Estimating A Model of Inefficient Cooperation and Consumption in Collective Households

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Abstract

Lewbel and Pendakur (2021) propose a model of consumption inefficiency in collective households, based on cooperation factors. We simplify that model to make it empirically tractable, and apply it to identify and estimate household member resource shares, and to measure the dollar cost of inefficient levels of cooperation. Using data from Bangladesh, we find that increased cooperation among household members yields the equivalent of a 13% gain in total expenditures, with most of the benefit of this gain going towards men.

JEL codes: D13, D11, D12, C31, I32. Keywords: Collective Household Model, Inefficiency, Bargaining Power, Sharing Rule, Demand Systems,

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cooperation factors may also directly a ect the utility levels of individual household members. LP's model preserve the advantages and properties of e cient household models, because even ine cient households are still conditionally e cient, conditioning on the level of the cooperation factor.

The BCL model is a very general collective household model, but it correspondingly has very demanding data requirements for estimation, and these carry over to LP's approach. See, e.g., Lewbel and Lin (2021) for general theory on identifying and estimating the BCL model with LP's cooperation factors.

Dunbar, Lewbel, and Pendakur (2013) (hereafter DLP) propose a restr.00iigy390.004Bs(era)0co

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Collective households models are those that assume that people, not households, have utility functions, and that households are economic environments in which people live. Efficient collective household models are those in which the people living in the household are assumed to reach the Pareto frontier. To learn about people's well-being within households, we need to learn about those economic environments. Becker (1965, 1981) and Apps and Rees (1988) provide examples of models that specify the entire economic environment of the household, including bargaining processes, preferences and sharing or publicness of goods.

Chiappori (1988, 1992) showed that efficient collective household models are generic in the sense that one need not specify the exact model of bargaining, preferences or sharing to learn about the within-household allocation of resources. He additionally showed that the assumption of Pareto efficiency is very strong: it implies that household decisions can be decentralized to the individual level. In that decentralized representation, the budget constraints faced by the household members summarize the economic environment of the household. These individual-level budget constraints have individual *shadow budgets* that define the consumption opportunities of individual household members. They also have *shadow prices* that account for sharing (and thus scale economies) within the household.

A key component of collective household models are *resource shares*. Resource shares are defined as the fraction of a household's total resources or budget (spent on consumption goods) that are allocated to each household member. A person's shadow budget is their resource share times the household budget. Resource shares are useful for several reasons. First, they are closely (usually monotonically) related to Pareto weights, and so are often interpreted as measures of the bargaining power of each household member. Second, they provide a measure of consumption inequality within households: if one member has a larger resource share than another member, then they have more consumption. Third, multiplying the resource share by the household budget gives each person's shadow budget. When this shadow budget is appropriately scaled to reflect scale economies, we can compare it to a poverty line and assess whether or not any (or all) household members are poor. In this paper, we identify and estimate resource shares allowing for possible inefficiency in household consumption, and we identify and estimate a measure of the economic cost of such inefficiency.

Resource shares and economies of scale are in general difficult to identify, because consumption is typically measured at the household level, and many goods are jointly consumed and/or shareable. Even the rare surveys that carefully record what each household member consumes face difficulty appropriately allocating the consumption of goods that are sometimes or mostly jointly consumed, like heat, shelter and transportation. Models are therefore generally required.

In this paper, we consider identification and estimation of resource shares in the inefficient collective household model of LP. Whereas most of the models of sharing in collective households constrain goods to be either purely private or purely public within a household, whereas we work with the more general model based on BCL, which also allows goods to be partly shared. Indeed our notion of inefficiency due to endogenous variability in scale economies requires a model with partial sharing. Models where goods are exogenously purely public or purely public do not allow for variability in scale economies.

A number of models of noncooperative household behavior exist. Gutierrez (2018) proposes a model that nests both cooperative and noncooperative behavior. Castilla and Walker (2013) provide a model and associated empirical evidence of inefficiency based on information asymmetry, that is, hiding income. Other evidence of income hiding includes Vogley and Pahl (1994) and Ashraf (2009). Ramos (2016) has exogenously determined domestic violence that affects the efficiency of home production. Other noncooperative models include Basu (2006) and Iyigun and Walsh (2007).

The model of LP is a two step program: first choosing the cooperation factor, and then, conditional on that choice, optimizing consumption. It is thus similar in spirit to models like Mazzocco (2007), Abraham and Laczo (2017), Chiappori and Mazzocco (2017), and

Lise and Yamada (2019). Other models with analogous stages are Lundberg and Pollak (1993), Gobbi (2018), and Doepke and Kindermann (2019). See also Lundberg and Pollak (2003), and Eswaran and Malhotra (2011). The key featuure of LP is that it allows the household's objective function determining the cooperation factor to di er from its objective in determining consumption. This di erence makes general ine ciency possible.

The LP model is very general, but is di cult to estimate, requiring both price variation and the estimation of nonlinear compound functions. These di culties are also faced with direct estimation of BCL's very general model. DLP o er simplifying restrictions to BCL, and in the this paper, we o er simplifying restrictions similar in spirit to those of DLP, that allow identi cation and estimation of LP's model using just Engel curve data. We use both restrictions on how preferences vary across people like those in DLP, and restrictions on price e ects like those imposed in Lewbel and Pendakur (2008).

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This section summarizes Lewbel and Pendakur (2021: LP). The next section shows identi- cation (semiparametric) and estimation of an empirically tractable model for estimation, which forms the theoretical contribution of260 (hoiibution)4iLrmanntributifo-423.99(th)]TJstricting shoth

shared their car (riding together) 1/2 of the time, then the houeshold needs to purchase less gasoline that it would have to if there were no sharing. For example, Person1 drives 100km and person2 drives 100km, but because 50km are driven together, the vehicle only drives 150km. Here, the upper left corner of the matrix A would be $3/4$ $(= 150/(100 + 100))$. This $3/4$ summarizes the extent to which gasoline is shared; If the household members didn't share the car at all, they'd have to buy $g_1^1 + g_2^1$ units of gasoline, instead of only buying $g^1 = (3/4)(g_1^1 + g_2^1)$ units.

terms of utilities of consumption only (U_j g_j for $j = 1; :::; J$). To distinguish between these e ciency concepts, LP de ne the latter as consumption e ciency and the former as total e ciency.

To illustrate, if cooperating and coordinating consumption at the level A_1 instead of A_0 requires more e ort, $u_j(1; v)$ $u_j(0; v)$ may be negative, re ecting member j's disutility from expending that extra e ort. Alternatively, $u_j(1; v)$ $u_j(0; v)$ may be positive if member j experiences direct joy or y ositivsf 222.595 (e-27e329.996 ap)-27.001 (erating)-331 (a)0.995 (222.595

for some function . The function could be exactly the Pareto weighted average of utility functions given by equation (1), $\sum_{j=1}^{J} R_j(p; y; f; v)\, !_j(p; y; f)$, meaning that the household uses the same criterion to choose f as it uses to choose consumption. At the other extreme, just one member of the household, say the husband $j = 1$, might unilaterally choose f, so just equals $R_1(p; y; f; v)$. Or if the parents are choosing the level of f, then might only contain the parent's utility functions. However, if household members have caring preferences, then even members who are not party to choosing f could have their utility functions included in , so e.g. parents deciding f could put some weight on children's utility functions in .

If equals equation (1), so the household maximizes the same objective function in both stages, then the household's choice of f is by construction totally e cient, but it could still be consumption ine cient. In contrast, if does not equal equation (1) (e.g., if only a subset of household members choose f), then f could be ine cient by both de nitions. We will for convenience just to refer to $f = 0$

$q = (q_1, \ldots, q_J)$.[1] Let $\;\; = (\;_1, \ldots, \;_J)$ denote the vector of prices of these private assignable goods.[2] In addition to q, the household purchases a K vector of quantities of goods g (at price vector p) which, as described in the previous section, is converted into the sum of private good equivalents $g_1, \ldots, g_J$ by the matrix A_f.

