

Inefficient Collective Households: Cooperation and Consumption

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Abstract

We propose a model of consumption inefficiency in collective households. Inefficiency depends on a “cooperation factor”, which can also affect both the allocation of resources within a household and the utility of household members. Households are conditionally efficient, conditioning on the value of the cooperation factor. This lets us exploit convenient modeling features of efficient households (like not needing to specify the bargaining process), while still accounting for—and measuring the dollar cost of—inefficiency. In data from Bangladesh, we find more cooperation is equivalent to a 13% gain in expenditures, with most of the benefit going towards men.

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1 Introduction

Collective household models of consumption often assume that the allocation and use of household resources is Pareto efficient. As observed by Becker (1981), Chiappori (1988, 1992) and many later authors, the efficiency assumption greatly simplifies analysis, construction, and estimation of such models. In particular, efficiency allows models to be estimated without specifying and solving for the specific bargaining process that is used by household members to allocate resources. Efficiency also means that households automatically satisfy decentralization rules analogous to the first and second welfare theorems, in which the consumption behavior of the household as a whole is equivalent to each household member maximizing their own utility function, subject to a shadow budget constraint. The shadow prices in this constraint embody scale economies associated with the sharing and joint consumption of goods, while the shadow budget incorporates the allocation of resources to each member. This decentralization leads to many modeling simplifications.

However, a common objection to the use of these efficient household models in the development literature is that very prominent examples exist of inefficient household behavior. An example is household members concealing money from each other, even to the point of paying outside money holders, or using low- (or negative) return savings instruments (e.g. Schaner 2015, 2017). Another example is actual or threatened domestic violence, which is widespread in some cultures and countries (e.g., Bloch and Rao 2002, Koç and Erkin 2011, Ramos 2016, Hughes, et. al. 2015, and Hidrobo, et. al. 2016).

We propose a collective household model that allows for the presence of some types of inefficiencies, but still maintains all the modeling properties and simplifications, such as decentralization theorems, that are associated with efficient household models. This model allows us to identify the resource share of each household member, defined as the fraction of the overall household budget consumed by that member (see Dunbar, Lewbel, and Pendakur 2013, hereafter denoted DLP), despite the presence of inefficiency. As DLP show, these resource shares may be used to construct measures of within-household inequality and person-level poverty measures. In addition, we identify a dollar measure of the costs to the household attributable to less efficient use of resources.

How can models that assume efficient allocations be applied to inefficient households? The intuition comes from the following analogy. Consider two different perfectly competitive economies, one of which has access to a superior production technology. Each economy can be *conditionally* Pareto efficient, conditioning on the technology they have access to, even though the one with inferior technology is *unconditionally* inefficient relative to the superior economy. Both economies, being conditionally efficient, satisfy all the modeling properties and simplifications (such as decentralization) that go with efficient economies. The same will be true of our households.

We start with the collective household model of Browning, Chiappori, and Lewbel (2013, hereafter denoted BCL), which includes what they call a “consumption technology function” that summarizes a household’s ability to share and jointly consume goods, or more generally to cooperate and thereby attain economies of scale in consumption. A household that has an inferior consumption technology is a household that has lower economies of scale to consumption, and as a result cannot attain as high a level of utility from goods for each of its members as could a household with a superior consumption technology. Nevertheless, households with each technology efficiently use the consumption technology they have, and so models of efficient household behavior can be applied to each.

We first derive this conditional efficiency result in the context of the BCL model. We then extend this model to allow for unconditional inefficiency, where a given household has access to the superior consumption technology but could still choose an inefficient level of sharing. An example could be where a husband shirks responsibility for household activities to increase his own utility, even if that results in inefficiency in the household’s consumption of goods.

We define the notion of a *cooperation factor* which, like a distribution factor (see Browning and Chiappori 1998), affects how resources are divided amongst household members and does not affect each member’s indifference curves over goods. But unlike distribution factors, cooperation factors may also directly affect the household’s consumption technology, and may affect the utility levels of individual household members.

Examples of cooperation factors could be direct indicators cooperation, e.g., measures of time spent together on household chores, or joint decision-making on how a couple’s money is

spent. More generally, cooperation factors could be behaviors that correlate with cooperation or failures to cooperate, such as money hiding or domestic abuse. Many variables that the previous literature considered to be distribution factors might also be cooperation factors.

Most models in the collective household literature assume all goods are either purely private or purely public within the household (i.e., are either not shared at all, or are completely shared). Such models cannot capture our notion of efficiency, or the concept of a cooperation factor, because the definition of goods as purely private or purely public rules out any variation in how much any particular type of good is shared. This is why we start from the BCL model; it is general enough to allow for variation in sharing both between and within goods, and hence it allows for variation in consumption efficiency across households.

The BCL model is a very general collective household model, but it correspondingly has very demanding data requirements for estimation. DLP propose a restricted version of the BCL model that has far lower data requirements and is much simpler to estimate. In the present paper we first generalize BCL to allow for inefficiency in consumption, and then we add assumptions similar to those of DLP to obtain a practical empirical model that can be readily estimated with generally available household-level consumer expenditure data.

We apply our model to data from Bangladesh. Like DLP, we use the model to identify and estimate separate measures of men's, women's, and children's resource shares, to evaluate the within-household distribution of consumption. Unlike previous applications, our model allows for possible inefficiencies in shared consumption.

In our data (as in most data sets) we cannot directly observe how much family members share or jointly consume goods. Instead, the cooperation factor in our application (which we denote as f) is a measure of the extent to which household members *jointly* make consumption decisions. Specifically, our indicator f equals 1 if the decisions of how much to spend on food, clothing, shelter, and health are each made jointly by the husband and wife in the household, and zero otherwise. Our reasoning is that cooperating on how much to purchase of each type of good is a logical prerequisite to, or a proxy for, coordinating and cooperating on how much to share of each good. We also consider a couple of analogous alternative proxies (based on time use and alternative cooperation measures) and obtain similar estimated effects.

Since f is a choice variable, and hence is endogenous, identification and estimation of our model requires an instrument for f . This instrument must be a variable that correlates with the household's choice of f , but does not directly impact the household's consumption allocation decisions. We also need an instrument for total expenditures, which too can be endogenous. For instruments we use household wealth, and village level leave-one-out average of f , with the latter indicating village level prevalence or norms for cooperation. Our instruments do *not* need to be randomly assigned or measured without error. Instead, they only must satisfy some separability conditions based on the properties of our model.

In our baseline model, we find that households that cooperate more have a gain in efficiency that is equivalent to about a 13% increase in total consumption expenditures.¹ Also, the share of household's consumption resources going to men in these more efficient households is about 2.7% greater than the share that men get in less efficient, less cooperative households. In contrast, the share of consumption going to children in more efficient households is smaller than that of children in less efficient households. Nonetheless, because the efficiency gain is large, all household members have a higher money-metric welfare in the more efficient households. A possible explanation for this shift in resource shares is that men dislike the effort required to cooperate and coordinate on joint consumption more than women do, and so require a greater share of the returns from cooperating to induce them to do so.

1.1 Literature Review

Expenditure surveys generally collect consumption data at the household level. Standard poverty and welfare measurements based on such data are also typically calculated at the household level. But well-being and utility apply to individuals, not households. When household resources are distributed unequally across household members, some members of households that are above the poverty line could still be impoverished, and some households that are below the poverty line could have members that, by hogging resources, are indi-

¹More precisely, if members of an inefficient household cooperated as much as those in efficient households did, then the consumption utility of the members of the inefficient household could be increased by an amount equivalent to giving that household 13% more money to spend on consumption goods.

vidually above the line. As a result, official measures of income and consumption, which are applied at the household level, can seriously mischaracterize the prevalence and distribution of poverty and inequality in a country.

For example, using the types of methods that we extend here, DLP find poverty rates for children in Malawi that are much higher than those of men, and much higher than official statistics say. Another example is Calvi (2019), who finds that in India, older women less access to consumption resources within households than do younger women. This results in poverty rates among older women that are much higher than those constructed by official household level surveys, which can explain the otherwise unexpectedly high mortality rate among older women in India.

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. Resource shares are useful for several reasons. First, they are closely 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.

Our primary goal will be identification and estimation of resource shares allowing for inefficiency, and on measuring the economic costs of inefficiency. Resource shares 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.

