or not there is an HIV-oriented NGO in the village; indicator of whether the woman has a chronic illness.
- Apply GMM to the model with number of kids rather than household size dummies.
- It is overidentified; we pass all overidentification tests.
- Wealth instruments are strong; number of kids instruments are weak (first-stage F-stat of 2.5).

Table 4: GMM Estimates: SAP&SAT, linear in s

instrumented:		SUR		GMM		GMM	
		Est	Std Err	Est	Std Err	Est	Std Err
1 kid	man	0.456	0.045	0.407	0.056	0.341	0.074
	woman	0.358	0.044	0.427	0.054	0.408	0.071
	kids	0.186	0.030	0.166	0.044	0.251	0.073
extra kid	man	-0.012	0.018	0.083	0.085	-0.008	0.095
	woman	-0.055	0.015	-0.148	0.073	-0.075	0.098
	kids	0.068	0.014	0.065	0.040	0.083	0.042
min age kids	man	0.003	0.009	0.056	0.040	0.004	0.043
	woman	-0.007	0.008	-0.056	0.034	0.000	0.044
	kids	0.004	0.006	0.000	0.019	-0.004	0.019
avg age kids	man	-0.004	0.009	-0.058	0.040	-0.010	0.043
	woman	0.009	0.008	0.058	0.035	0.007	0.044
	kids	-0.005	0.006	-0.001	0.019	0.003	0.019
prop girl kids	man	-0.015	0.030	0.030	0.033	-0.026	0.038
	woman	0.063	0.029	0.026	0.027	0.090	0.040
	kids	-0.048	0.016	-0.056	0.024	-0.065	0.033
man educ	man	0.008	0.010	0.020	0.010	0.013	0.012
	woman	-0.001	0.010	-0.016	0.010	-0.006	0.012
	kids	-0.008	0.005	-0.004	0.005	-0.007	0.008
wom. educ	man	-0.047	0.011	-0.044	0.012	-0.058	0.014
	woman	0.033	0.011	0.028	0.012	0.042	0.015
	kids	0.014	0.006	0.016	0.007	0.016	0.009

- Basically, the results from the SUR hold up.
- Hausman tests don't reject the exogeneity null.
- If you instrument just number of kids, you can still see: that women's shares decline in the number of kids; that there's a gender bias towards boy-children; and that women's education helps women and children.
- But, if you instrument both number of kids and log-expenditure, the std errs balloon out so much you can no longer see that women's shares decline in the number of kids.

Table 5: Estimated Resource Shares and Poverty Rates

		Mean	SD	Min	Max	PovRate Unequal	PovRate Equal
1 kid	man	0.463	0.087	0.245	0.762	0.686	0.850
	woman	0.402	0.071	0.168	0.587	0.766	
	kid	0.135	0.047	0.008	0.260	0.954	
2 kids	man	0.516	0.078	0.282	0.786	0.547	0.916
	woman	0.273	0.063	0.075	0.475	0.885	
	kids	0.211	0.044	0.059	0.326	0.970	
3 kids	man	0.521	0.081	0.219	0.795	0.522	0.948
	woman	0.244	0.065	0.002	0.512	0.889	
	kids	0.236	0.042	0.112	0.374	0.996	
4 kids	man	0.441	0.080	0.170	0.701	0.538	0.972
	woman	0.267	0.066	0.043	0.532	0.838	
	kids	0.293	0.037	0.178	0.402	0.989	
All hhlds	man	0.489	0.088	0.170	0.795	0.582	0.913
	woman	0.304	0.093	0.002	0.587	0.842	
	kids	0.207	0.070	0.008	0.402	0.974	
Persons	all	0.235	0.177	0.008	0.795	0.855	0.924

Resource Share Estimates

- Because covariates are correlated with household size, marginal effects don't tell the whole story.
- Although they were not restricted to be reasonable, all estimated resource shares are in $[0, 1]$.
- Similar patterns in levels emerge:
 - men eat about 44 to 52 per cent, women eat 24 to 40 per cent.
- Across the population, the average resource share of a child is 10 per cent.

Poverty Estimates

- There's a lot of poverty.
- Using per-capita (equal) shares of income against a (PPP) U\$2/day poverty threshold, we find household-level poverty rate of 92.4 per cent (WB reports 90.5 per cent in 2004).
- Using estimated (unequal) resource shares, we find that 58 per cent of households have a poor man, 84 per cent of households have a poor woman, and 97 per cent of households have a poor child.
- Thus, accounting for the within-household distribution of resources has a substantial effect on measured poverty.
- The poverty rate of men seems to drop with household size, but that of women and children seems to rise with household size.

- We provide a model of childrens' resources in collective households which
 - treats kids as people;
 - is easyish-to-estimate; and
 - has resource shares that are semi-parametrically identified in an Engel curve setting.
- We implement the model with Malawian data and find that kids eat mom's pie.
- So treating woman/children as a blob masks important inequality.