In addition to introducing private assignable goods q, we further generalize the LP model by allowing prices to affect u_j (since there is no *a priori* economic reason for excluding them, and like v, prices appearing in u_j only affect the determination of f, not the demand functions for goods). We also generalize LP by including additional observed household-level demographic variables z (which can affect both tastes and Pareto weights) to allow for observable heterogeneity across households. Taking all this into account, the LP model of equation (1) becomes

$$\max_{g_1, q_1, \ldots, g_J, q_J} \sum_{j=1}^{J} \left(U_j \left(q_j, g_j, z \right) + u_j (f, v, z, p, \;, y) \right) \omega_j (f, z, p, \;, y) \tag{6}$$

$$\text{such that } p'g + \sum_{j=1}^{J} \;_J q_j = y \text{ and } g = A_f \sum_{j=1}^{J} g_j.$$

A further generalization is to include additional random variables to the model that correspond to unobserved taste heterogeneity. To save notation, we defer that step to the Appendix.

This model yields household demand functions for vectors of goods g and q, analogous to those of equation (3). But for the private assignable goods q, these demand functions greatly simplify, because for each private assignable good the quantity q_j that is consumed by member j is the same as the quantity purchased by the household. For these private

[1] Some results in DLP go through if these goods are only assignable but not private. So, e.g., when food is the assignable good, it could still have a coefficient in the A matrix that doesn't equal one (and so technically isn't private). This could arise if, e.g., food waste is lower in larger households. For simplicity, we follow DLP, but our results could also be generalized to allow the assignable good to be non-private. See Lechene, Pendakur and Wolf (2021). This would mainly entail extra notation, and adding some restrictions to Assumptions A5 and A6 in the Appendix.

[2] In practice, the private assignable goods may have the same price for each member, making $\;_1 = \cdots = \;_J$.

assignable goods, the household demand equations arising from the household model of equation (6) have the form

$$q_j = H_j\left(p^0 A_f;\ \ ; z;\ \ _j(p;\ \ ; y; f; z)\, y\right) \qquad (7)$$

where H_j is the Marshallian demand function for q_j, the assignable good of person j that comes from the utility function $U_j\ \ q_j; g_j; z$. Compared to the demand equations (3), which give demands for all goods, the summation and multiplication by A_f drop out of the demands for private assignable goods given above.

Note that the resource share functions $_j$ may now depend on the additional variables and z that we've introduced into the model. But importantly, as a result of the household's consumption optimizing behavior and the separability between U_j and u_j, the variable v does not appear in this equation. This is what makes v be a valid instrument for f (see the Appendix for details).

We now make some simplifying assumptions (again, details are in the Appendix) to transform this model of price-dependent demand equations into a model of Engel curves giving demands at xed prices. First, we assume that the resource share function $_j$

utility over consumption is semiparametrically restricted to have the form

$V_j = \ln$

ing variation in tastes, and $"_j$ is an error term that comes from $"_j$ ($_j$; p), the unobserved taste shifter (see the Appendix). Here, (f; z) is a money-metric ine ciency measure that equals (A $_f$ p; z) at the xed price vector p; it is a measure of the dollar costs of ine ciency as described below.

We prove in the Appendix that the functions in equation (9) are each nonparametrically point identi ed. This includes showing that the levels of the resource shares $_j$ (f; z), and the ine ciency measure (f; z), are nonparametrically identi ed.

Recall our assumption that the household uses equation (5) to choose f, i.e., the household maximizes some function of the utilities $U_j + u_j$ for some or all of the members j. We show in the Appendix that in general the resulting value of f is endogenous (i.e., it is correlated with $"_j$), but also that v (even if not randomly assigned) is a valid instrument for f. We discuss our instruments v in detail in the Data section.

Inspection of equation (9) shows that the cooperation factor f has two e ects on household Engel curves for private assignable goods. One is that it a ects resource shares $_j$. The second e ect, which is based on A_f, a ects the Engel curve through the function (f; z). Inspection of equations (8) and (9) shows that a change ln (f; z) has the same e ect on utility and on budget shares as the same change in ln y. This then provides a dollar measure of the unconditional e ciency loss (or gain) to the household resulting from choosing $f \neq 1$.

Since ln (0; z) = 0, a change from f = 0 to a level of f = 1 is equivalent, in terms of consumption of goods, to a change in the household's budget from y to y (f; z). The change in sharing resulting from an increase in f has the same e ect on demands, and on the

$\{1, \ldots, J\}$. Recall that f is endogenous and has a valid instrument w. The budget y could also be endogenous, for two reasons: first, because it's a choice variable, and second, because in our data, the observed y is partly constructed and so may contain measurement error.

Let r be a vector of observed variables that may affect the determination of y. If one considers the dynamic optimization problem of the household, given the household's income and assets, we can assume the household first decides how much to spend on consumption

Given limitations on the size of the data set and complexity of the model, it is more practical to estimate the model parametrically, as follows. By construction, the budget shares w_j give the share of the household budget y spent on the assignable good j (food, in our empirical work below) for all the members of type j. Each of these members has a log-shadow budget of $\ln y \quad \ln N_{jh} + \ln \quad _j (f;\ z)$. Now, letting be a vector of parameters, we parameterize each of the functions in equation (10), and incorporate N_j, to obtain unconditional moments

$$E \quad \frac{w_j}{_j\,(f;\ z;\ \ )} \quad _j\,(z;\ \ ) \quad (z;\ \ )\,(\ln y \quad \ln N_{jh} + \ln \quad _j\,(f;\ z;\ \ ) + \ln \quad (f;\ z;\ \ )) \quad (r\,;z) \quad = 0 \tag{11}$$

Equation (11) holds for any vector of bounded functions $(r\,;z)$. We construct an estimator for by choosing functions $(r\,;z)$ as discussed in the Appendix, and applying Hansen's (1982) Generalized Method of Moments (GMM).

We reiterate that, while equation (11) is only estimated for private assignable goods (food in our empirical application), we obtain estimates of resource shares and the dollar cost of e ciency that apply to *all* goods. We are not assuming, e.g., that a man's spending on food is proportional to his spending on other goods. He could, e.g., have a strong preference (or need) for food, resulting in high food consumption, but still have a relatively low resource share giving him little to spend on other goods. (An example would be if $_j\,(z;\ \ )$ were large but $_j\,(f;\ z;\ \ )$ were small.) The intuition for the identi cation is that, if you inverted a single man's Engel curve for food, you could see what his total budget for all goods must be, based on how much he spends just on food. Analogously, by estimating each household member's Engel curves for food, we can back out what each member's shadow budget for all goods must be, and hence their resource shares. See DLP and Lechene et al (2021) for further discussion of this intuition.

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for each, rather than for total men, total women, and total children. However, that would then require estimating a separate model for every possible household composition, e.g., a separate model for households with 2 children vs those with 3.

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5.1 Data

We use data from the 2015 Bangladesh Integrated Household Survey. This dataset is based on a household survey panel conducted jointly by the International Food Policy Research Institute and the World Bank. In this survey, a detailed questionnaire was administered to a sample of rural Bangladeshi households. This data set has two useful features for our model: 1) it includes person-level data on food consumption as well as total household expenditures on food and other goods and services; and 2) it includes questions relating to cooperation on consumption decisions. The former allows us to use food, a large and important element of consumption, as an assignable good to identify our collective household model parameters. The latter allows us to divide households into those that cooperate more vs less on consumption decisions, which we treat as a cooperation factor.