The earlier literature on collective household models, which assumes that households reach a Pareto efficient allocation of resources, includes Becker (1965, 1981), Chiappori (1988, 1992), Browning, Bourguignon, Chiappori, and Lechene (1994), Browning and Chiappori

(1998), Vermeulen (2002), and Chiappori and Ekeland (2009). This literature showed that, even if one knew the entire demand vector-function of a household (that is, how much the household buys of every good and service as a function of prices, income, and other observed covariates), one still could not identify the level of each household member's resource share.

However, this earlier work also shows that one can generally identify how these resource shares would change in response to a change in observed covariates such as distribution factors (defined as variables that affect resource shares but not preferences). Other papers that make use of this result include Bourguignon and Chiappori (1994), Chiappori, Fortin and Lacroix (2002), and Blundell, Chiappori and Meghir (2005). Most of this earlier work also constrains 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.

Some interesting questions can be addressed without identifying levels of resource shares. However, many fundamental policy questions, such as correctly identifying the prevalence of women's or children's poverty, requires identifying resource share levels. A number of previous approaches exist to address the fundamental nonidentification of resource share levels just from household demand data. One direct approach, taken e.g. by Menon, Perali and Pendakur (2012) and Cherchye, De Rock and Vermeulen (2012), is to collect as much detailed data as possible on the separate consumption of each household member, rather than just observing household-level consumption. However, this method requires detailed and difficult data collection, and is likely to suffer from considerable measurement errors when trying to allocate public and shared goods to individual household members.

A second approach is taken by Cherchye, De Rock and Vermeulen (2011). While the levels of resource shares cannot be identified without additional assumptions, these authors show that it is possible to obtain bounds on resource shares, using revealed preference inequalities. Cherchye, De Rock, Lewbel, and Vermeulen (2015) considerably tighten these bounds by combining Slutsky symmetry restrictions with revealed preference inequalities. Bounds can be further tightened, sometimes leading to point identification of shares, by further combining revealed preference inequalities with assumed restrictions regarding marriage markets. See, e.g., Cherchye, De Rock, Demuynck, and Vermeulen (2014).

A third method is to point-identify the level of resource shares from household level data by imposing additional restrictions either on preferences, or on the household's allocation process, or both. Papers that use these methods include Lewbel (2003), Lewbel and Pendakur (2008), Couprie, Peluso and Trannoy (2010), Bargain and Donni (2009, 2012), Lise and Seitz (2011), BCL, DLP, and Dunbar, Lewbel, and Pendakur (2019).

One feature that all of the above cited works have in common is that they assume the household is efficient, in that it reaches the Pareto frontier. While many of the above papers cite evidence supporting these efficient collective models (see, e.g., Bobonis 2009), other papers reject Pareto efficiency within the household, including Udry (1996), Dercon and Krishnan (2003), Walther (2018), and the laboratory experimental evidence in Jakiela and Ozier (2016).

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).

One can think of our framework as a two period game, or a two step program: first choosing the cooperation factor, and then, conditional on that choice, optimizing consumption. However, dynamic considerations like these raise a host of issues associated with uncertainty about future incomes, prices, and power, as well as potentially limited commitment. We abstract from these complications by treating our model as static, where both steps occur sequentially, but in a single time period. Nevertheless, our framework is related to models that have static efficiency but may be intertemporally inefficient, or have limited commitment. Examples include Mazzocco (2007), Abraham and Laczó (2017), Chiappori and Mazzocco (2017), and Lise and Yamada (2019). This is also related to Lundberg and Pollak (2003), who consider the case where a one-off decision in one period affects future bargaining power, and to Eswaran and Malhotra (2011), who model domestic abuse as a vehicle for enhancing future bargaining power.

We allow the household’s objective function determining the cooperation factor to differ from its objective in determining consumption. This difference makes general inefficiency possible. Other models with analogous stages are Lundberg and Pollak (1993), Gobbi (2018), and Doepke and Kindermann (2019).

2 A Class of Inefficient Collective Household Models

In this section we first summarize the BCL model, and generalize it to allow for household inefficiency. We then further generalize the model by allowing the source of inefficiency, the cooperation factor, to be endogenous. This general model could be estimated with sufficiently rich consumption and price data. We next provide simplifying assumptions that allow the model to be estimated with readily available cross section household survey data on household budgets, consumption levels of a few goods, and demographic data. For ease of exposition, derivations here are presented somewhat informally. Formal assumptions and proofs regarding the derivation of the model are provided in the Appendix.

2.1 Collective Households with Varying Consumption Technologies

For simplicity, start with a household consisting of just two members, a husband and a wife, indexed by $j = 1, 2$. Let g denote the vector of continuous quantities of goods purchased by the household. Let p denote the vector of market prices of the goods in g . Let y be the household’s budget, that is, total expenditures, which is the total amount of money the household spends on goods. We begin with a simplified version of the BCL model. Given prices p and a budget y , the purchased quantity vector g is determined by

$$\max_{g_1, g_2} U_1(g_1) \omega_1(p, y) + U_2(g_2) \omega_2(p, y) \tag{1}$$

$$\text{such that } p'g = y, \quad g = A(g_1 + g_2)$$

Here $p'g = y$ is the usual linear budget constraint, g_1 and g_2 are private good equivalents (described below) for person 1 and 2, and A is a matrix. The functions U_1 and U_2 are the utility functions of members 1 and 2, respectively, while ω_1 and ω_2 are the so-called “Pareto Weights” of each member. Each member’s Pareto weight summarizes that member’s relative bargaining power in a bargaining model, or the relative weight of their utility function in a household social welfare function. The fact that these weight functions can depend on prices p and the budget y is what makes the collective household model more general than a unitary model².

Each utility function $U_j(g_j)$ depends on a quantity vector of goods g_j that member j consumes. Goods can be partly shared, and so are not constrained to be purely privately consumed or purely publicly consumed within the household. In equation (1), $g = A(g_1 + g_2)$ is the “consumption technology function”, which describes the extent to which each good is shared by the household members. Each household member j consumes (and gets utility from) the quantity vector g_j , which BCL call “private good equivalents.”

The square matrix A summarizes how much goods are shared. Suppose A were diagonal (it need not be, but this case is useful for understanding sharing). The extent to which each element of $g_1 + g_2$ exceeds the corresponding element of g is the extent to which that good is shared by household members. For example, suppose that g^1 , the first element of g , was the quantity of gasoline consumed by a couple. If both household members shared their car (riding together) 1/2 of the time, then, in terms of the total distance traveled by each member, it is as if member 1 consumed a quantity g_1^1 of gasoline and member 2 consumed a quantity g_2^1 where $g^1 = (3/4)(g_1^1 + g_2^1)$. For example, Person 1 drives 100km and person 2 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 (which summarizes the extent to which gasoline is shared).

Non-zero off-diagonal elements of A allow the sharing of one good to depend on the purchases of other goods, e.g., more gasoline might be shared by households that purchase less public transportation. As a result, the model is also equivalent to some restricted forms

²A unitary model is one that is observationally equivalent to the behavior of a single utility maximizing individual. See, e.g., Chiappori (1988, 1992)

of home production, e.g., a household that wastes less food by cooperating and coordinating on the production of meals could be represented by having a lower value of the k 'th element on the diagonal of the matrix A , where g^k is the quantity of purchased food.

Because the structure given in (1) optimizes a weighted average of utilities, it yields an efficient allocation and may have a decentralized representation. Given some regularity conditions (see the Appendix for details), there exist resource share functions $\eta_j(p, y)$ such that the household's behavior is equivalent to each member j solving the program

$$\max_{g_j} U_j(g_j) \quad \text{such that} \quad p'Ag_j = \eta_j(p, y)y \quad (2)$$

Each η_j is the fraction of the household's total resources y that are claimed by member j . Resource shares sum to one, so that with two household members we have $\eta_1 + \eta_2 = 1$. Equation (2) is the key decentralization result: the couple's behavior is observationally equivalent to a model where each member j chooses a consumption vector g_j to maximize their own utility function, subject to their own personal budget constraint, which has shadow price vector $A'p$ and shadow budget $\eta_j(p, y)y$.

Let $g_j = h_j(p, y)$ be the demand equations that would be obtained from maximizing the utility function $U_j(g_j)$ under the linear budget constraint $p'g_j = y$. Each member j faces the constraint in equation (2), so

$$g_j = h_j(p'A, \eta_j(p, y)y) \quad (3)$$

and $g = A(g_1 + g_2)$ so the household's demand equations are

$$g = A(h_1(p'A, \eta_1(p, y)y) + h_2(p'A, \eta_2(p, y)y)). \quad (4)$$

BCL show that if the demand functions h_j are known, then the consumption technology matrix A and the resource share functions $\eta_j(p, y)$ are generically identified from household demand data. They suggest that the h_j demand functions could be identified from observing the demands of people living alone.

