Resource Shares
With and Without Distribution Factors

preliminary results: please do not cite

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Introduction

- Topics
  - Identification of Resources Shares in Collective Household Models
    - New Identification Theorem
  - Effect of Credit, and Micro-Credit, on children's resource shares.
    - New empirical work with cool Malawian data.
    - Show how credit take-up affects the within-household distribution of resources.
    - Correct for endogenous credit takeup.

Microcredit

- Microcredit is ubiquitous – in 2010, 137.5 million people worldwide were received microcredit.
    - See State of the Microcredit Summit Campaign.
- It is fast growing. Women receiving microcredit increased from 10.3 million to 113 million between 1999 and 2010.
- One of the founding hopes of the microcredit revolution is that lending to poor women would make women and their children better off. See Yunus and Jolis (2003).
    – Microcredit has easy appeal – access to small loans gives opportunities for entrepreneurship.
    – Microcredit might create freedom in Sen's sense: choice and agency equal goodness.
- plausible channels to household decisions and allocations:
    – microcredit is start-up capital, or
    – availability of microcredit reduces need for buffer stock savings.

Microcredit (continued)

- Difficult to control for endogeneity of take-up.
- Pitt and Khandker (1998) use eligibility criteria (land holdings)---they find a positive causal effect of microcredit on consumption.
  - But whose consumption?
  - Morduch (1998) and Roodman and Morduch (2012) complain about exogeneity in the above...
- Experimental designs can be used:
  - e.g. Crépon et al. (2011), Banerjee et al. (2010) and Karlan and Zinman (2010).
  - Nelson (2011) has a neat natural experiment in Thailand, and finds that credit expansion increases child labour. But are kids worse off?
- These studies typically find some effects on total household consumption, but not much on specific spending categories.
- They don't speak to the within-household allocation.

Microcredit in Malawi

- Brune et al. (2010) examined microsaving commitment accounts via an experimental design
  - found commitment accounts increased total household expenditure. (Commitment accounts do not allow funds to be withdrawn except on prespecified dates.)
- We investigate the effect of microcredit on the within-household distribution of resources.
  - How does it affect childrens' resources?
- The data are rich and provide plausible (and cool) instruments for the endogeneity of credit take up.
- We focus on microcredit loans as being distinct from other credit, such as business and social loans

Collective Households

- Collective Household models
  - People have utility, not households. But, you can still learn stuff from household behaviour. See Becker (1964 and on), Apps and Rees (1980s and early 1990s), Chiappori (1990s on), Cherchye, De Rock and Vermeulen (L3, 2000s).
- Efficient Collective Households (Chiappori etc)
  - Household are economic environments--- machines that make budget constraints faced by people. Prices or budgets faced by individuals may be observed or not.
  - Assume households reach an efficient allocation (GE decentralisation result—needs no consumption externalities), equivalent to
    - $\text{Max}_{q1,q2}\ m(q,y,d)u_1(q_1)+u_2(q_2)$
  - If we knew the budget constraints (shadow prices, shadow budget) faced by individuals, we could do standard consumer surplus.
  - Pareto weight *m* maps into a resource share *n*.

Resource Shares

- Each person gets to spend a fraction, called their *resource share*, of the household budget.
  - Different resource shares for different people.
- They spend it on goods at within-household prices. These prices may be unobserved.
- Bigger resource share = more consumption.
- Useful for inequality, poverty, social welfare.

Identification of Resource Shares from Demand Data

- *Distribution factors* affect resource shares but not preferences/ shadow prices.
- Chiappori (many papers, many coauthors) and others: if you know (or assume) the shadow prices, the **derivatives** of resource shares with respect to distribution factors are identified from behaviour (nice survey of identification results in Bourgignon, Browning, Chiappori 2008) .
  - Cannot identify the **level** of resource shares.
  - Don’t need price variation.
    - L3 (2012): you can get the **level** of the resource share if you collect data on individual consumption of all goods. ☺

- Browning, Chiappori and Lewbel (BCL 2012): efficient household with known preferences and observed price variation---shadow prices and the *level* of resource shares are identified.

Resource Shares Independent of Expenditure

- **If BCL model holds *and* resource shares are independent of household expenditure:**
- Lewbel and Pendakur 2008
  - with a strong preference restriction: levels of resource shares and cost of shadow price differences are semiparametrically identified for couples without price variation.
  - Donni (many years, many coauthors) extends to cover children.
- Dunbar, Lewbel and Pendakur 2013
  - With a weaker preference restriction and an ***assignable good***: levels of resource shares are semiparametrically identified for adults and children without price variation.
- Dunbar, Lewbel and Pendakur 2013b (new!)
  - With **no preference restriction**, a distribution factor and an assignable good: levels of resource shares are nonparametrically identified for adults and children without price variation.