The questionnaire was initially administered to 6503 households in 2012, drawn from a representative sample frame of all Bangladeshi rural households. Of the 6436 households that remained in the sample in 2015, we drop 13 households with a discrepancy between people reported present in the household and the personal food consumption record, and 9 households with no daily food diary data, leaving 6414 households with valid data.

De ne the composition of a household to be its number of aduult men, number of adult women, and number of children (we de ne children as members aged 14 or less). To eliminate households with unusual compositions, we select households that have at least 1 man, 1 woman and 1 child, and for which there are at least 100 households with the given composition in our data. The resulting sample consists of households with 1 or 2 men, 1 or 2 women, and 1 or 2 children, plus additional nuclear households with 1 man, 1 woman and 3 or 4 children. This eliminates roughly half of the 6414 households, leaving us with 3238 households with our selected compositions and valid data. Of these, we drop 328 households that report zero food consumption for either men, women or children, leaving us with

3000 households in our nal estimation sample. Households are indexed by $h = 1; :::; H$, so $H = 3000$ in our main estimation sample.

The survey contains 2 types of data on food consumption: 7-day recall data at the household level on quantities (in kilograms) and prices of food consumption in 7 categories: Cereals, Pulses, Oils; Vegetables; Fruits; Proteins; Drinks and Others; and 1-day diary data at the person level food intakes of quantities (and not prices) of the same categories.[5] These consumption quantities include home-produced food and purchased food and gifts. They include both food consumed in the home (both cooked at home and prepared ready-to-eat food), as well as food consumed outside the home (at food carts or restaurants). Thus, we have the widest possible de nition of food consumption.

We begin with the one-day recall diary of individual-level quantities of food in the 7 categories. These are the quantities of food that are consumed by fo the

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aindividualT26.97t T26.97 cary00ngaalyWV we follow Deaton (1993) and use village-level unit values to aggregate up to household-level food spending by category. Let $_p$ be the village-level unit value equal to village-level aggregate spending divided by village-level agregate quantity, $_p = \sum_h S_{ph} = \sum_h Q_{ph}$, where the summation is over all the households observed in a village. Let q_{jph} be the observed quantity of category p for all people of type j in household h from the one-day diary data. One-day diary data do not include spending data. For each household, we take shares of each category, $q_{ph} = \sum_j q_{jph}$

Our models are also conditioned on a set of demographic variables z_h. We include several types of observed covariates in z_h. We condition on household size and structure, defined as a set of 10 dummy variables covering all combinations of 1 or 2 men, 1 or 2 women, and 1 or 2 children plus the additional nuclear families consisting of 1 man, 1 woman, and 3 or 4 children. The left-out dummy variable is the indicator for a household with 1 man, 1 woman and 2 children (the largest single composition). We call this particular nuclear household type the reference composition.

We also include other variables in z_h that may affect both preferences and resource shares: 1) the average age of adult males divided by 10; 2) the average age of adult females divided by 10; 3) the average age of children divided by 10; 4) the average education in years of adult males; 5) the average education in years of adult females ; 6) the fraction of children that are girls minus $0{:}5$; and, (7) the log of marital wealth (aka: dowry). We do not normalize dichotomous composition variables or the fraction of girl children. However, we normalize all other elements of z to be mean-zero for households with the reference composition.

Together the above normalizations give $z_h = 0$ for a reference household defined by reference composition and all covariates equal to the mean values for the reference composition. We also normalize the log of household expenditure, $\ln y_h$, to be mean 0 for the reference composition. All these normalizations simplify the economic interpretation of our estimated coefficients, since by these constructions the coefficients directly equal either estimates of the behavior of the reference household type, or (in the case of coefficients of z_h) they describe departures from the reference household's behavior.

In our empirical application, we take the cooperation factor for household h, f_h, to be an indicator of cooperation on consumption decision making. Specifically, our recall survey asks of the female respondent: Who decides how to spend money on the following items? The items we look at are food, clothing, housing, and health care, and the response options are self , husband , self and husband , or someone else . We take $f_h = 1$, indicating a more cooperative household, if the answer for all four of these consumption categories is, self and husband. Otherwise, the household is assigned the less cooperative $f_h = 0$. Our reasoning is that cooperating on how much to purchase of each type of consumption good is a logical prerequisite to cooperating on how much to jointly consume of each good. We also, for comparison, consider two other measures of cooperation as possible cooperation factors (see discussion of Table 4 below for details).

of these assignable food aggregates. This is in sharp contrast to other research identifying resource shares from assignable goods (e.g., Calvi 2019; Lechene et al 2021) that uses clothing instead of food as the assignable good, where clothing shares may be less than 1 per cent of the household budget. Second, the cooperation factor f_h has a mean of $0{:}59$. The village-level leave-out average of f has a standard deviation of $0{:}493$, which suggests that much of the variation in f is at the village level.

5.2 Instruments

Our model has two endogenous regressors: the log of household total expenditures, $\ln y_h$, and the cooperation factor f_h. As discussed earlier, if we assume that the consumption allocation decision in our model is separable from the decision of how to allocate household income between total consumption and savings, then functions of household wealth are valid instruments for $\ln y_h$. This time separability is a standard assumption in the consumer demand literature, including in collective household models (see, e.g., Lewbel01 (v)26.99v

y_h

whose members cooperate on consumption decisions is likely to correlate with an individual's own decision to likewise cooperate. Roughly, village level average $\bar{f}$ (leaving out household h) is a valid instrument in our model if the choice of f in households other than household h is unrelated to the unobserved preference heterogeneity in member's demand functions for food in household h. See the Appendix for a formal definition of conditions under which this instrument is is valid.

For estimation, we do not need to distinguish which elements of the instrument list r_h are intended to be specifically instruments for f_h vs for y_h (i.e., elements of v vs elements of e in the Appendix). In particular, though we argue that $\bar{f}_h$ should primarily correlate with f_h and wealth should primarily correlate with y_h, either or both could affect both. Moreover, since we do not know the functional forms by which f_h and y_h depend on $\bar{f}_h$ and wealth, we let our instrument list r_h consist of r_{1h} and r_{2h}, where r_{1h} consists of the first through fourth powers of $\bar{f}_h$ and r_{2h} consists of the first through fourth powers of log wealth. We use these powers to flexibly capture how f_h and y_h might depend on these instruments. Descriptive statistics for our instruments are given at the bottom of Table 1b.

If our model were linear, then our nonlinear GMM estimator would (apart from weighting matrix) reduce to a linear two stage least squares. The first stage of that two stage least squares would consist of regressing the endogenous f and $\ln y$ on the instruments and exogenous regressors.

To assess the strength of our instruments, we ran those first stage linear regressions. In Table 2 we give regression estimates and associated standard errors from a linear regression of our endogenous regressors f_h and $\ln y_h$ on our 18 demographic variables z_h and our 8 instruments r_h. Standard errors are clustered at the village (i.e., the Upazila) level.

Table 2 shows that f_h is difficult to predict, with an R^2 of just 0.17, but the instruments collectively appear strong, in that the F-statistic for the relevance of the instruments (conditional on covariates) is 62. As expected, the village-level average instruments do most of the work here, with an F-statistic of 121, and the log-wealth instruments are also jointly insigni cant in this equation. The low R^2 of this regression emphasizes the point that we can't (and don't try to) actually model the decision to cooperate. All we need are su ciently

$$_j\ (z_h;\quad) = l_{j0} + l_j^{0} z_h;$$

$$\ln\quad(f_h; z_h;\quad) = (a_0 + a_1^{0} z_h)\, f_h,$$

and

$$(z_h;\quad) = b_0 + b_1^{0} z_h:$$

The vector   is therefore de ned as all the coe cients in $a_0; a_1^{0}; b_0; b_1^{0}$1lTj /T1_(b)]TJ /T1_4 1.955 Tf(978. Tf b)]TJ /T1_4 1.955

parameters). The use of village-level instruments can induce correlations in the moments across households within village, so we report standard errors that are clustered at the village level.