A feature of this model is that, the more that goods are jointly consumed, the lower is the

shadow price vector $A'p$ relative to market prices p , reflecting the greater efficiency associated with increased sharing. In the gasoline example above, the shadow price of gasoline is $3/4$ that of the market price. This means that the household's actual expenditures on gasoline, $g^1 p^1$, is equal to the cost of buying the sum of what the couple consumed, $g_1^1 + g_2^1$, at the shadow price of $(3/4)p^1$. If the couple had consumed the total quantity of gasoline $g_1^1 + g_2^1$ without any sharing, it would have cost $(g_1^1 + g_2^1)p_1$ dollars instead of what they actually spent, $g^1 p^1 = (3/4)(g_1^1 + g_2^1)p_1$. The difference between these two is the dollar savings they obtained by sharing gasoline.

Analogous gains are obtained with each good that is shared to some extent. The more efficient the household is, (i.e., the more they share consumption), the greater is the difference between what they would have had to spend on all goods if they hadn't shared, which is $p'(g_1 + g_2) = p'A^{-1}g$, relative to what they actually spent, which is $y = p'g$. Thus, the matrix A embodies the scale economies due to sharing that are available to the household. Note that sharing and jointly consuming goods requires cooperation and coordination among household members.

Now consider two couples that differ in how much they are able to (or how much they choose to) cooperate and coordinate consumption. Then these two couples will differ in how much they share or jointly consume goods, and so will have different consumption technology matrices A_0 and A_1 . Suppose the couple with A_1 is more efficient in their consumption, meaning that they share more. Then, even if both couples bought the same market quantity of goods g , the couple with A_1 would have higher consumption of private good equivalents, and so be able to obtain higher utility for its members. By the above logic, this increased efficiency in dollar terms equals the difference between $p'A_0^{-1}g$ and $p'A_1^{-1}g$.

Note that it is possible for the couple with A_0 to share more of some goods, and less of others, than the couple with A_1 . What makes the couple with A_0 less efficient is that, at their given p and y , their shadow budget $p'A_0^{-1}g$ is less than the corresponding shadow budget of the couple with A_1 .

Even though the couple with A_0 is inefficient relative to the couple with A_1 , each is conditionally efficient, conditioning on each couple's ability or willingness to share and cooperate. Equivalently, each is conditionally efficient, conditioning on the consumption technology

matrix that they possess (either A_0 or A_1). And because each is conditionally efficient, each household’s decision problem can be represented by the decentralized program (2).

Now suppose we have two sets of households. One set has consumption technology matrix A_0 and the other set has A_1 . Even though the former households are inefficient, we can still apply and estimate the collective household model for each set of households separately. In particular, we can treat inefficient households as if they were Pareto efficient, satisfying decentralization and other properties of efficiency, because they are conditionally efficient, conditioning on their particular consumption technology matrix A_0 .

In all of this discussion, we have for simplicity spoken as if A_1 is always superior to A_0 , but the reality could be more complicated. For example, A_1 could imply more sharing of some goods and less sharing of others. In that case, it would depend on the household’s particular demand functions, prices, and budgets which one is actually more efficient.

2.2 Collective Households With Endogenous Inefficiency

In the previous subsection, each household possessed an ability to cooperate (in terms of sharing consumption) given by a matrix A_f . We call the f index a “cooperation factor”. A cooperation factor is an observable behavior f that affects the household’s level of cooperation and hence their level of sharing. As noted earlier, examples of cooperation factors could be direct indicators of cooperation (like the degree to which consumption decisions are made jointly), or behaviors associated with likely cooperation or failures to cooperate, such as money hiding or domestic abuse. We will now let f be an endogenous choice. Again derivations here are presented informally for ease of exposition. Formal assumptions, theorems and proofs are in the appendix.

Here we generalize the model of the previous section. First, we allow for an arbitrary number of household members instead of two. Second, we incorporate f into the model, reflecting all of its potential impacts on the household. Third, we let f be a choice variable. The resulting model of the household is now

$$\max_{g_1, g_2, \dots, g_J} \sum_{j=1}^J (U_j(g_j) + u_j(f, v)) \omega_j(p, y, f) \quad (5)$$

$$\text{such that } p'g = y, \quad g = A_f \sum_{j=1}^J g_j$$

The new variable v is discussed below. As before, assume the most efficient value for A is A_1 . The factor f appears in three places in this model. First, f affects sharing through A_f . Second, f appears in the Pareto weight functions ω_j , showing its potential impact on relative power, and the associated allocation of resources, among household members. Third, member utility levels have a consumption component $U_j(g_j)$ a non-consumption component $u_j(f, v)$, and f directly affects member utilities through the u_j functions.

The term $u_j(f, v)$ is the utility member j directly experiences (not including his or her utility over goods) from living in a household with a cooperation level given by f . The variable v is any observed covariate (or vector of covariates) that affects any household member's utility associated with f , but does not affect the rest of the model. The role of the variable v for identification and estimation is discussed below.

To illustrate, if cooperating and coordinating consumption at the level A_1 instead of A_0 requires more effort, $u_j(1, v) - u_j(0, v)$ may be negative, reflecting member j 's disutility from expending that extra effort. Alternatively, $u_j(1, v) - u_j(0, v)$ may be positive if member j experiences direct joy or satisfaction from cooperating that more than compensates for the extra effort that is involved.

Generalizing the model to equation (5) means that the resource share functions η_j now depend on f , and the demand equations (3) and (4) become

$$g_j = h_j(p'A_f, \eta_j(p, y, f) y) \quad (6)$$

and

$$g = A_f \sum_{j=1}^J h_j(p'A_f, \eta_j(p, y, f) y) \quad (7)$$

Substituting in equations (6), the level of utility attained by member j , call it R_j , is therefore given by

$$R_j(p, y, f, v) = U_j(h_j(p'A_f, \eta_j(p, y, f) y)) + u_j(f, v) \quad (8)$$

Now consider what happens to this model when f becomes a choice variable. First, as discussed in the previous section, the household remains conditionally efficient, conditioning

on the chosen level of f , so equations (6), (7) and (8) continue to hold. Second, we must consider how f is chosen. We assume that the household chooses f to maximize some function of the utilities of the household members, that is,

$$f = \arg \max \Psi (R_1(p, y, f, v), \dots, R_J(p, y, f, v)). \quad (9)$$

for some function Ψ , and where g_1, g_2, \dots, g_J are given by equations (6). The function Ψ could be exactly the Pareto weighted average of utility functions given by equation (5), 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 Ψ just equals $R_1(p, y, f, v)$. Or if the parents are choosing the level of f , then Ψ 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 Ψ , so e.g. parents deciding f could put some weight on children's utility functions in Ψ .

Relative to $f = 0$, choosing $f = 1$ has three effects on household members. First, $f = 1$ lowers shadow prices $p'A_f$, reflecting that fact that, by increasing cooperation, the total effective quantities for consumption by the household, $\sum_{j=1}^J g_j$, are increased. This means that one or more members will have their utility over goods increase relative to $f = 0$. Second, $f = 1$ could raise or lower each $u_j(f, v)$, depending on whether each member j gets direct utility or disutility from cooperating. For example, a household might choose $f = 0$, foregoing the gains in consumption from cooperating, if some or all members experience substantial disutility from the effort required to coordinate and cooperate. Third, choosing $f = 1$ could change each member's resource share η_j . So, e.g., if member 1 is choosing f by himself, he might inefficiently choose $f = 0$, even if he doesn't mind cooperating, if choosing $f = 0$ increased his own resource share more than enough to compensate for the loss associated with a higher shadow price for goods.

We will *not* need to actually specify or estimate equation (9), which determines the choice of f . This is important because we may know very little both about which members of the household are making the f decision, and little about the functions u_1, \dots, u_J .

However, the presence of the u_j functions complicates the definition of efficiency. In particular, $f = 0$ might maximize equation (5), and so is efficient in the sense of being on the household's Pareto frontier of member's total utilities ($U_j(g_j) + u_j(f, v)$ for $j = 1, \dots, J$). But at the same time $f = 0$ could be inefficient in terms of consumption, i.e., leading to a lower shadow budget $p'A_0^{-1}g$, or equivalently, not being on the household's Pareto frontier in terms of utilities of consumption ($U_j(g_j)$ for $j = 1, \dots, J$). To distinguish between these efficiency concepts, we define the latter as *consumption efficiency* and the former as *total efficiency*.