Expenditure-Dependence

- There are identification theorems that use the restriction that resource shares are independent of household expenditure.
- One can write structural models yielding this (DLP 2013, online appendix)
- About a dozen papers explicitly use this restriction; many more implicitly use them.
- What does the empirical evidence say? Tough, because the restriction is not testable in an Engel curve setting.
  - Lewbel+L3 (2012) test it in a setting with price variation, and find it is ok.
- It can be tested via stated preference.

Menon, Perali and Pendakur 2012

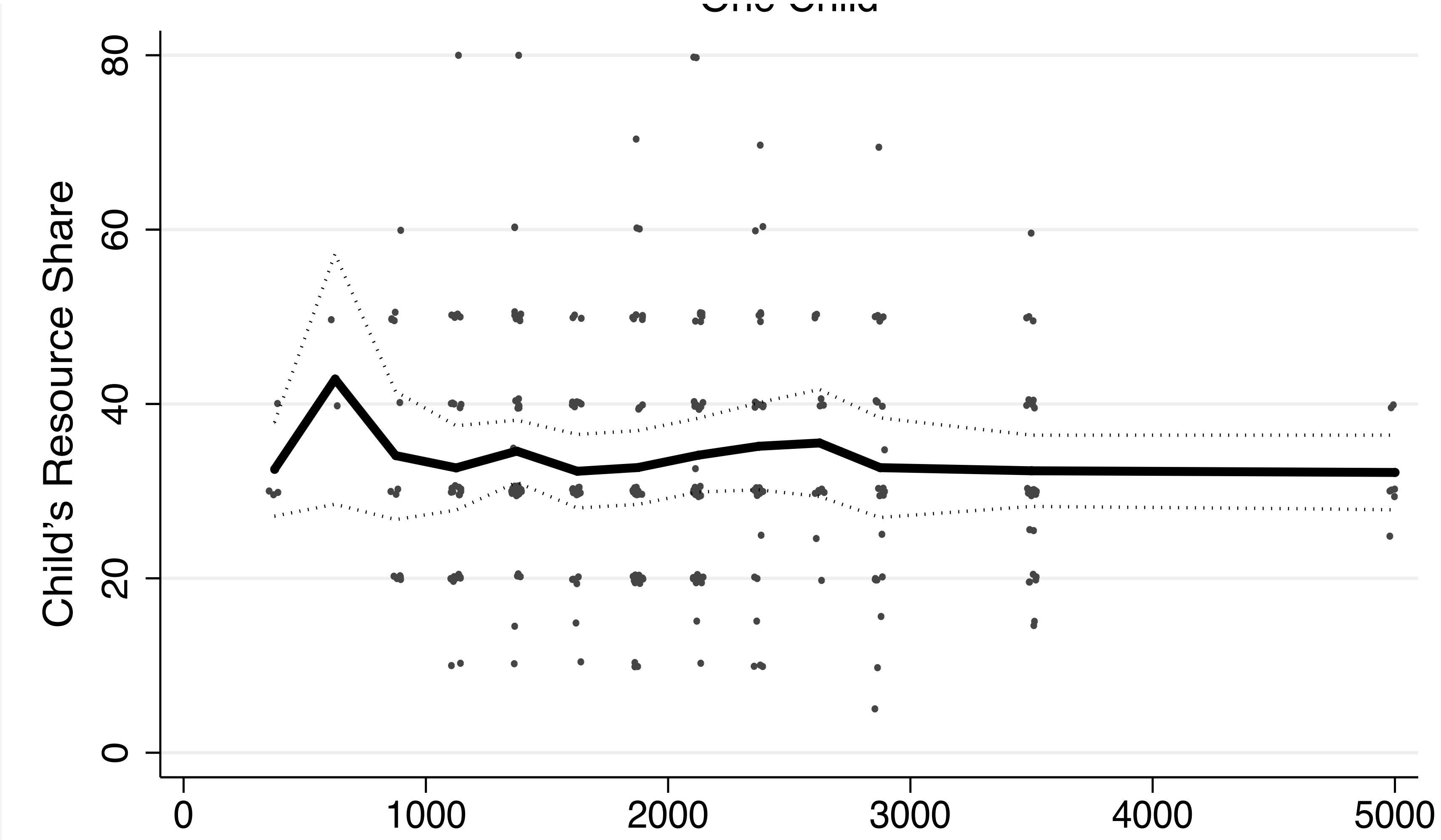
- "On the Expenditure-Dependence of Resource Shares" is a note which asks: do children's resource shares depend on household expenditure?
- There is no formal structural model.
- Instead, we rely on the household head's answer to the question: "Of the monthly expenditure of your household, what you spend in percent for your children?".