5.4 Model Estimates

Our main GMM estimation results are given in Tables 3 to 5. In these tables we focus on a subset of the most relevant coefficients. The full set of baseline model parameter estimates are reported in the Appendix in Table A2.[7] The standard errors in these tables are all clustered at the village level.

Identification requires exogeneity of the instrument vector $(r; z)$. The bottom rows of Tables 3 to 5 present estimated J test statistics to assess this exogeneity restriction. The J tests are tests of the hypothesis that the elements of $(r; z)$ are all uncorrelated with the errors ε_j.

We have scaled and normalized the regressors as described earlier, so that the estimated coefficients a_0, k_{j0} and c_j in Tables 3, 4, and 5 equal the values of the functions of interest for the reference household type z_0 (1 man, 1 woman and 2 children, with $z = 0$). In the first row in each of these tables, we provide estimates of a_0, which equals $\ln(1; z_0;)$ for the reference household, i.e., the response of log-efficiency to f (more precisely, the percent change in total budget y that would be equivalent to the gain in efficiency associated with $f = 1$). The next rows provide $k_{j0} = {}_j(0; z_0)$ and $c_j = {}_j(1; z_0) \quad {}_j(0; z_0)$ for each member type j in the household. These equal, for the reference household, member j's resource share when the household is inefficient, and the change in that resource share if the household switched to being efficient.

The next block of rows report, for each type j, the proportional difference in type j's shadow budget between $f = 0$ and $f = 1$. This is the effect of cooperation on type j's money

[7] A previous version of this paper included an indicator of domestic abuse as a cooperation factor and log-wealth as a regressor. In Appendix B Table A1, we include these variables in the covariate list z. Their inclusion does not affect our major conclusions.

metric consumption utility. When $f = 0$

varying , we relax the assumption that is xed by replacing $(z_h;) = b_0$ with $(z_h;) = b_0 + b_1^0 z_h$. The general patterns we observe in our baseline estimates are still seen here, but with larger standard errors (presumably because of multicollinearity multiplies ln , and now both functions vary with z).

GMM estimators based on many more moments than parameters can have poor nite-sample performance, due to imprecision in estimation of the GMM weighting matrix. To check for this possibility, in the rightmost columns of Table 3, labelled less overidenti - cation , we re-estimate the baseline model using only the rst and second powers of log household wealth and village-average f as instruments. This reduces the number of elements of $(r_h; z_h)$ to 57, which reduces the total number of GMM moments from 315 to 171 (the number of baseline model parameters is still 89). As expected, this use of fewer moments means less identifying power and hence mostly larger standard errors. However, the direction of results remains unchanged: Cooperating increases men's resource shares at the expense of women and (mainly) children's shares, but everyone's money metric utility is increased. Given the similarity in results, we do not see evidence of signi cant nite sample issues regarding GMM estimation of the baseline model.

In our discussion of Table 2, we argued that our instruments are relevant. To provide some evidence that our instruments are also valid, at the bottom of Table 3 we give estimated values of Hansen's J-statistic. These are tests of the hypothesis that the instruments are jointly exogenous. We give the value of the J-statistic, its degrees of freedom and p-value. The estimated p-values of $0{:}23$, $0{:}24$ and $0{:}77$. None are close to $0{:}05$, so we do not reject the null of instrument validity in any of the models.

In Table 4, we consider 3 alternatives for our cooperation factor f. The idea here is that f is a proxy for cooperation, and so other proxies related to cooperation should behave similarly. In the leftmost column, labeled (4), we use a weaker de nition of f, setting it equal to 1 if the woman reports that consumption decisions regarding housing are made jointly, and 0 otherwise. In our baseline case, it equals 1 if additionally, consumption decisions regarding food, health care and clothing are made jointly. This alternative definition focusses on shelter, the most shareable of these goods. In comparison to the baseline, we see essentially the same estimates, though with a slightly larger estimate of m and slightly larger estimated standard errors.

In column (5), we turn to a different type of proxy for cooperation. In the theory section above, our examples of sharing in the household consumption technology sometimes depended on simultaneous usage of a shareable good by multiple household members (such as shared vehicles). The BIHS collects a 24-hour time use diary for the husband and wife, accounting for 24 different activities/time uses in each of 96 fifteen-minute time-blocks. We define shareable consumption time uses as: eating/drinking; commuting; travelling; watching TV/ listening to radio; reading; sitting wiith family; exercise; social activities; hobbies; and, religious activities. These activities are time-uses that are amenable to joint consumption. In column (5), we present estimates from a model identical to the baseline specification except that the cooperation factor f is defined to be a dummy variable equal to 1 if the husband and wife spent any time during the 24-hour diary doing the same shareable consumption activity at the same time. The resulting estimates that are similar in spirit to our baseline estimates. However, they are not identical: the estimated consumption e 01 (ev)2(are)-343.998 (s)-3 variable equal to 1 if the husband and wife spent any time doing the same non-private activity at the same time. Here, we see a much smaller, and statistically insignificant estimate, of $\ln$ equal to 0.056. However, the estimated marginal effects of the cooperation factor on resource shares are essentially equal to those in column (5). Consequently, we see smaller effects on money-metric welfare, driven by the smaller efficiency effect of cooperation. Our takeaway is that our specific choice of cooperation factor in the baseline specification (joint decisions on consumption choices on food, shelter, health care and clothing) is not idiosyncratically driving our findings. Other reasonable choices for the cooperation factor yield similar results.

We consider the possibility that depends on household size in Table 5. The function, which gives the percentage cost of inefficiency associated with the cooperation factor $f = 0$ vs the efficient $f = 1$, is a novel feature of our model. In Table 5, we consider alternative specifications for this cost of inefficiency function. The leftmost block of Table 5, column (10), imposes the restriction $a_0 = a_1 = 0$, which makes $\ln = 0$. This specification imposes the constraint that f does not affect efficiency, and so makes f a distribution factor but not a cooperation factor. Column (11) allows the economies of scale associated with f to vary by household size. In this specification, $\ln (f_h; z_h;) = a_0 + a_1 \ln \frac{n}{4} f_h$. This maintains the construction that $\ln = a_0$ for the reference household, which has $n = 4$ members. Finally, in the third block of Table 5, column (12), we let a_1 be a vector of coefficients on household size and on all the elements of z except the household composition dummies.

Consider first column (10) where we don't allow for any inefficiency. The estimated values of the constant terms in resource shares are virtually identical to those of our baseline specification (estimates (1)), and the estimated marginal effect of f on these resource shares has an efficiency gain of 10 per cent with cooperation. But the estimated value of the scalar a_1 is large, at about 0.5, implying much larger efficiency gains in larger households. For the largest households in our sample, which have 6 members, the predicted efficiency gain is $\exp\left(0.100 + 0.501 \ln \frac{6}{4}\right) - 1 = 35$ per cent. For the smallest households in our sample

For interested readers, we consider 3 other robustness-oriented exercises in Appendix Table 3. They did not yield any interesting economic insights.