If Ψ equals equation (5), so the household maximizes the same objective function in both stages, then the household's choice of f is by construction totally efficient, but it could still be consumption inefficient. In contrast, if Ψ does not equal equation (5) (e.g., if only a subset of household members choose f), then f could be inefficient by both definitions.³ We will for convenience just to refer to $f = 0$ as inefficient, both because we don't know Ψ , and because, regardless of Ψ , $f = 0$ means the household is consumption inefficient. One of the objects we'll estimate is the dollar cost of this consumption inefficiency.

One argument for why households should behave efficiently is that these consumption and cooperation decisions are, in reality, a repeated game, giving households opportunities to learn efficient behavior. This could be an argument for assuming Ψ equals equation (5), but our model is agnostic on this point. We do not take a stand on whether the household chooses Ψ in a way that promotes either total or consumption efficiency.

Note, however, that when the household chooses $f = 0$, there could be an incentive for side payments. For example, if only member 1 gets to choose f , and very much dislikes cooperating, then other members could find it utility-improving to bribe him into choosing $f = 1$ instead of $f = 0$. The model implicitly incorporates side payments, by letting the resource shares depend on f . Increasing member 1's resource share at the expense of other members is equivalent to a side payment from other members to member 1. In this example, member 1 would have a higher resource share with $f = 1$ than $f = 0$, reflecting the redistribution needed to induce member 1 to choose $f = 1$.

³We do not address the question of when f might be consumption efficient even if Ψ does not equal equation (5), but note that the question is closely related to Becker's Rotten Kid theorem (see, e.g. Becker 1974 and Bergstrom 1989).

Given sufficient data, the household’s demand equations (7) could be estimated as described by BCL. They show identification of the model on the basis of observing both household demand functions for all goods and individual demand functions for all goods. The latter may be observed via observing the demand functions of single individuals. Thus, without further assumptions, BCL does not identify the resource shares of children (who do not live alone as singles).

The main additional complication here is that f would be an endogenous regressor. However, this is where the role of the covariate v comes in. As can be seen in equation (9), the variable v affects the choice of f , (through the $u_j(f, v)$ functions), and so correlates with the household’s choice of f . However, by equations (6) and (7), v does not otherwise affect the household’s demand functions for goods. This is because v only affects the u_j functions, not utility from goods consumption U_j or Pareto weights ω_j . This means that v is a valid instrument for the endogenous f in the demand equations.

An important feature of our model is that we do *not* need to actually specify or estimate equation (9). To deal with endogeneity of f , all we need is to observe some variable v . For example, in our empirical application, an instrument v will be the (leave-one-out) average value of f in the household’s village, which is a measure of the prevalence or norms regarding intrahousehold cooperation in the village. This is assumed to affect household members’ propensity to cooperate, without otherwise impacting utility over consumption goods. As long as v has these properties, it does not need to be randomly assigned to be valid as an instrument for our model.

Given estimates of the model, particularly of A_f , we could calculate dollar costs of inefficiency on consumption, such as the difference between $p'A_0^{-1}$ and $p'A_1^{-1}$. However, we will not be able to identify or estimate the functions $u_j(f, v)$, e.g., we can’t estimate how much individual members like or dislike cooperating.

A complication of the original BCL model is that, like many earlier collective household models, it does not identify the resource shares of children. Thus, without additional assumptions, our extension here would similarly not identify impacts on children (or any type of household member who cannot be observed living alone). We address this issue, and overcome other data limitations, in the next subsections.

2.3 General Model Identification

BCL and Lewbel and Lin (2020) give alternative conditions under which the demand functions, resource share functions, and A matrix in BCL are nonparametrically either point identified or generically identified (see also Chiappori and Ekeland 2009).⁴

A similar argument to theirs shows identification of our general model above. In particular, suppose we impose the minimal regularity needed to guarantee that equation (9) is maximized by only one value of f , which depends on v . For example, if f is discrete then we only need to rule out knife edge cases where multiple values of f yield the exact same value for the function Ψ regardless of the values of the other covariates. Then, conditional on any given value of v and hence of f , our general model reduces to BCL, and so the demand functions, resource share functions, and A matrix in our model can also be identified, using the arguments in BCL and Lewbel and Lin (2020).

To construct estimators based on these general identification arguments, one must observe a great deal of relative price and total expenditure variation, and estimate many complicated, high dimensional functions. Additionally, the demand functions of each household member must be observed, e.g., by observing those household members living alone (for example, observing women's demand via the consumption behaviour of single women). This means that identifying the BCL model with children or the very elderly may be impossible without added assumptions.

Rather than formalizing these general identification arguments and constructing associated estimators, we now instead make a number of simplifying assumptions, which then will allow us to obtain both point identification and associated estimators that do not have such heavy data requirements, and so will be much more empirically tractable.

2.4 Empirically Practical Identification and Estimation

As noted above, estimation of our extension of the BCL model would be complicated. DLP propose a restricted version of the BCL model that has many convenient features for empirical

⁴Informally, features of a model are said to be "generically identified" if there are only rare exceptional cases in which they are not identified. More formally, generic identification means that the subset of all possible data generating processes consistent with the model for which the features are not identified has measure zero. See, e.g., McManus (1992) and Lewbel (2019).

work. Here we propose restrictions, similar to those used in DLP, to obtain a version of our inefficient collective household model that has many advantages for empirical work, including: 1) the model can be estimated using readily available “Engel curve” data, that is, cross sectional data on expenditures without price variation; 2) the model identifies resource shares for children as well as adult household members, and 3) despite lacking price variation, the model still identifies the economic cost of inefficiency. Further, we extend the model of the previous section to allow for both observed and unobserved preference heterogeneity, and to letting households have more than one member of each type (in particular, multiple children). As in the previous subsections, we summarize our main results in the text here, while providing formal assumptions, derivations, and identification proofs in Appendix A.

As in DLP, our estimating equations are based on private, assignable goods. A good j is *private* if it is consumed by a single member and its diagonal element of the matrix A equals one, meaning it cannot be jointly consumed at all. A good j is *assignable* if the researcher knows which household member consumes it. Assume now that each household member j consumes a quantity q_j of a good that is private and assignable to member j .⁵ This is another good, in addition to the K vector of quantities of goods g_j that each household member j consumes. Let $\pi = (\pi_1, \dots, \pi_J)$ denote the vector of prices of these private assignable goods.⁶

We further generalize the 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 now include 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,

⁵Some 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. This would mainly entail extra notation, and adding some restrictions to Assumptions A5 and A6 in the appendix.

⁶In practice, the private assignable goods will often all have the same price, making $\pi_1 = \dots = \pi_J$. For example, the private assignable good could be rice if we observed how much rice each household member eats, and rice has the same market price for all household members. As with DLP, some of the formal assumptions of our model are easier to satisfy when the private assignable goods all have the same price.

the model of equation (5) becomes

$$\max_{g_1, q_1, \dots, g_J, q_J} \sum_{j=1}^J [U_j(q_j, g_j, z) + u_j(f, v, z, p, \pi, y)] \omega_j(f, z, p, \pi, y) \quad (10)$$

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

Note the budget constraint is comprised of spending on private assignables q_j and market purchases of the shared unassignable goods g , which are converted to the sum of private equivalents $\sum_{j=1}^J g_j$ by the matrix A_f .

This model yields household demand functions for vectors of goods g and q , analogous to those of equation (7). 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 assignable goods, the household demand equations arising from the household model of equation (10) have the form

$$q_j = H_j(p' A_f, \pi, z, \eta_j(p, \pi, y, f, z) y) \quad (11)$$

where H_j is the Marshallian demand function for the good q_j that comes from the function $U_j(q_j, g_j, z)$ (person j 's utility from goods). Note the resource share functions η_j may now depend on the additional variables π and z that we've introduced into the model. But importantly, as a result of the household's consumption optimizing behavior, 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 fixed prices. First, we assume that the resource share function η_j does not depend on y . This assumption is also made by DLP, who provide a range of theoretical and empirical arguments in support of this assumption.

Let $V_j(\pi_j, p, y, z)$ denote the indirect utility function corresponding to the maximization of the direct utility function from consumption $U_j(q_j, g_j, z)$ under the hypothetical linear

budget constraint $q_j\pi_j + g_jp = y$. The actual utility level over goods attained by member j in the household (which does not include the u_j component of utility) equals this indirect utility function V_j evaluated at the household's shadow prices $A_f p$ and member j 's shadow budget $\eta_j(\pi, A_f p, f, z) y$.