The Data

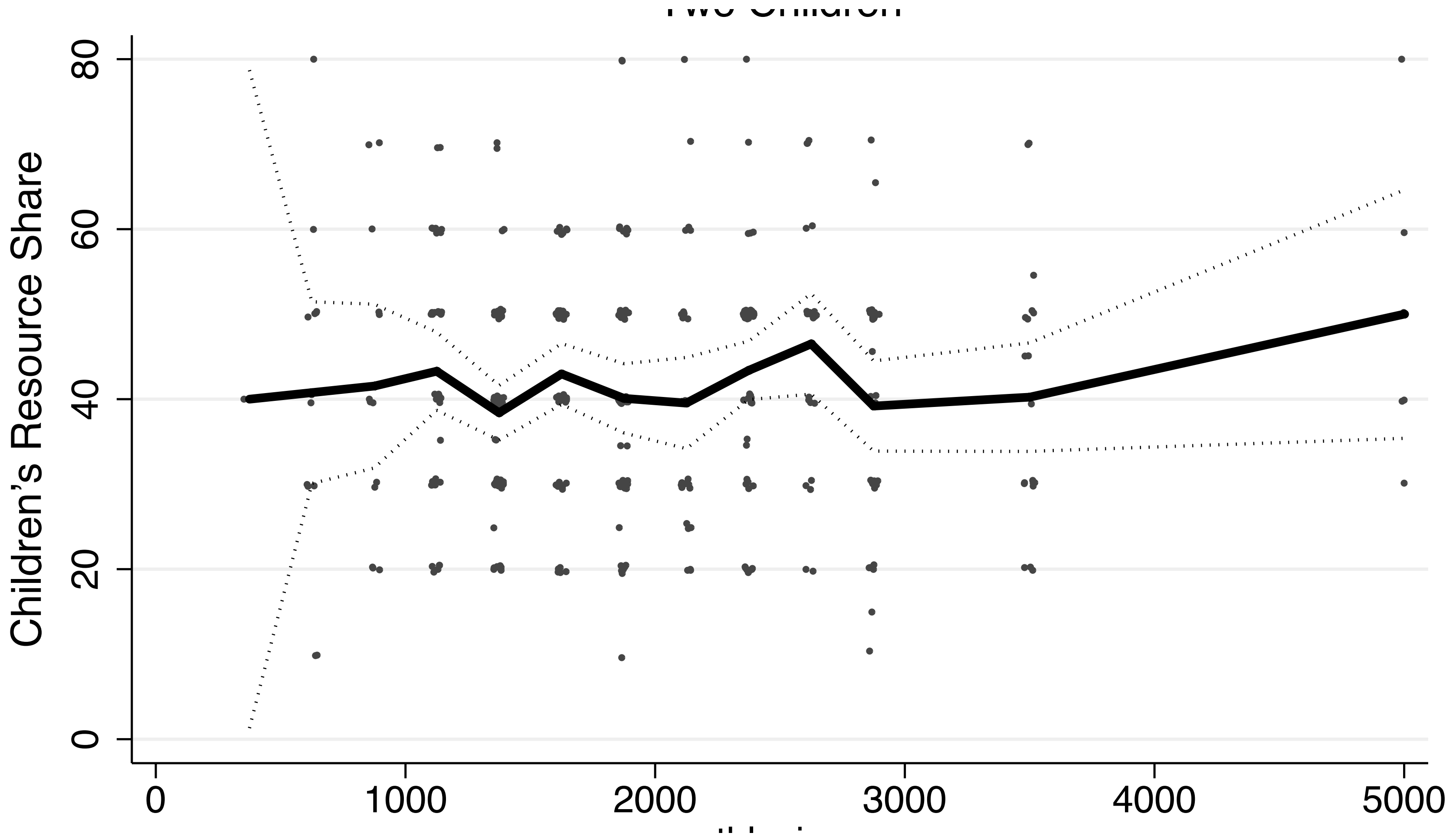
- Household data from a survey sponsored by the Italian International Center of Family Studies (CISF).
  - Nationwide survey
  - Conducted in 2009
  - computer assisted telephone interviews
  - 4,017 interviews, representative sample of Italian households from the population households with land-based or cellular telephone service.
- Our sample excludes:
  - Households with: no children
  - Households with: any children aged 18 or more, or four or more children;
  - single-parent households, Multigenerational households*;
  - Households in the highest income group (topcoded)*;
  - Households reporting either 0% or 100% as the children's resource share*;
- final sample comprises 794 households with two adult parents and 1-3 children aged 18 or less.

- *you can bring these groups back in---it doesn't change any result.