We have three main bottom line empirical results. First, we find that our measure of cooperation f is indeed a cooperation factor, i.e., it affects the efficiency of household consumption and it affects resource shares. We find efficiency gains due to increased sharing and cooperation on the order of 13 per cent or more of the household's total budget, and increased cooperation increases men's resource shares by about 2.7 percent, at the expense of women and (mostly) children. Second, we find that net effect of these shifts is that cooperation increases money-metric utility from consumption for all household members, but it proportionally increases men's money-metric utility far more than that of women and children. Third, we find evidence that the efficiency effects are largest in larger households,

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Tables

Table 1a: Distribution of Household Structures				
men	women	children	variable name	mean
1	1	1	m1_f1_c1	0.189
		2	constant	0.255
		3	m1_f1_c3	0.101
		4	m1_f1_c4	0.030
1	2	1	m1_f2_c1	0.087
		2	m1_f2_c2	0.085
2	1	1	m2_f1_c1	0.079
		2	m2_f1_c2	0.054
2	2	1	m2_f2_c1	0.071
		2	m2_f2_c2	0.048

Statistics are for the 3000 observations of households from the BIHS 2015 comprised of nuclear households

Table 2: "First Stage"

		cooperation, f			log-budget, ln y		
		est	std err	t	est	std err	t
Constant		0.178	0.042	4.24	0.039	0.039	1.00
Covariates	average age of males/10	0.002	0.008	0.25	-0.005	0.007	-0.72
	average age of females/10	-0.022	0.012	-1.92	0.016	0.011	1.43
	average education of men/10	-0.006	0.003	-2.21	0.025	0.003	9.55
	average education of women/10	0.011	0.003	3.31	0.032	0.003	10.18
	average age of children/10	0.067	0.025	2.68	0.116	0.024	4.92
	fraction girl children	-0.020	0.020	-0.98	0.038	0.019	2.05
	log of marital wealth	0.002	0.003	0.61	0.004	0.002	1.62
Composition	m1_f1_c1	-0.018	0.025	-0.72	-0.139	0.024	-5.87
	m1_f1_c3	0.059	0.031	1.93	0.052	0.029	1.82
	m1_f1_c4	0.005	0.051	0.10	0.119	0.047	2.51
	m1_f2_c1	-0.106	0.033	-3.17	0.111	0.031	3.54
	m1_f2_c2	-0.028	0.034	-0.83	0.162	0.032	5.10
	m2_f1_c1	-0.052	0.036	-1.47	0.056	0.033	1.68
	m2_f1_c2	0.035	0.040	0m29-0.720.031			-1.92era

Table 3: Estimated Efficiency and Resource Shares, Varying Models								
			(1) Baseline		(2) Varying		(3) Less Overid.	
function	person	variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
ln	all	constant	0.121	0.035	0.099	0.043	0.139	0.077
resource shares	men, $_m$	constant	0.308	0.012	0.298	0.013	0.411	0.033
		f	0.027	0.005	0.026	0.005	0.035	0.010
	women, $_f$	constant	0.330	0.014	0.335	0.016	0.343	0.029
		f	-0.005	0.005	-0.003	0.006	-0.01	0.008
	children, $_c$	constant	0.362	0.020	0.367	0.021	0.247	0.041
		f	-0.022	0.007	-0.023	0.008	-0.026	0.011
Change in Welfare	men		0.228	0.054	0.199	0.062	0.248	0.111
	women		0.111	0.043	0.095	0.051	0.117	0.089
	children		0.061	0.035	0.034	0.043	0.03	0.079
N			3000		3000		3000	
J-stat	val [df] p		206.4 [192]	0.23	189.2 [176]	0.24	72.2 [82]	0.77

Statistics are for the 3000 observations of households from the BIHS 2015 comprised of nuclear households with 1-4 children plus households with 2 men or 2 women and 1 or 2 children. The sample includes only households with consistent food data with nonzero food spending in the 24-hour food diary for each type of household member (men, women and children). We report 2-step GMM estimates, with standard errors are clustered at the village level, of the marginal effects of f on efficiency ln , resource shares and money-metric welfare $_j$. Unconditional moments are defined by instruments multiplied by each of the 3 equations, where instruments are $(1; r_{1h}; z_h)$ $(1; r_{2h})$. In columns (1) and (2), r_{1h} and r_{2h} are the first four powers of village-average f and log-wealth, respectively. In column (3), r_{1h} and r_{2h} are the first two powers of village-average f and log-wealth, respectively. In columns (1) and (3), is a constant; in column (3) is a linear index in z.

Table 4: Estimated Efficiency and Resource Shares, Varying Cooperation Factors								
			(4) Joint Housing		(5) Shareable		(6) Non Private	
function	person	variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
ln	all	constant	0.133	0.040	0.141	0.069	0.056	0.080
resource shares	men, $_m$	constant	0.281	0.013	0.293	0.014	0.280	0.013
		f	0.031	0.005	0.040	0.008	0.040	0.007
	women, $_f$	constant	0.351	0.017	0.363	0.017	0.361	0.016
		f	-0.010	0.006	-0.01	0.007	-0.01	0.007
	children, $_c$	constant	0.367	0.021	0.344	0.02	0.358	0.021
		f	-0.022	0.008	-0.03	0.011	-0.030	0.009
Change in Welfare	men		0.269	0.063	0.309	0.092	0.208	0.100
	women		0.110	0.048	0.12	0.084	0.029	0.090
	children		0.074	0.045	0.051	0.081	-0.032	0.078
N			3000		3000		3000	
J-stat	val [df] p		202.9 [192]	0.28	179.7 [192]	0.73	190.9 [192]	0.51

We report 2-step GMM estimates, with standard errors are clustered at the village level, of the marginal effects of f on efficiency ln , resource shares and money-metric welfare $_j$. Unconditional moments are defined by instruments multiplied by each of the 3 equations, where instruments are $(1; r_{1h}; z_h)$ $(1; r_{2h})$, where r_{1h} and r_{2h} are the rst four powers of village-average f and log-wealth, respectively. Compared to

Appendix:

August 2, 2022

1 Formal Assumptions and Proofs

Here we formally derive our model, and prove that it is semiparametrically point identified. To simplify the derivations and assumptions, we first prove results without unobserved random utility parameters (as would apply if, e.g., our data consisted of many observations of a single household, or of many households with no unobserved variation in tastes). We then later add unobserved error terms to the model, corresponding to unobserved preference heterogeneity.

Let f, r, y, p, , and z be as defined in the main text. Note that the first few Lemmas below will not impose the restriction that f only equal two values.

ASSUMPTION A1: Conditional on f, r, y, p, , and z, the household chooses quantities to consume using the program given by equation (6) in the main text.

Assumption A1 describes the collective household's conditionally efficient behavior. For each household member j, U_j is that member's utility function over consumption goods, u_j is that members additional utility or disutility associated with f, and ω_j is that member's Pareto weight.

As can be seen by equation (6) in the main text, the way that private assignable goods q_j differ from other goods g is that each q_j only appears in the utility function of individual j

given the same budget constraint. because the terms in equation (6) in the main text that are not in (2) do not depend on $g_1; q_1; \ldots g_J; q_J$. With that replacement, the proof of Lemma 1 then follows immediately from the results derived in BCL. BCL only considered $J = 2$, but the extension of this Lemma to more than two household members, and to carrying the additional covariates, is straightforward. Note that the resource share functions $_j$ in Lemma 1 do not depend on r, because r, including the component v, does not appear in either equation (2) or in the budget constraint, and so cannot a ect the outcome quantities.

Our empirical work will make use of cross section data, where price variation is not observed. Most of the remaining assumptions we make about resource shares and about the U_j component of utility are the same, or similar, to those made by DLP, and for the same reason: to ensure identi cation of the model without requiring price variation.

ASSUMPTION A3. The resource share functions $_j(p; \; ; y; f; z)$ do not depend on y.

DLP give many arguments, both theoretical and empirical, supporting the assumption that resource shares do not vary with y. Given Assumption A3, we hereafter write the resource share function as $_j(\; ; p; f; z)$.