The second main simplifying assumption we make is that this attained level of indirect utility over consumption is semiparametrically restricted to have the form

$$V_j = [\ln \eta_j(\pi, A_f p, f, z) + \ln y - \ln s_j(\pi_j, p, z) + \varepsilon_j^*(\pi_j, p) + \ln \tau(A_f p, z)] [m_j(A_f p, z) - \beta(z) \ln \pi] \quad (12)$$

for some functions s_j , τ , m_j , and β , where, without loss of generality $\ln \tau(A_0 p, z) = 0$. Here $\varepsilon_j^*(\pi_j, p)$ is an unobserved taste shifter, i.e., a random utility parameter.

The restrictions imposed by equation (12) have empirical support, e.g., the popular Deaton and Muellbauer (1980) Almost Ideal Demand System model is a special case of equation (12). This equation also satisfies the SAP (similar across people) restriction used by DLP, which they show also has empirical support.⁷

The decentralization described in the previous subsections carries over to this model. As shown in the appendix, this allows us to apply Roys identity to equation (12) to obtain the household's demand functions for each private assignable good j . The resulting demand functions are most conveniently represented in budget share form. Let $w_j = \pi_j q_j / y$ be the budget share for each private assignable good j , giving the fraction of the household's budget y that is spent on buying member j 's private assignable good. The demand functions determining each q_j can therefore be multiplied by π_j / y to give corresponding demands expressed in terms of budget shares w_j .

We will estimate our model using data from a single price regime, so both p and π are treated as constants, which can then be absorbed into the functions that comprise the budget share demand equations. After introducing the random utility parameters, deriving the budget share demand functions from equation (12) using Roy's identity, and treating all prices as constants, we obtain budget share demand functions that we show in the Appendix

⁷Equation (12) also implies restrictions on A_f relative to the range of possible vectors p . These restrictions are comparable to those imposed by other empirical consumer demand models. See Lewbel and Pendakur (2008) and Appendix A for details.

take the Engel curve form

$$w_j = \eta_j(f, z) [\gamma_j(z) - \beta(z) (\ln y + \ln \eta_j(f, z) + \ln \delta(f, z)) + \varepsilon_j] \quad (13)$$

Here $\eta_j(f, z)$ is member j 's resource share function, $\gamma_j(z)$ and $\beta(z)$ are functions representing variation in tastes, ε_j is an error term that comes from the random utility parameters, and $\delta(f, z)$. Here, $\delta(f, z)$ is a money-metric inefficiency measure that equals $\tau(A_f p, z)$ at the fixed level of prices; it reveals the dollar costs of inefficiency as described below. In the Appendix we add random utility parameters to the model, which end up producing ε_j above.

We prove in Appendix A that the functions in equation (13) are each nonparametrically identified. This includes showing that the levels of the resource shares, $\eta_j(f, z)$, and the inefficiency measure $\delta(f, z)$, are nonparametrically identified.

Recall our assumption that the household uses equation (9) 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 ε_j), but also that v is a valid instrument for f .

Inspection of equation (13) shows that the cooperation factor f has two effects on the budget shares of private assignable goods. One is that it affects resource shares η_j . The second effect, which is on A_f , affects the Engel curve demands through the function $\delta(f, z)$. Inspection of equations (12) and (13) shows that a change in $\ln \delta(f, z)$ has the same effect on utility and on budget shares as the same change in $\ln y$. This then provides a dollar measure of the unconditional efficiency loss (or gain) to the household resulting from choosing $f \neq 1$.

Since $\ln \delta(0, z) = 0$, a change from $f = 0$ to a level of $f > 0$ is equivalent, in terms of consumption of goods, to a change in the household's budget from y to $y\delta(f, z)$. The change in sharing from an increase in f has the same effect on demands, and on the member's attained utility levels over goods, as a corresponding change in total expenditures y . The term $\delta(f, z)$ measures the size of this change. Note that although we identify and estimate $\delta(f, z)$ using just the private assignable goods, this function actually measures the impact of f on the efficiency of consumption of *all* goods, because it is equivalent in everyone's utility function to a change in the total budget y .

All of the derivations in this section go through allowing the cooperation factor f to take many different values (where we have normalized the most efficient case to be $f = 1$). However, in our empirical application we will just let f take on two values, 0 and 1, as in our earlier discussions.

The model we estimate is based on equation (13) for each private assignable good $j \in \{1, \dots, J\}$. Recall that f is endogenous. 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 are assuming it first decides how much to spend on consumption this period (that is, if first chooses y), and then decides what fraction of y to spend on buying each good. Thus, functions of the household's income or wealth make good instruments for y . We assume ε_j is uncorrelated with r , either because the measurement error in y is unrelated to r , or (if y is endogenous) because ε_j is only based on random utility associated with the within period budget allocation, not the utility of saving vs spending. Elements of v might also be correlated with or include these measures of income, assets, or wealth, so to be as general as possible, we let r also include v .

Dividing (13) by $\eta_j(f, z)$ and rearranging yields conditional moments of the form

$$E \left(\frac{w_j}{\eta_j(f, z)} - \gamma_j(z) - \beta(z) (\ln y + \ln \eta_j(f, z) + \ln \delta(f, z)) \mid r, z \right) = 0$$

We show in the Appendix that all the functions in this expression can be nonparametrically identified from these conditional moments.

However, 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. First, let N_j be the number of members in the household of type j , and assume that the N_j members of type j get an equal amount of the budget $\eta_j(f, z)y$ assigned to type j . Thus, the resource share of any one member of type j is $\eta_j(f, z)/N_j$ and the shadow budget of any one member of type j is

$\eta_j(f, z) y / N_j$.⁸

Our budget shares w_j give the share of the household budget y spent on the assignable good (food, in our empirical work below) for all the members of type j . Each of these members has a log-shadow budget of $\ln y - \ln N_{jh} + \ln \eta_j(f, z)$. Now, letting θ be a vector of parameters, we parameterize each of the functions in the above equation, and incorporate N_j , to obtain unconditional moments

$$E \left[\left(\frac{w_j}{\eta_j(f, z, \theta)} - \gamma_j(z, \theta) - \beta(z, \theta) (\ln y - \ln N_{jh} + \ln \eta_j(f, z, \theta) + \ln \delta(f, z, \theta)) \right) \phi(r, z) \right] = 0 \quad (14)$$

Equation (14) holds for any vector of bounded functions $\phi(r, z)$. We construct an estimator for θ by choosing functions $\phi(r, z)$ as discussed in the Appendix, and applying Hansen's (1982) Generalized Method of Moments (GMM).

Finally, it is important to reiterate that, while equation (14) is only estimated for private assignable goods (food in our empirical application), we obtain estimates of resource shares and the dollar cost of efficiency that applies to all goods. We are not assuming, e.g., that men'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 household resource share for all other goods. The intuition for the identification 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 for further discussion of this intuition.

⁸We have food consumption for each household member, and so could in theory estimate resource shares 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.

3 Application to households in Rural Bangladesh

3.1 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 who are likely to 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.

Define the *composition* of a household to be its number of adult men, number of adult women, and number of children (we define 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 final estimation sample. Households are indexed by $h = 1, \dots, H$, 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.⁹ 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 definition 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 each individual in the household, and so do not include leftovers or food served to guests. These 24-hour person-level food intakes are collected for each category for each of up to 19 household members. We multiply each individual’s share of the household’s one-day quantities in each category by household-level weekly quantity to get individual-level weekly quantity by category. These are summed over the 7 categories and multiplied by village-level unit values (analogous to prices, see Deaton 1997) to get total individual-level weekly expenditure on food, and are multiplied by 52 to get individual-level annual food spending. Finally, we aggregate individuals by type to yield adult male food spending, s_{mh} , adult female food spending, s_{fh} , and children’s food spending, s_{ch} .

Specifically, let Q_{ph} be the observed quantity (in kilograms) of category p , $p = 1, \dots, 7$, for household h and let S_{ph} be the observed spending for the weekly food recall data. For each household, the price paid per kilogram is S_{ph}/Q_{ph} . Instead of using household level prices, we follow Deaton (1993) and use village-level unit values to aggregate up to household-level food spending by category. Let π_p be the village-level unit value equal to village-level aggregate spending divided by village-level aggregate quantity, $\pi_p = \sum_h S_{ph} / \sum_h Q_{ph}$, where the summation is over all the households observed in a village. Let \tilde{q}_{jph} be the observed quantity of category p for all people of type j in household h from the one-day diary data.