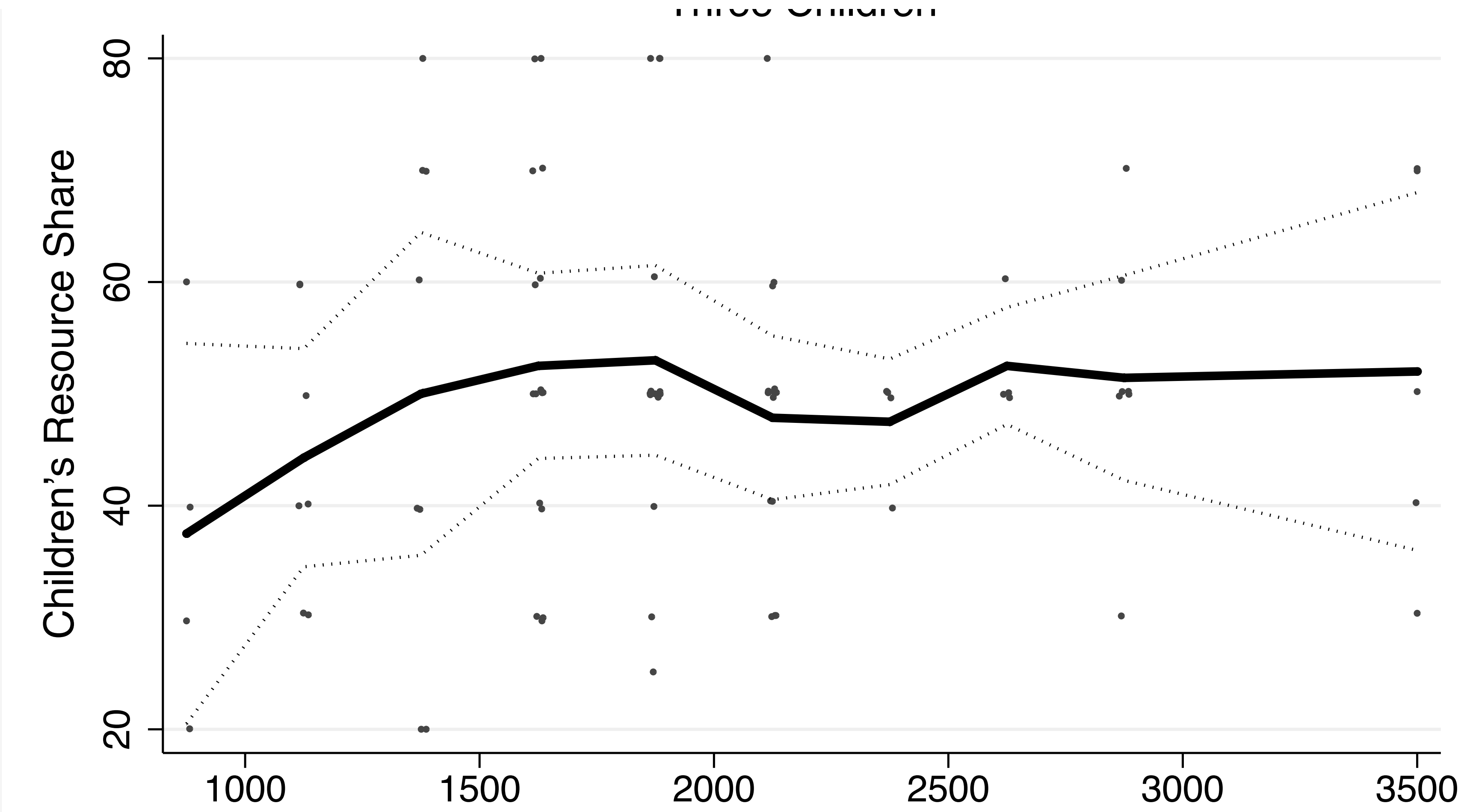
One Child



Two Children



Three Children



Resources Shares Seem Independent of Expenditure

- The data do not scream that resource shares vary much with household expenditure.
- Identification theorems like ours that depend on this restriction may be okay.

Identification Theorems: Notation

- People $j=m,f,c$ live together in a household.
- y is household total expenditure, d are distribution factors.
- Each person gets a resource share η^j and so gets a shadow budget of $\eta^j y$.
  - η^j can depend on y,d.
  - η^j sum to 1.
- A *Household's* Engel curve (budget share) for assignable good for person j is $W^j(y,d)$. **It is observed**.
- A *person's* shadow Engel curve (budget share), $w^j(y)$, describes what they would do if living alone facing the shadow price vector and budget. **It is not observed**.

Browning, Chiappori, Lewbel (BCL)

- efficient collective household model
  - No consumption externalities; shadow prices linear in market prices; efficient allocation is reached.
- They show identification of
  - Shadow prices and Resource shares (which may depend on y)
  - They do not need distribution factors d
  - But they need both price variation (to get shadow prices) and observed preferences $w^j(y)$ of people $j=m,f,c$ (to get resource shares).
    - Might observe $w^j(y)$ for m,f, but not c.

BCL Engel Curves

- Given the BCL model, household demands for **private assignable goods** are

$$W^j(y)=\eta^j(y)w^j(\eta^j(y)y)$$

remember: w^j gives person j's budget share at shadow prices.