For the next assumption, recall that an indirect utility function is de ned as the function of prices and the budget that is obtained when one substitutes an individual's demand functions into their direct utility function.

As noted in the main text, this is a class of functional forms that is widely known to t empirical continuous consumer demand data well. Examples of popular models in this class include the Christensen, Jorgenson, and Lau (1975) Translog demand system and Deaton and Muellbauer's (1980) AIDS (Almost Ideal Demand System) model.[1]

LEMMA 2: Let Assumptions A1, A2, A3, and A4 hold. Then the value of $U_j(q_j; g_j; z)$

However, our empirical analyses will only make use of the private assignable goods q_j with demands given by equation (5).

ASSUMPTION A5. Let $\ln M_j(\ _j; A_f p; z) = m_j(A_f p; z) \quad (z) \ln \ _j$ for some functions m_j and .

There are two restrictions embodied in Assumption A5. One is that the functional form of $\ln M_j$ in terms of prices is linear and additive in $\ln \ _j$, and the other is that the function (z) does not vary by j. The functional form restriction of log linearity in log prices is a common one in consumer demand models, e.g., the function M_j in Deaton and Muellbauer's (1980) AIDS (Almost Ideal Demand System) satis es this restriction. Assumption A5 could be further relaxed by letting depend on p (though not on A_f) without a ecting later results.

To identify their model, DLP de ne and use a property of preferences called similarity across people (SAP), and provide empirical evidence in support of SAP. The restriction that not vary by j su ces to make SAP hold for the private assignable goods (but not necessarily for other goods).

ASSUMPTION A6. Let $\ln S_j(\ _j; A_f p; z) = \ln s_j(\ _j; p; z) \quad \ln \ (A_f p; z)$ for some functions s_j and . Without loss of generality, let $\ln \ (A_0 p; z) = 0$.

Assumption A6 assumes separability of the e ects of $_j$ and f on the function S_j. DLP discuss various ways in which the matrix A_f can drop out of a function of prices, as required in the function s_j.[2] This assumption is not vital, but will be helpful for making the cost of an ine cient choice of f identi able. Assuming $\ln \ (A_0 p; z) = 0$ in Assumption A6 is without

[2] For example, one way A_f drops out is if A_f is block diagonal, with one block that does not vary by f, and with s_j only depending on $_j$ and the prices in that block. Alternatively, linear constraints could be imposed on the elements of A_f, with s_j depending only on the corresponding functions of prices, that, by these constraints, do not vary with A_f. Analogous restrictions are often imposed on demand systems. For

loss of generality, because if it does not hold then one can make it hold if one rede nes and s_j by subtracting ln $(A_0 p; z)$ from both ln $(f; p; z)$ and ln $s_j(\ _j; p; z)$.

It will be convenient to express our demand functions in budget share form. De ne $w_j = q_j \ _j = y$. This budget share is the fraction of the household's budget y that is spent on buying person j's assignable good q_j.

LEMMA 3: Given Assumptions A1 to A6, the value of $U_j(q_j; g_j; z)$ attained by household member j is given by

$$[\ln \ _j(\ ; A_f p; f; z) + \ln y \quad \ln s_j(\ _j; p; z) + \ln \quad (A_f p; z)]\,[m_j(A_f p; z) \quad (z) \ln \ _j] \qquad (6)$$

and the budget share demand functions for each private assignable good are given by

$$w_j = \ _j(\ ; A_f p; f; z)\,[\ _j(\ _j; p; z) + \quad (z)(\ln y + \ln \ _j(\ ; A_f p; f; z) + \ln \quad (A_f p; z))]\,. \qquad (7)$$

that were functions of $A_f p$ as just functions of f, since with xed prices the only source of variation of $A_f p$ is just variation in f).

LEMMA 4: Given Assumptions A1 to A7, the value of $U_j(q_j; g_j; z)$ attained by household member j is given by

$$[\ln \; _j(f;z) + \ln y \quad \ln s_j(z) + \ln \quad (f;z)]\, M_j(f;z) \tag{8}$$

and the budget share Engel curve functions $w_j = W_j(f;z;y)$ for each private assignable good are given by

$$W_j(f;z;y) = \; _j(f;z)\,[\; _j(z) + \quad (z)\,(\ln y + \ln \; _j(f;z) + \ln \quad (f;z))]\,. \tag{9}$$

Lemma 4 entails a small abuse of notation, where we have absorbed the values of p and into the de nitions of all of our functions, noting that any function of $A_f p$ remains a function of f even if j

The function $_j(f; z; y)$ is identi ed because it is de ned entirely in terms of identi ed functions. By equation (9), $_j(f; z; y) = \ _j(z) \quad (z) \ln \ (f; z)$. It follows from Assumption A6 that $\ln \ (0; z) = 0$, so $_j(z)$ and $(f; z)$ are identi ed by

$$_j(z) = \ _j(0; z; y) \quad \text{and} \quad \ln \ (f; z) = \frac{_j(f; z; y) \quad _j(0; z; y)}{(z)}$$

evaluated at any value of y (or, e.g., averaged over y).

Lemma 5 shows that, given the household demand functions, the resource share functions $_j(f; z)$ are identi ed, so our model, like DLP, overcomes the problem in the earlier collective household literature of (the levels of) resource shares not being identi ed. Lemma 5 also shows identi cation of the preference related functions $_j(z)$ and (z), and identi cation of our new cost of ine ciency function $(f; z)$.

LEMMA 6: Let Assumptions A1 to A7 hold. Assume f is determined by maximizing $(U_1 + u_1; :::; U_J + u_J)$ for some function. Then $f = \arg\max \ (R_1(p; y; f; v); :::R_J(p; y; f; v))$ where $R_j(f; y; v; z)$ is given by

$$R_j(f; y; v; z) = (\ln \ _j(f; z) + \ln y \quad \ln s_j(z) + \ln \ (f; z)) M_j(f; z) + u_j(f; v; z)$$

The proof of Lemma 6 is then that, by equation (8) and the de nition of u_j, for any f the level of $U_j + u_j$ attained by member j is given by the function $R_j(f; y; v; z)$.

The above analyses apply to a single household. Our data will actually consist of a cross section of households, each only observed once. To allow for unobserved variation in tastes across households in a conveniently tractible form, replace the function $\ln S_j(\ _j; A_f p; z)$ with $\ln S_j(\ _j; A_f p; z) \quad "_j$ where $"_j$ is a random utility parameter representing unobserved variation in preferences for goods. This means that $"_j$ appears in member j's utility function U_j. We assume these taste parameters vary randomly across households, so $E("_j \mid r; z) = 0$.

Similarly, replace $u_j(f;r;z)$ with $u_j(f;r;z) + e_{jf}$ where e_{jf} represents variation in the utility or disutility associated with the choice of f. The errors e_{jf} and "e_j can be correlated with each other and across household members.

Substituting these de nitions into the above equations, we get

$$w_j = \;_j(f;z)[\;_j(z) + \;(z)(\ln y + \ln \;_j(f;z) + \ln \;(f;z)) + "_j] \tag{10}$$

where $"_j = \;(z)"e_j$ so $E("_j \mid r;z) = 0$, and f is now determined by

$$f = \arg\max \; \tilde{R}_{1f};\ldots;\tilde{R}_{Jf}, \text{ where } \tilde{R}_{jf} = R_j(f;y;r;z) + (M\;_j(f;z) = \;(z))"_j + e_{jf} \tag{11}$$

We will want to estimate the Engel curve equations (10) for $j = 1;\ldots;J$. Equation (11) shows that f is an endogenous regressor in these equations, because f depends on both $"_j$ and e_{jf}. As discussed in the main text, we do not try to empirically identify or estimate equation (11), because both the functions R_j and errors e_{1f} depend on u_j, and there may be important determinents of u_j (the direct utility or disutility from cooperation) that we cannot observe. However, we will require at least one instrument for f.