⁹Module O1 (Food Consumption) and Module X2 (Intra-Household Food Distribution) actually collect food quantities and intakes, respectively, in nearly 300 categories. We aggregate these to 7 higher-level categories to make more sensible unit-values (described below). Module O1 gathers information from the female enumerator (who responds to most of the survey instrument); Module X2 gathers information from the female responsible for cooking that day. From Module X2, we use the weight of ingredients, rather than cooked weights, in our aggregation procedure.

One-day diary data do not include spending data. For each household, we take shares of each category, $\left(\tilde{q}_{jph}/\sum_j \tilde{q}_{jph}\right)$, and attribute to each type of person j their share of weekly quantities in each category, multiply these by the unit value of that category, multiply by 52 to generate food spending by type: $s_{jh} = 52 * \sum_p \pi_p \left(\tilde{q}_{jph}/\sum_j \tilde{q}_{jph}\right) Q_{ph}$.

Note that all references to the “village level” in this paper actually refer to data collected at the Upazila level, which are official administrative units in Bangladesh, one level below the district. There were 492 Upazilas in Bangladesh in 2015, of which 281 are represented in this exclusively rural dataset.

The model uses assignable good budget-shares of household-level total expenditure. Our household-level total expenditure measure is equal to twelve times the sum of household-level monthly spending, including imputed consumption of home produced goods. These spending levels derive from one-month duration recall data in the questionnaire. Specifically, this includes monthly-level recall data on purchases and home-produced values of: rent, food, clothing, footwear, bedding, nonrent housing expense, medical expenses, education, remittances, devotional/sacrificial goods¹⁰, entertainment, fines and legal expenses, utensils, furniture, personal items, lights, fuel and lighting energy, personal care, cleaning, transport and telecommunication, use-value from assets, and other miscellaneous items. This constructed total expenditures variable, denoted y_h , represents the total flow of consumption of goods and services into the household, which includes purchases, home produced goods and consumption flows from assets. The assignable food budget-shares of each type of person, $j = m, f, c$, are denoted w_{jh} and are given by $w_{jh} = s_{jh}/y_h$.

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:

¹⁰These are: jakat, fitra, daan, sodka, kurbani, milad, and other religious offerings.

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).

In addition to the above covariates, our model has a vector of instruments r_h that consist of powers of log household wealth, and powers of the village-level (leave-one-out) average value of f . We assign a wealth of 1 Taka to the 165 households reporting zero wealth, so that (unnormalized) log household wealth is defined for all observations. Like with the covariates z_h , we normalize log-wealth to have an average of zero for the reference household. We do not normalize village-level average f .

Table 1a gives summary statistics regarding household structures. The 10 summarized household structures each correspond to a dummy variable included in the list of demographic shifters z_h (except for the omitted reference household). Nuclear households (with only 1 adult male and 1 adult female) account for roughly half of the households in our sample. Roughly 30 per cent of households have 3 adults.

Table 1b gives summary statistics on the log of household expenditures $\ln y_h$, assignable food budget shares w_{jh} , additional demographic shifters (the elements of z_h other than household structure dummies), the cooperation factor f_h , and our instrumental variables. Recall that all continuous regressors (except the fraction of girls) and instruments are normalized to average zero for households with 1 man, 1 woman and 2 children. However, they do not average zero for the entire sample. We measure age and education in decades, and total expenditure, marital wealth, household wealth and income in Taka, the currency of Bangladesh. These units are chosen to keep the standard deviations of dependent variables, covariates and instruments roughly comparable.

We note a couple of important features of these data. First, the assignable good budget shares (w_{mh} , w_{fh} and w_{ch}) are large; roughly 10 per cent of the household budget goes to each of these assignable food aggregates. This is in sharp contrast to other research (e.g., Calvi 2019) 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.

3.2 Instruments

Our model has two endogeneous 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., Lewbel and Pendakur 2008). We discuss time separability formally in the Appendix. Another reason y_h could

potentially be endogeneous is measurement error, stemming from, e.g., purchase mismeasurement, or infrequency of expenditures on some consumption items. Functions of wealth are also valid instruments for dealing with expenditure measurement issues (see, e.g., Banks, Blundell, and Lewbel 1997).

Now consider instruments for f_h . In the derivation of our model, the cooperation factor f_h is determined by Equation (9) which, after adding in additional covariates and unobserved heterogeneity, becomes equation (26) in the Appendix. We do not attempt to specify and estimate this equation. Among other obstacles to doing so, we have little theory to guide us regarding the covariates in or the functional forms of the u_j functions that give the direct utility or disutility household members get from cooperating.

Without estimating a model for f_h , what we require is an instrument v_h for f_h . This instrument does not need to be randomly assigned, but it does need to correlate with the choice of f_h , while not (after conditioning on other covariates) directly affecting the household's food consumption decisions (in terms of the model, v_h must appear in one or more of the u_j functions, but not appear in the functions U_j and ω_j for $j = 1, \dots, J$).

Our primary instrument for f_h is the leave-one-out village level average value of f (the average excluding household h). The idea is that variation in the local prevalence of families whose members cooperate on consumption decisions is likely to correlate with an individual's own decision to likewise cooperate. Roughly, village level average 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 .

To more formally define conditions under which village-level average f is a valid instrument, assume that the household h random utility parameters \tilde{e}_{1fh} and \tilde{e}_{jh} defined in Appendix A are independent across households. Let \bar{f}_h equal the expected value of f_h conditional on being a household other than h in the village. Then \bar{f}_h is the probability that a randomly chosen household in the village, other than household h , cooperates. Assume that we include \bar{f}_h in the function R defined in Appendix A. Taking the conditional mean of Equation (26) across households other than household h in the village then shows that \bar{f}_h equals a function of the joint distribution of $y_{h'}$, $r_{h'}$, $z_{h'}$, $\tilde{e}_{1fh'}$ and $\tilde{e}_{1h'}$ across all households

h' other than h in the village. It follows that \bar{f}_h is a useful instrument in that it affects the choice of f (by being in R) and is a valid instrument in the quantity demand equations because \bar{f}_h is independent of household h 's specific value of $\tilde{\varepsilon}_{jh}$ and hence of ε_{jh} .

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 \tilde{r} 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.

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 of the significance of the instruments 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 jointly insignificant 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 sufficiently strong instruments, which our F-statistic indicates is the case (being, e.g., much larger than the rule of thumb level of 10).

Although we can't treat this regression as a formal model of cooperation, it is still suggestive regarding covariates. The regression shows that village level average cooperation is positively correlated with a household's individual decision to cooperate f_h , as expected. It is also positively correlated with the education of women and age of children, and negatively

correlated with the age of women, suggesting that it may respond to women's bargaining power.

The household log budget $\ln y_h$ is fitted with an R^2 of 0.43 and an F-statistic of the instruments of 101. Here, the log-wealth instruments do most of the work, with an F-statistic of 186. But, the cooperation instruments are also relevant in this equation, with an F-statistic of 9.

The above results provide evidence for the relevance our instruments. For further reassurance that the instruments are valid for our model, we later test the exogeneity of the instruments via overidentification tests.

3.3 Parametric Specification

By equation (14), our estimator applies GMM to estimate the parameter vector θ using moments of the form $E(\varepsilon_{jh}\phi(r_h, z_h)) = 0$ where the errors ε_{jh} are given by

$$\varepsilon_{jh} = \frac{w_{jh}}{\eta_j(f_h, z_h, \theta)} - \gamma_j(z_h, \theta) - \beta(z_h, \theta) (\ln y_h - \ln N_{jh} + \ln \eta_j(f_h, z_h, \theta) + \ln \delta(f_h, z_h, \theta)). \quad (15)$$

In our most general specification, the functions η_j , γ_j , δ and β are specified as

$$\eta_j(f_h, z_h, \theta) = k_{j0} + k'_j z_h + c_j f_h,$$

$$\gamma_j(z_h, \theta) = l_{j0} + l'_j z_h,$$

$$\ln \delta(f_h, z_h, \theta) = (a_0 + a'_1 z_h) f_h,$$

and

$$\beta(z_h, \theta) = b_0 + b'_1 z_h.$$

The vector θ is therefore defined as all the coefficients in $a_0, a'_1, b_0, b'_1, k_{j0}, k'_j, c_j, l_0$, and l'_j for $j \in \{m, f, c\}$ (for adult males, adult females and children). Note the definition of δ enforces the restriction that $\ln \delta = 0$ when f_h is zero. To impose the constraint that resource shares sum to one, we impose $\sum_{j \in \{m, f, c\}} k_{j0} = 1$, $\sum_{j \in \{m, f, c\}} k'_j = 0$, and $\sum_{j \in \{m, f, c\}} c_j = 0$.