- BCL: $\eta^j(y)$ is identified if $w^j(y)$ is observed.
- Not identified if $w^j(y)$ are unknown.
  - You might observe men's and women's $w^j(y)$ via singles, but how can you observe $w^j(y)$ for children?
  - Too many subscripts (5) of functions depending on y.
- Can add distribution factors d to resource shares if you want: then you'd write $\eta^j = \eta^j(y,d)$

Identification Without *d* (DLP 2013)

- DLP (2013) theorems also identify n^j without d.
- Model: BCL + 3 private assignable goods
- Add resource shares independent of household budget: $n^j(y)=n^j$

$$\rightarrow \quad W^j(y)=n^j w^j(n^j y)$$

- Still too many subscripts.
  - But, if $w^j=w$ so that people have identical preferences, then it is identified.

- **DLP 2013 Theorems**: model is semiparametrically identified under similarity restrictions on preferences (the restrictions are semiparametric)
  - Insight: preferences don't need to be identical; they just need to be *similar*.

- Works without observed $w^j(y)$, without observed price variation, works with even for children.
- Intuition is easy to see with a linear model (in a couple of slides)

Identification with *d* (DLP 2013b)

- Bring in *d*, keep n^j independent of *y*, so $n^j(d,y)=n^j(d)$:
$$W^j(y,d)=n^j(d)w^j(n^j(d)y)$$
- Let *d* be discrete with values indexed by *t*, so $n^j(d)=n^j{}_t$:
$$W^j{}_t(y)=n^j{}_t w^j(n^j{}_t y)$$
- Since the function w^j does not vary with *t*, and since $n^j{}_t$ sum to *1* for each t, we can get a signal on w^j from every *t*.

Theorem: if *d* (and *y*) have enough support points, then $n^j{}_t$ and $w^j(y)$ are nonparametrically identified from behaviour.

- Nonparametrically identified
- unlike DLP 2013, no preference restriction.
- Like DLP 2013, assume n^j independent of *y*, don't observe $w^j(y)$, can identify with children.
- Intuition is easy to see in a linear model (next slides)

Linear Individual Engel Curves

- For any given household size (number of kids) $s=1 \ldots 4$, let individuals $j=m,f,c$ have Engel curve functions for their private assignable good (clothing):
- $w^j_s(y)=a^j_s + b^j_s\, lny$
  - Here s is the number of children in the household.
  - Household size s affects shadow prices, and so affects demands through the parameters a^j_s and b^j_s.
  - Engel curves are linear at all price vectors, including the shadow price vectors associated with $s=1,..,4$.

Household Engel Curves

- For any given household size (number of kids) $s=1\ldots4$, observed household Engel curves for j's private assignable good is:
- $W^j_s(y,d)=\eta^j_s(d)w^j(\eta^j_s(d)y)$
- $\Rightarrow W^j_s(y,d)=\eta^j_s(d)[\ \alpha^j_s + \beta^j_s\ (lny+ln\eta^j_s(d))\ ]$
  – Household Engel curves are linear in *lny*
  – Kids' share is a lump shared by *s* kids, so their private good demand is
  – $W^c_s(y,d)=\eta^j_s(d)[\ \alpha^j_s + \beta^j_s\ (lny\text{-}lns+ln\eta^j_s(d))\ ]$

Identification without Distribution Factors: SAP and SAT

- Kill distribution factors
- $W^j_s(y) \quad = n^j_s[\, a^j_s + b^j_s\,(lny + lnn^j_s)\,]$

  $= n^j_s\, b^j_s\, lny + \ldots$
- Too many things have j,s indices---we need restrictions.
- Similar Across People (SAP): $b^j_s = b_s$
  - For a given s, there are 3 slopes wrt lny
  - For a given s, there are 3 unknowns: 2 n^j_s and b_s
- Similar Across Types (SAT): $b^j_s = b^j$
  - With 3 sizes s, there are 9 slopes wrt lny
  - With 3 sizes s, there are 9 unknowns: 6 n^j_s (2 for each of 3 household sizes) and 3 b^j.
- Corresponding rank conditions are in the paper.

Identification with Distribution Factors (IDF)

- distribution factors d do not affect prefs (a^j_s and b^j_s).
- Consider a single household size, so drop s.
- $W^j(y,d) = n^j(d)[\ a^j + b^j(lny+lnn^j(d))\ ]$
- Rewrite d as an index, t, of the resource share: $n^j(d)=n^j_t$
- $W^j_t(y) \quad = n^j_t[\ a^j + b^j\ (lny+lnn^j_t)$

  $= n^j_t\ b^j\ lny + ...$
- Order Condition: For a single household size, and without restricting b^j
  - with 3 support points t, there are 9 slopes wrt lny
  - there are 9 unknowns: 6 n^j_t and 3 b^j
- Corresponding Rank Conditions are available.