Another source of error in our model is that, in our data, y is a constructed variable (including imputations from home production), and so may su er from measurement error. We will therefore require instruments for y. Our current collective household model is static. This is justi ed by a standard two stage budgeting (time separability) assumption, in which households rst decide how much of their income and assets to save versus how much to spend in each time period, and then allocate their expenditures to the various goods they purchase. The total they spend in the time period is y, and the household's allocation of y to the goods they purchase is given by equation (6) in the main text. These means that variables associated with household income and wealth will correlate with y and so are potential instruments for y.

member j, but need not apply to the utility or disutility associated with f, that is, $u_j(f; v; z)$. So at least some of these income and wealth variables could be components of v. Let e denote a vector of potential instruments for y. These are measures related to income or wealth that are not already included in v.

(b

Assume there exists values v_0 and v_1 such that $u_j(f; v_0; z) \neq u_j(f; v_1; z)$ for some member j who's utility appears in . Then it follows from equation (11) that f varies with v, so v can

vv1lnr (b)-28.00375 1.794 Tdv-365-28.00375 1.7003.86uor

serve as an instrument for f. Similarly, assume that $\ln y$ correlates with e, which can serve as instruments for $\ln y$ (elements of v could also be instruments for y). Based on equation (10), we then have conditional moments

vvvvvwith

$$E \quad \frac{w_j}{{}_j(f; z)} \quad {}_j(z) \quad (z)(\ln y$$

not required for parametric identi cation, are listed in Assumption A8.

ASSUMPTION A8. Add unobservable heterogeneity terms $\tilde{e}_j$ and $\tilde{e}_{jf}$ to the model by replacing the function $\ln S_j(\ _j; A_f p; z)$ with $\ln S_j(\ _j; A_f p; z) \quad \tilde{e}_j$ and $u_j(f; v; z)$ with $u_j(f; v; z) + \tilde{e}_{jf}$, for $j = 1; :::; J$. Assume f is determined by maximizing , where is linear, so $\ \tilde{R}_{1f}; :::\tilde{R}_{Jf} = \sum_{j=1}^{J} \tilde{e}_j \tilde{R}_{jf}$ for some constants $\tilde{e}_1,...,\tilde{e}_J$. Let $e = \sum_{j=1}^{J} \tilde{e}_j (\tilde{e}_{j1} \quad \tilde{e}_{j0})$. De ne $\tilde{y}(\tilde{\varepsilon}; v; z)$ by $\ln \tilde{y}(\tilde{\varepsilon}; v; z) = E(\ln y \mid \tilde{\varepsilon}; v; z)$. Assume the following: The function $\tilde{y}(\tilde{\varepsilon}; v; z)$ is di erentiable in a scalar $\tilde{\varepsilon}$ with a nonzero derivative. The error e is independent of $y; \tilde{\varepsilon}; v; z$ and $("_j; e)$ is independent of $\tilde{\varepsilon}$ conditional on $(v; z)$. $E("_j \mid \tilde{\varepsilon}; v; z) = 0$. The functions $M_j(f; z)$ do not depend on f. There exist values v_1 and v_0 of v such that $\sum_{j=1}^{J} \tilde{e}_j u_j(f; v_1; z) \neq \sum_{j=1}^{J} \tilde{e}_j u_j(f; v_0; z)$.

THEOREM 1: Let Assumptions A1 to A8 hold. Then the functions $\ _j(f; z)$, $\ (f; z)$, $\ _j(z)$, and $\ (z)$ are identi ed.

To prove Theorem 1, rst observe that, with f binary, it follows from equation (11) that $f = 1$ if $\sum_{j=1}^{J} \tilde{e}_j [R_j(1; y; r; z) + (M_j(1; z) = \ (z)) "_j + \tilde{e}_{j1}]$ is greater than $\sum_{j=1}^{J} \tilde{e}_j [R_j(0; y; r; z) + (M_j(0; z) = \ (z)) "_j + \tilde{e}_{j0}]$, where the function R_j is given by Lemma 6. Taking the di erence in these expressions, and using the assumption that $M_j(f; z)$ doesn't depend on f, we get that $f = 1$ if and only if

$$\sum_{j=1}^{J} \tilde{e}_j [(\ln \ _j(1; z) + \ln \ (1; z)) M_j(z) + \ _j(1; v; z)$$
$$(\ln \ _j(0; z) + \ln \ (0; z)) M_j(z) \quad \ _j(0; v; z)] + e$$

is positive. This means that $f = \tilde{f}(v; z; e)$ for some function $\tilde{f}$. More precisely, f obeys a threshold crossing model where f is one if a function of v and z given by the above expression is greater than $\ e$, otherwise f is zero.

Now, again exploiting that f is binary,

$$E(w_j \mid \tilde{e}; v; z; y) = E[W_j(f; z; y) + \ (z) \ln \ (f; z)\,\tilde{\varepsilon}_j \mid \tilde{e}; v; z; y]$$

$$= E[W_j(1; z; y) f + \ (z) \ln \ (1; z) f \tilde{\varepsilon}_j + W_j(0; z; y)(1 \quad f) + \ (z) \ln \ (0; z)(1 \quad f)\tilde{\varepsilon}_j \mid \tilde{e}; v; z; y]$$

$$= W_j(0; z; y) + [W_j(1; z; y) \quad W_j(0; z; y)]\, E(f \mid \tilde{e}; v; z; y)$$
$$+ \ (z)[\ln \ (1; z) \quad \ln \ (0; z)]\, E(f \tilde{\varepsilon}_j \mid \tilde{e}; v; z; y).$$

Next, observe that, since $W_j(f; z; y)$ is linear in $\ln y$, $E[W_j(0; z; y) \mid \tilde{e}; v; z] = W_j(0; z; \tilde{y})$ and $E[W_j(1; z; y) \mid \tilde{e}; v; z] = W_j(1; z; \tilde{y})$ where $\tilde{y} = \tilde{y}(\tilde{e}; v; z)$. Averaging the above expression over y, and noting that $f = \tilde{f}(v; z; e_1)$, we get

$$E(w_j \mid \tilde{e}; v; z) = W_j(0; z; \tilde{y}) + [W_j(1; z; \tilde{y}) \quad W_j(0; z; \tilde{y})]\, E(f \mid \tilde{e}; v; z)$$
$$+ \ (z)[\ln \ (1; z) \quad \ln \ (0; z)]\, E(f \tilde{\varepsilon}_j \mid \tilde{e}; v; z).$$

and by the conditional independence assumptions regarding $\tilde{\varepsilon}_j$ and e_1,

$$E(w_j \mid \tilde{e}; v; z) = W_j(0; z; \tilde{y}) + [W_j(1; z; \tilde{y}) \quad W_j(0; z; \tilde{y})]\, E(f \mid v; z)$$
$$+ \ (z)[\ln \ (1; z) \quad \ln \ (0; z)]\, E(f \tilde{\varepsilon}_j \mid v; z).$$

Now the functions $E(w_j \mid \tilde{e}; v; z)$ and $\tilde{y}(\tilde{e}; v; z)$ (the latter defined by $\ln \tilde{y}(\tilde{e}; v; z) = E(\ln y \mid \tilde{e}; v; z)$) are both identified from data (and could, e.g., be consistently estimated by nonparametric regressions. So the derivatives of these expressions with respect to $\tilde{e}$ are identified. This means that the following expression is identified.