Due to multicollinearity, in our baseline specification we take $a_1 = 0$ and $b_1 = 0$ (we relax

these restrictions in other specifications). We are particularly interested in the estimates of c_j , which gives the response of the resource shares to f_h , and the estimate of a_0 , which gives the response of the household scale economies to f_h .

The 16 demographic variables comprising z_h are given in Tables 1a and 1b. Our vector of instruments r_h is comprised of r_{1h} , the first through fourth powers of the natural log of household wealth, and r_{2h} , the first through fourth powers of the natural log of the village leave-one-out average of f for each household. These instruments are summarized at the bottom of Table 1b.

Our moment equations (14) require a vector of functions $\phi(r_h, z_h)$. In theory, any vector of functions satisfying the rank condition for identification would suffice. For statistical efficiency (i.e., lower standard errors), one wants to choose functions that highly correlate with the components of the model. In our baseline specification, scaled budget shares $w_j/\eta_j(f_h, z_h)$ are close to linear in $(1, f_h, z_h) \times (1, \ln y_h)$, where \times indicates element-wise multiplication, deleting redundant elements. We therefore want to choose $\phi(r_h, z_h)$ to be highly correlated with the elements of $(1, f_h, z_h) \times (1, \ln y_h)$. So, we replace f_h with r_{1h} and $\ln y_h$ with r_{2h} in that expression to get

$$\phi(r_h, z_h) = (1, r_{1h}, z_h) \times (1, r_{2h}).$$

This yields a vector $\phi(r_h, z_h)$ with 105 elements (including the constant), for each of three demand equations, resulting in a total of 315 moments for GMM estimation. Our baseline model has 89 parameters, so our model is overidentified (having more moments than 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.

3.4 Model Estimates

Our main GMM estimation results are given in Tables 3 to 6. In these tables we focus on a subset of the most relevant coefficients. The full set of baseline model parameter estimates are reported after the Appendix in Table A2.¹¹ The standard errors in these tables are all

¹¹A previous version of this paper included an indicator of domestic abuse as a cooperation factor and log-wealth as a regressor. In Appendix Table A1, we include these variables in the covariate list z . Their

clustered at the village level.

As discussed in the appendix, identification of the model requires $\beta \neq 0$ and hence either $b_0 \neq 0$ or $b_1 \neq 0$. As can be seen in Table A2, the estimates of b_0 and b_1 are statistically significantly different from zero. These estimated coefficients show that, as usual, food budget share Engel curves slope downwards.

Identification also requires exogeneity of the instrument vector $\phi(r, z)$. The bottom rows of Tables 3 to 6 present estimated J test statistics to assess this exogeneity restriction. The J -tests are tests of the hypothesis that the elements of $\phi(r, z)$ 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 $\ln \delta(1, z_0, \theta)$ 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 $k_{j0} = \eta_j(0, z_0)$ and $c_j = \eta_j(1, z_0) - \eta_j(0, z_0)$ 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 metric consumption utility. When $f = 0$, the shadow budget of type j is $\eta_j(0, z)y$. When $f = 1$, the efficiency gain is equivalent to raising the household's budget from y to $\delta(1, z)y$, and type j 's resource share changes to $\eta_j(1, z)$. Together, these mean type j 's shadow budget when $f = 1$ becomes $\eta_j(1, z)\delta(1, z)y$. The relative change in type j 's money metric utility in going from an inefficient to an efficient household is therefore

$$\Delta_j \text{ money metric} = \frac{\eta_j(1, z)\delta(1, z) - \eta_j(0, z)}{\eta_j(0, z)}$$

inclusion does not affect our major conclusions.

Equivalently, if the household switches from inefficient to efficient, member type j 's shadow budget is multiplied by Δ_j . If $\Delta_j > 0$, then type j 's utility over consumption goods increases if the household chooses the efficient $f = 1$ instead of $f = 0$. This Δ_j for each member type j is reported in the third block of rows. Finally, as noted above, the bottom row of each of these tables gives J tests of instrument validity.

Table 3 has 3 blocks of columns. The leftmost block of columns presents results from estimation of our baseline model. In the baseline model, all demographic variables z are included in $\gamma_j(z)$, and $\eta_j(f, z)$ but $a_1 = 0$ and $b_1 = 0$, so that β and δ take the simplest possible forms, $\beta(z_h, \theta) = b_0$ and $\ln \delta(f, z, \theta) = a_0 f_h$.

The top cell of column (1) in Table 3 gives the estimate of a_0 as 0.121, equivalent to $\delta(1, z, \theta) = \exp a_0 = 1.13$, which means that changing f from zero to one increases efficiency by an amount equivalent to increasing the household's total expenditures budget y by 13 per cent (equals $\exp(0.121) - 1$). Note that while we expected, and obtained, $\delta(1, z, \theta) > 1$ (more efficient consumption when $f = 1$), this inequality was not imposed upon estimation.

The next block of column (1) gives estimates of resource shares, specifically, the constant terms equal the estimated resource shares for a household comprised of one adult male, one adult female and two children, when the cooperation factor $f = 0$. These estimates say that in these households the man gets 31 per cent of household resources, the woman gets 33 per cent, and the two children split the remaining 36 per cent. These estimates are similar to what DLP found in poor households in Malawi, and to what Brown, Calvi and Penglase (2018) find when applying the DLP model to Bangladesh data.

The estimated values of c_j in this block give the marginal effects of f on resource shares. These show that cooperation increases men's resource shares by 2.7 percentage points, and lowers women's and children's shares by 0.5 and 2.2 percentage points, respectively. Although these estimated effects on resource shares are small, they have z statistics of 5.4, 1.1 and 3.2 for men, women and children, respectively. So, the estimated effects are statistically significant for adult males and for children. One possible explanation for these results could be that men dislike the effort associated with consumption coordination and cooperation more than women, and so must be given a larger share of the gains from cooperation than other household members, to induce them to cooperate.

The third rows of estimates give Δ_j , the net effect of cooperation on the shadow budget (money metric utility) of each household member type j . Men’s gain in money metric utility from cooperating is large, with an estimated gain of about 23 per cent. Their gain is large because they gain both from greater efficiency and because their resource share increases (i.e., they get a proportionally larger slice of a larger pie). In contrast, women and children lose in resource share, but gain even more from efficiency (a smaller slice of a larger pie), so the net effect of cooperation is positive for them as well. Women gain a statistically significant 11 per cent in their money metric, and children gain a marginally statistically significant 6 per cent. Since all members gain in money metric utility from cooperation, the reason that many households do not cooperate must be due to the direct disutility experienced by one or more household members from the effort (or other aspects) of cooperating. In terms of the model, having $f = 1$ empirically increases U_j for all members j , so it must therefore decrease u_j for at least one member in any household that chooses $f = 0$.

The middle and rightmost panels of Table 3 report estimates of resource shares and efficiency measures for two alternative model estimates. In the middle columns, labelled “varying β ”, we relax the assumption that β is fixed by replacing $\beta(z_h, \theta) = b_0$ with $\beta(z_h, \theta) = b_0 + b'_1 z_h$. The general patterns we observe in our baseline estimates are still seen here, but with larger standard errors (presumably because of multicollinearity— β multiplies $\ln \eta$, and now both functions vary with z).

GMM estimators based on many more moments than parameters can have poor finite-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 overidentification”, we re-estimate the baseline model using only the first and second powers of log household wealth and village-average f as instruments. This reduces the number of elements of $\phi(r_h, z_h)$ 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 significant finite 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 fail to 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. The blocks of columns here are labeled (4) to (6), to distinguish them from the blocks in Table 3 that are labeled (1) to (3). In the leftmost column, labeled (4), we use a weaker definition 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. The 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 $\ln \delta$ 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 efficiency gain due

to cooperation is larger, with an estimated value of $\ln \delta$ of 0.141, and the estimated effect of cooperation on male resource shares is larger, increasing male resource shares by 4 percentage points. This results in larger effects on money-metric welfare: in the baseline estimates, men’s welfare increased by roughly 20 per cent; in column (5), we see an estimated impact exceeding 30 per cent.

In column (6), we allow for a broader definition of time-uses amenable to cooperation. We define *non-private* time uses as: all shareable consumption time-uses; school (including homework); shopping/getting service; weaving/textiles; cooking; domestic work; and, caring for children/elderly. In column (6), we present 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 doing the same non-private activity at the same time. Here, we see a much smaller, and statistically insignificant estimate, of $\ln \delta$ 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.