Malawian Expenditure Data

- Same data as DLP 2013, but with a new wave added.
- Malawian Integrated Household Survey Waves 2 and 3 (2004-5 and 2010-11, World Bank, Malawi Statistics Office).
- About 10k households each year
- Ask about micro-credit take-up
- Linked to micro-credit availability

Data Details

- Malawi Integrated Household Surveys, 2004-2005 and 2010-2011:
  - 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 in each wave.
  - 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 non-urban married couples with 1-4 children aged less than 15
- We have about 20-40 households in each of about 100 villages in each year
- Private assignable good is men's, women's and children's clothing (including footwear).

The Data

Table 1: Malawian Wave 2 and 3 IHS Data Descriptives

5745 obs		Mean	SD	min	max
wave 3		0.518	0.500	0.000	1.000
lny		-0.299	0.557	-1.700	1.969
clothing shar	man	0.014	0.022	0.000	0.479
	woman	0.010	0.022	0.000	0.529
	children	0.013	0.019	0.000	0.264
hh size *s*	1 child	0.290	0.454	0.000	1.000
	2 children	0.295	0.456	0.000	1.000
	3 children	0.247	0.432	0.000	1.000
	4 children	0.168	0.374	0.000	1.000
dist facts *d*	business	0.028	0.166	0.000	1.000
	microcredit	0.029	0.167	0.000	1.000
		0.075	0.264	0.000	1.000
163 obs	lnbusiness	-0.027	1.224	-3.223	3.157
165 obs	lnmicrocredi	0.037	0.966	-3.720	3.219
433 obs	lnsocial	-0.074	1.091	-3.337	3.401

Notes: avg bus loan Kw4216, avg micro Kw11,100, avg social loan Kw1960

Model

- Assignable good: clothing (including footwear) for each person: male, female, children (pooled)
- Recall the model, add an error term e
- $W^j_s(y,d)=n^j_s(d)[\ a^j_s + b^j_s\ (lny+lnn^j_s(d))\ ]+e$
  - SAP: $b^j_s=b_s$;   SAT: $b^j_s=b^j_;$ IDF: b^j_s unrestricted
- Demographic controls z.
    - 17 variables: survey year, 2 region dummies, 2 year*region dummies; avg and min age of children; girl proportion; age and education of both adults; ln distance to to road and daily market, season of expenditure recall, christian and muslim dummies.

- a^j_s , n^j_s linear in $s,z(,y)$ for each j.
- b^j_s linear in s,z,j (could do for s,z for each j, but overkill)

Distribution Factors

- 6 Credit-oriented distribution factors
  - Dummies for “do you have an outstanding loan”
    - Business credit (about 3% of households), including the grocer (about half of business credit), 70% to males.
    - Microcredit (about 3% of households), about 75% explicit women’s micro-credit, 85% of loans go to female creditors
    - Social credit (about 7% of households), 80% to males.
  - Loan size “what is the total loan amount?”
    - Median-normed, realed to 2004, and logged:
      - Ln(business loan/2500Kw)
      - ln(microcredit loan/7000Kw)
      - Ln(social loan/1000Kw)

Endogeneity

- These credit-oriented distribution factors might be endogenous (to clothing budget shares)
  - Credit take-up might be correlated with preferences or needs for clothing if, e.g., both are used in a home business, or both are driven by unobserved factors
  - in this case, credit may not really be a distribution factor because it affects preferences.
  - I'll show that credit is not too endogenous.
- Credit is correlated with total expenditure
  - It is 5% higher for households with business loans
  - It is 20% higher for those with microcredit loans.
  - It is 11% higher for those with social loans.

Instruments

- Instruments (all interacted with wave)
  - Interviewer counts of durable values and total wealth
  - Presence of a branch office, regional office or head office of a micro-finance organisation in your village
  - Village mobility indicators for husband and wife
  - Measures of income and illness shocks
  - Distances to: government primary schools, markets, banks
- The data also have interviews with the (self-proclaimed) elders in each village.

Instruments: Elder Interviews

- Compared to five years ago, have conditions in your community for access to non-agricultural business credit sources become:
  - Much worse
  - Worse
  - About the same
  - Better
  - Much better
- Similar questions on the community's willingness to help others, level of interpersonal trust

Instruments

Table 1b: Malawian Wave 2 and 3 Instruments

	Mean	SD	min	max
ln(durables)	7.10	3.08	0.00	14.46
ln(wealth)	8.00	2.88	0.00	14.47
wife mobility indicator	0.52	0.50	0.00	1.00
years since husband move	1.09	1.92	0.00	21.33
years since wife moved	0.89	1.49	0.00	20.00
income shock indicator	0.20	0.40	0.00	1.00
illness shock indicator	0.31	0.46	0.00	1.00
willingness to cooperate	3.48	1.07	1.00	5.00
generalized trust	3.24	1.16	1.00	5.00
microcredit office in villag	0.12	0.33	0.00	1.00
ln(distance to bank)	2.95	1.19	-4.61	5.35
access to nonag credit	2.39	1.04	1.00	5.00