$$\frac{\partial E(w_j \mid \tilde{e}; v; z)}{\partial \ln \tilde{e}} \Big/ \frac{\partial \ln \tilde{y}(\tilde{e}; v; z)}{\partial \ln \tilde{e}} = \frac{\partial W_j(0; z; \tilde{y})}{\partial \ln \tilde{y}} + \frac{\partial [W_j(1; z; \tilde{y}) \quad W_j(0; z; \tilde{y})]}{\partial \ln \tilde{y}} E(f \mid v; z) \tag{14}$$

Taking the difference between the above expression evaluated at $v = v_1$ and at $v = v_0$ then gives (and so identifies)

$$\frac{\partial[W_j(1;z;\tilde{y}) - W_j(0;z;\tilde{y})]}{\partial \ln \tilde{y}} [E(f \mid v_1;z) - E(f \mid v_0;z)]$$

and, since $E(f \mid v;z)$ is also identified, this identifies $\partial[W_j(1;z;\tilde{y}) - W_j(0;z;\tilde{y})] = \partial \ln \tilde{y}$. We can then solve equation (14) for $\partial W_j(0;z;\tilde{y}) = \partial \ln \tilde{y}$ where all the terms defining this derivative are identified. Taken together, the last two steps identify $\partial W_j(f;z;\tilde{y}) = \partial \ln \tilde{y}$ for $f = 0$ and for $f = 1$.

Given these identified functions and derivatives, we may then duplicate the proof of Lemma 5, (replacing y with $\tilde{y}$, to[(,)-320aEo27.997 (w)2, theat-326 993 (;f 17.4e.955 Tf 10.047.0

Appendix Table 1: GMM Estimates, Varying Covariates

			(1) Include Abuse		(2) Include Wealth		(3) Include both	
function	person	var	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
ln	all	const	0.135	0.037	0.159	0.068	0.191	0.069
	men	const	0.302	0.012	0.298	0.017	0.323	0.018
		f	0.028	0.005	0.035	0.005	0.031	0.006
	women	const	0.306	0.013	0.25	0.02	0.241	0.02
		f	0.003	0.004	0.007	0.004	0.011	0.005
	children	const	0.392	0.02	0.452	0.023	0.435	0.024
		f	-0.03	0.006	-0.042	0.007	-0.042	0.007
Change	men		0.251	0.056	0.311	0.094	0.326	0.097
in	women		0.154	0.046	0.204	0.081	0.266	0.091
Welfare	children		0.056	0.037	0.064	0.073	0.094	0.074
N	ons		3000		3000		3000	
J: value	[df] p		194.6	0.34	180	0.63	182.4	0.48
			[187]		[187]		[182]	

Appendix Table 2
Number of parameters = 89
Number of moments = 315
Initial weight matrix: Unadjusted Number of obs = 3,000
GMM weight matrix: Cluster (uzcode)
(Std. Err. adjusted for 281 clusters in uzcode)

	Estimate	Robust Std. Err.		Estimate	Robust Std. Err.
eta_m			eta_f		
one	0.3082	0.0120	one	0.3299	0.0144
avg_age_men	-0.0022	0.0035	avg_age_men	0.0125	0.0040
avg_age_women	-0.0208	0.0049	avg_age_women	-0.0322	0.0054
avg_edu_men	0.0036	0.0015	avg_edu_men	0.0059	0.0014
avg_edu_women	0.0007	0.0019	avg_edu_women	-0.0026	0.0018
avg_age_children	-0.0341	0.0129	avg_age_children	-0.0559	0.0128
frac_girl	0.0559	0.0096	frac_girl	-0.0221	0.0093
ln_dowry	0.0030	0.0013	ln_dowry	-0.0011	0.0012
m1_f1_c1	0.0435	0.0193	m1_f1_c1	0.0078	0.0182
m1_f1_c3	-0.0506	0.0157	m1_f1_c3	-0.0651	0.0182
m1_f1_c4	-0.0052	0.0170	m1_f1_c4	-0.1040	0.0216
m1_f2_c1	0.0514	0.0159	m1_f2_c1	0.0986	0.0202
m1_f2_c2	-0.0512	0.0144	m1_f2_c2	0.1275	0.0218
m2_f1_c1	0.1232	0.0236	m2_f1_c1	-0.0451	0.0158
m2_f1_c2	0.1452	0.0236	m2_f1_c2	-0.0371	0.0178
m2_f2_c1	0.0826	0.0211	m2_f2_c1	0.1094	0.0206
m2_f2_c2	0.0461	0.0303	m2_f2_c2	0.1539	0.0319
f, cooperation	0.0269	0.0050	f, cooperation	-0.0052	0.0047
gamma_m			gamma_f		
one	0.3012	0.0139	one	0.2382	0.0123
avg_age_men	0.0030	0.0039	avg_age_men	-0.0055	0.0034
avg_age_women	0.0165	0.0062	avg_age_women	0.0234	0.0058
avg_edu_men	-0.0058	0.0017	avg_edu_men	-0.0057	0.0013
avg_edu_women	-0.0021	0.0019	avg_edu_women	0.0024	0.0018
avg_age_children	-0.0661	0.0121	avg_age_children	-0.0630	0.0096
frac_girl	-0.0391	0.0092	frac_girl	0.0333	0.0085
ln_dowry	-0.0022	0.0016	ln_dowry	0.0031	0.0010
m1_f1_c1	0.0063	0.0189	m1_f1_c1	0.0410	0.0156
m1_f1_c3	0.0220	0.0186	m1_f1_c3	0.0312	0.0183
m1_f1_c4	-0.0416	0.0188	m1_f1_c4	0.0542	0.0314
m1_f2_c1	-0.0730	0.0140	m1_f2_c1	0.0313	0.0162
m1_f2_c2	-0.0154	0.0158	m1_f2_c2	-0.0269	0.0152
m2_f1_c1	0.0007	0.0183	m2_f1_c1	0.0020	0.0131
m2_f1_c2	-0.0322	0.0193	m2_f1_c2	-0.0156	0.0153
m2_f2_c1	-0.0115	0.0184	m2_f2_c1	-0.0199	0.0138
m2_f2_c2	-0.0090	0.0319	m2_f2_c2	-0.0806	0.0158

GMM estimation, continued
GMM weight matrix: Cluster (uzcode)
(Std. Err. adjusted for 281 clusters in uzcode)

	Estimate	Robust Std. Err.		Estimate	Robust Std. Err.
beta			gamma_c		
one	-0.1679	0.0041	one	0.1675	0.0179
lndelta			avg_age_men	0.0149	0.0046
one	0.1214	0.0349	avg_age_women	-0.0311	0.0059
			avg_edu_men	0.0079	0.0014
			avg_edu_women	0.0015	0.0018
			avg_age_children	0.1352	0.0140
			frac_girl	0.0106	0.0099
			ln_dowry	0.0021	0.0013
			m1_f1_c1	-0.0440	0.0234
			m1_f1_c3	0.0184	0.0225
			m1_f1_c4	0.0888	0.0328
			m1_f2_c1	-0.0482	0.0210
			m1_f2_c2	-0.0225	0.0251
			m2_f1_c1	-0.0926	0.0185
			m2_f1_c2	0.0338	0.0276
			m2_f2_c1	-0.0320	0.0240
			m2_f2_c2	0.1128	0.0632

per cent. Cooperation now increases male and female resource shares by roughly 4 and 1 percentage points, respectively, and decreases children's resource shares by roughly 5 percentage points. At a gross level, these results are qualitatively the same as the baseline (men gain a lot, women a little and children's money metric change is insignificant), but the estimated magnitudes are somewhat larger.

The nuclear households in our data have 1 adult man and 1 adult woman and one to four children. We also have 1325 non-nuclear households, 44 (i9ttfving25)-341.995ei (tear)-342.006mo(are)-341.995t (hly)]TJ /T1_1 9.963 T

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