Endogeneity Correction

- GMM to deal with endogeneity
  - Many instruments (32 excluded instruments for 3 loan dummies and 3 loan sizes)
  - Weak-ish instruments, first stage:
    - takeup: 3, 1.8 and 4.2 for business, microcredit and social loans ;
    - size: 2, 2.7 and 3.8 for lnsize of each.
- Hideously overidentified (many instruments)
  - Instruments for GMM are constructed variables:
  - Get predictions from probits and tobits
  - Plug into an initial estimate of the derivatives of the GMM objective function.
  - Puts a lid on overidentification

Resource Shares: NLSUR

Table 2: Estimated Levels of Resource Shares

(nonlinear) SUR Estimatior		SAP		SAT		IDF	
hh size	person	Coef	*Std Err*	Coef	*Std Err*	Coef	*Std Err*
1 child	man	0.47	*0.05*	0.32	*0.06*	0.35	*0.06*
	woman	0.31	*0.05*	0.41	*0.06*	0.36	*0.05*
	child	0.23	*0.03*	0.27	*0.05*	0.30	*0.05*
2 children	man	0.48	*0.05*	0.35	*0.06*	0.36	*0.06*
	woman	0.25	*0.04*	0.33	*0.05*	0.28	*0.05*
	children	0.27	*0.04*	0.32	*0.05*	0.36	*0.05*
3 children	man	0.48	*0.05*	0.31	*0.06*	0.33	*0.06*
	woman	0.25	*0.04*	0.38	*0.06*	0.32	*0.05*
	children	0.26	*0.04*	0.31	*0.05*	0.35	*0.05*
4 children	man	0.44	*0.06*	0.30	*0.06*	0.32	*0.06*
	woman	0.25	*0.05*	0.35	*0.06*	0.29	*0.06*
	children	0.31	*0.04*	0.35	*0.06*	0.39	*0.06*
test against IDF: chi2, df, (		11.2, 2 df, (0.004)		6.2, 3 df, (0.103)			
Hausman test: chi2, df, (p		5.7, 138 df, (1)		17.4, 137 df, (1)		N/A	
J-test: chi2, df, (pval)		84, 69 df, (0.105)		93, 70 df, (0.045)		86, 67 df, (0.059)	

Notes: 5745 obs; asympt se's clustered at the village-year level (178 clusters)

Table 2b: Estimated Levels of Resource Shares

(nonlinear) SUR Estimatioı		IDF	
hh size	person	Coef	*Std Err*
1 child	man	0.35	*0.06*
	woman	0.36	*0.05*
	child	0.30	*0.05*
2 children	man	0.36	*0.06*
	woman	0.28	*0.05*
	children	0.36	*0.05*
3 children	man	0.33	*0.06*
	woman	0.32	*0.05*
	children	0.35	*0.05*
4 children	man	0.32	*0.06*
	woman	0.29	*0.06*
	children	0.39	*0.06*

Resource Shares: GMM

Table 3: Estimated Levels of Resource Shares							
GMM Estimation--*d,y* end		SAP		SAT		IDF	
hh size	person	Coef	*Std Err*	Coef	*Std Err*	Coef	*Std Err*
1 child	man	0.44	*0.08*	0.30	*0.07*	0.32	*0.07*
	woman	0.31	*0.06*	0.35	*0.07*	0.34	*0.07*
	child	0.25	*0.05*	0.34	*0.06*	0.34	*0.06*
2 children	man	0.43	*0.08*	0.32	*0.07*	0.34	*0.07*
	woman	0.27	*0.06*	0.30	*0.07*	0.28	*0.07*
	children	0.30	*0.06*	0.38	*0.07*	0.38	*0.07*
3 children	man	0.40	*0.09*	0.28	*0.07*	0.31	*0.07*
	woman	0.30	*0.07*	0.35	*0.08*	0.32	*0.07*
	children	0.31	*0.06*	0.37	*0.07*	0.37	*0.07*
4 children	man	0.35	*0.10*	0.25	*0.08*	0.27	*0.08*
	woman	0.28	*0.07*	0.30	*0.08*	0.28	*0.08*
	children	0.37	*0.08*	0.45	*0.08*	0.45	*0.08*
Hausman test: chi2, df, (pv		5.7, 138 df, (1)		17.4, 137 df, (1)		N/A	
J-test: chi2, df, (pval)		84, 69 df, (0.105)		93, 70 df, (0.045)		86, 67 df, (0.059)	
test against IDF: chi2, df, (		10.5, 2 df, (0.005)		4.6, 3 df, (0.206)			

Notes: 5745 obs; asympt se's clustered at the village-year level (178 clusters)

Table 4: Estimated Responses of Resource Shares to Credit Variables

		NLSUR Estimation					
		SAP		SAT		IDF	
dist. Factor	person	Coef	*Std Err*	Coef	*Std Err*	Coef	*Std Err*
Business Loa	man	0.033	*0.020*	0.029	*0.019*	0.026	*0.019*
	woman	-0.020	*0.016*	-0.018	*0.018*	-0.015	*0.017*
	child	-0.013	*0.013*	-0.011	*0.014*	-0.010	*0.016*
Microcredit l	man	-0.037	*0.026*	-0.021	*0.024*	-0.025	*0.023*
	woman	0.004	*0.017*	-0.014	*0.021*	-0.012	*0.020*
	children	0.033	*0.017*	0.035	*0.017*	0.038	*0.019*
Social	man	-0.004	*0.013*	0.000	*0.011*	0.002	*0.011*
	woman	0.007	*0.011*	0.004	*0.012*	0.003	*0.011*
	children	-0.003	*0.009*	-0.004	*0.009*	-0.005	*0.011*
ln(Bus Loan $	man	-0.005	*0.014*	0.001	*0.014*	0.002	*0.014*
	woman	0.006	*0.011*	0.002	*0.012*	0.005	*0.012*
	children	-0.001	*0.007*	-0.003	*0.007*	-0.007	*0.009*
ln(Mic. Loan	man	-0.002	*0.027*	0.008	*0.020*	0.006	*0.020*
	woman	-0.003	*0.013*	-0.017	*0.018*	-0.016	*0.017*
	children	0.005	*0.022*	0.009	*0.020*	0.010	*0.024*
ln(Soc. Loan)	man	-0.003	*0.009*	0.006	*0.008*	0.005	*0.008*
	woman	-0.001	*0.006*	-0.010	*0.008*	-0.006	*0.007*
	children	0.004	*0.006*	0.003	*0.006*	0.001	*0.007*
exclusion of ln(.)		4.6, 6 df, (0.597)		3.1, 6 df, (0.796)		2.4, 6 df, (0.887)	
test against IDF		11,2, 2 df, (0.004)		6.2, 3 df, (0.106)			

Table 4b: Credit Dummies

		NLSUR	
		IDF	
dist. Factor	person	Coef	*Std Err*
Business Loa	man	0.026	*0.019*
	woman	-0.015	*0.017*
	child	-0.010	*0.016*
Microcredit l	man	-0.025	*0.023*
	woman	-0.012	*0.020*
	children	**0.038**	*0.019*
Social	man	0.002	*0.011*
	woman	0.003	*0.011*
	children	-0.005	*0.011*

GMM Estimates: Credit

Table 5: Estimated Responses of Resource Shares to Credit Variables

		GMM Estimation					
		SAP		SAT		IDF	
dist. Factor	person	Coef	*Std Err*	Coef	*Std Err*	Coef	*Std Err*
Business Loa	man	0.15	*0.26*	0.04	*0.13*	0.03	*0.13*
	woman	-0.11	*0.36*	-0.02	*0.19*	-0.01	*0.18*
	child	-0.04	*0.30*	-0.03	*0.19*	-0.02	*0.18*
Microcredit l	man	0.26	*0.28*	0.33	*0.14*	0.35	*0.15*
	woman	-0.35	*0.28*	-0.56	*0.21*	-0.56	*0.22*
	children	0.09	*0.13*	0.23	*0.16*	0.21	*0.17*
Social	man	0.33	*0.14*	0.12	*0.07*	0.12	*0.07*
	woman	-0.22	*0.16*	-0.20	*0.09*	-0.19	*0.09*
	children	-0.11	*0.15*	0.08	*0.08*	0.07	*0.09*
ln(Bus Loan $	man	0.15	*0.48*	-0.01	*0.19*	-0.01	*0.20*
	woman	-0.40	*0.34*	-0.12	*0.22*	-0.10	*0.23*
	children	0.25	*0.30*	0.13	*0.23*	0.11	*0.24*
ln(Mic. Loan	man	1.04	*0.42*	-0.14	*0.14*	-0.13	*0.15*
	woman	-0.95	*0.42*	0.41	*0.28*	0.40	*0.28*
	children	-0.09	*0.19*	-0.27	*0.24*	-0.27	*0.24*
ln(Soc. Loan)	man	0.03	*0.26*	0.00	*0.13*	0.00	*0.13*
	woman	0.29	*0.23*	0.09	*0.16*	0.08	*0.16*
	children	-0.32	*0.21*	-0.09	*0.13*	-0.08	*0.13*

Patterns

- Can identify levels of resource shares without preference restrictions
- Microcredit divert from mom and dad to kids
- Business loans and social loans don’t do much to the within-household distribution.
- Size of loans matter to household expenditure, but not to the within-household allocation

Next Steps

- Have real-er estimates
  - Add childless couples
  - Allow resource shares to have a unobserved (and independent) distribution factors via generalised random coefficients (Lewbel and Pendakur 2012)
    - Can then compute a structural Average Treatment Effect
  - Go semiparametric (no preference restriction required for IDF)
  - Use first-wave data to get better village-level instruments, and/or more N.