In Table 5, we consider three alternatives regarding data construction in our baseline model. In the leftmost column, labeled (7), we retain the previously dropped 238 households that had zero food intake for any member type (adult males, adult females or children). We dropped these households because they likely indicate measurement issues. However, if these zeroes result instead from infrequency that is correlated with regressors (e.g., if significant numbers of households are so poor that some members don’t eat every day), then excluding these households could lead to bias. In comparison with the baseline estimates, we see slightly smaller estimates of resource shares for men in the reference household type, and slightly larger estimates of resource shares for women and children. However, the estimated marginal effect of cooperation f on resource shares is very similar to the baseline estimates: cooperation increases male resource shares by about 3 percentage points, has roughly no effect on female resource shares and reduces children’s resource shares by 3 percentage points.

The estimated efficiency gain from cooperation is also very similar to baseline, with $\delta = \exp(0.135)$, or about 14 per cent. The resulting money metric utility gains Δ_j from efficiency are 28 per cent for men, 14 per cent for women, and 5 per cent for children, compared to the baseline estimates of 23, 11, and 6 percent.

In the middle panel, we consider some additional sample restrictions that may be sensible. In this model we exclude: a) households where the female respondent is not married; b) households in the top or bottom percentile of the distribution of budgets; and c) households that report zero wealth. The restriction a) is relevant because our cooperation indicator specifically refers to husbands, and respondents in households where the female respondent is not married may not consider the response “self and husband” to be valid. The restriction b) is used because outliers in the budget may have excessive influence on the slopes of estimated Engel curves. The restriction c) is because reported zero wealth may actually be mismeasured wealth. These restrictions result in the loss of 302 observations (roughly 10 per cent of the sample).

The resulting estimates in column (8) are somewhat different from the baseline. The estimated value of $\ln \delta$ is 0.173, which is a bit larger than that in the baseline. The associated efficiency gain δ is about 19 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, having either more than 1 adult man or more than 1 adult woman. These non-nuclear households are a mix of polygamous and multi-generational households. Our model and data might be less appropriate for these non-nuclear households, since our cooperation factor f is only reported by “the main” adult female in the household, and primarily refers to joint decision making by the main adult woman and her husband. Column (9) in Table 4 reports result from estimating the model just with nuclear households, which greatly reduces the sample size.

Again, we see similar patterns as in the baseline case. Cooperation increases efficiency,

and induces a shift in resource shares from children towards adult men, with a statistically insignificant impact on the resource shares of women. However, the estimated marginal effect of cooperation f on $\ln \delta$ is much smaller in these nuclear households than in the baseline model, with an estimated value of 0.078. This means that cooperation induces an efficiency gain of only $(\exp 0.078)$ 8 per cent in nuclear households, compared with 13 per cent for all households.

The main difference between nuclear households and the full sample is that the nuclear subsample has smaller households on average. This suggests that the efficiency gains δ may depend on household size. Having more people in a household means goods can be jointly consumed by more household members, leading to greater efficiency. In our model, this can arise because more people sharing a good means a smaller element of A for that good, and hence a lower shadow price.

We consider the possibility that δ depends on household size in Table 6. The function δ , 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 6, we consider alternative specifications for this cost of inefficiency function. The leftmost block of Table 6, column (10), imposes the restriction $a_0 = a_1 = 0$, which makes $\ln \delta = 0$. 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, $\ln \delta(f_h, z_h, \theta) = (a_0 + a_1 \ln \frac{n}{4}) f_h$. This maintains the construction that $\ln \delta = a_0$ for the reference household, which has $n = 4$ members. Finally, in the third block of Table 6, 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 is the roughly the same in these two specifications. This suggests that leaving out the inefficiency channel does not substantially bias estimates of the levels of resource shares¹².

¹²This is reassuring for previous applications of similar models like DLP that don't allow for inefficiency, suggesting that those models will still do a good a job of estimating resource shares, even if they miss the effects of inefficiency.

The estimated value of a_0 in column (11) indicates that a nuclear family with 4 members has an efficiency gain δ 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 (nuclear family with 3 members), the efficiency gain is statistically indistinguishable from zero.¹³

In column (12), we allow δ to depend additionally on all other demographics (apart from household composition). Here, we see that the large size of the coefficient a_1 on $\ln \frac{n}{4}$ shown in column (8) is not driven by the exclusion of other demographic shifters to δ . However, the estimated standard errors on a_0 and a_1 are noticeably larger in column (9), presumably due to multicollinearity with having the same z variables appearing in multiple functions in the model.

The bottom panel of Table 6 gives estimates of the change in the money metric of consumption utility for each type of person in response to cooperating. The upper rows give an estimate of this welfare loss of people in the reference household type; the lower row give an estimate of this welfare loss for the largest households (nuclear households with 4 children). For the model where $\delta = 1$ shown in column (10), these welfare gains and losses are equal to the changes in resource shares, since in that model imposes no variation in efficiency.

The estimates given in column (11) of the proportionate changes in money metric utility due to cooperation for the reference household are similar to those reported in the baseline, with men, women and children gaining roughly 20, 9 and 5 per cent, respectively. For people living in the largest households, the efficiency gains are larger, so the money metric gains are also larger. In these largest households, the estimated money metric gains for men, women and children are 46, 32 and 30 per cent, respectively.

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

¹³This is a very strong dependence on household size, but well within the bounds allowable by the model. Specifically, BCL implies Barten scales between $1/n$ and 1, which we can use to calculate an approximate maximum value for δ of $\frac{1}{2} \ln n$.

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, which is consistent with a model where the opportunities for sharing increase in the number of household members.

4 Conclusions

We provide a general framework for analyzing the effects of what we call “cooperation factors” on collective household behavior. A cooperation factor is any variable that can: induce inefficiency in consumption by reducing cooperation and sharing; affect resource shares like a distribution factor; and/or, directly affect the utility of household members (additively separably from consumption).

Our example of a cooperation factors is a direct indicator of coordination and cooperation on consumption, i.e., a self report of joint consumption decision making. Other possible cooperation factors might be behaviors that correlate with cooperation, or with failures to cooperate. Examples could be measures of time spent together on consumption, or evidence of money hiding, or domestic abuse. Still other examples could be almost any variable that in the previous literature was considered to be a distribution factor.

A common objection to the application of collective household models, particularly in developing countries, is that most such models assume households are Pareto efficient, while behaviors like domestic abuse or money holding provide evidence of inefficiency. A convenient feature of cooperation factors is that they allow for inefficiency while still maintaining the modeling advantages of efficient collectives.

We take our general cooperation factors model, simplify it to reduce data requirements, and apply it to household survey data from Bangladesh. Our empirical estimates are that

cooperation increases household consumption efficiency by an amount roughly equal to a 13% increase in total household resources, and that men claim a proportionally larger share of those gains than do women and children.

Why do men gain more than other household members from cooperating? Why don't all households cooperate and coordinate on joint consumption, given the large efficiency gains that accrue from doing so? Our model suggests that at least some household members must experience direct disutility associated with cooperation (perhaps costs in time and effort), and these disutilities may be larger for men, requiring them to be compensated more in terms of resource shares to agree to the cost (in utility) of cooperating.

An interesting avenue for future work would be to apply this model to other sources of household inefficiency, such as domestic violence or household members hiding money. It could also be useful to extend the model to include home production from, e.g., farming or sewing. Our consumption technology can be interpreted as a restricted form of home production, but it would be useful to further generalize that side of the model, since home production could be another important channel for inefficiency.

5 Appendix A: Formal Assumptions and Proofs

Here we formally derive our model, and prove that it is 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.

Let f , r , y , p , π , and z be as defined in the main text (recalling that r contains all of the elements of both \tilde{r} and v). 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 , π , and z , the household chooses quantities to consume using the program given by equation (10).

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 member's additional utility or disutility associated with f , and ω_j is that member's Pareto weight.

As can be seen by equation (10), 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 (which makes it assignable to that member) and these goods are unaffected by the matrix A_f in the budget constraints, meaning that they are not shared or consumed jointly (which makes them private goods).

We next assume some regularity conditions. These assumptions ensure sensible and convenient restrictions on economic behavior like no money illusion, preferring larger consumption bundles to smaller ones, and the absence of corner solutions in the household's maximization problem.

ASSUMPTION A2: Each $\omega_j(f, z, p, \pi, y)$ function is differentiable and homogeneous of degree zero in p , π , and y . Each $U_j(q_j, g_j, z)$ function is concave, strictly increasing, and twice continuously differentiable in g_j and q_j . For each f , the matrix A_f is nonsingular with all nonnegative elements and a strictly positive diagonal. The variable y and each element of p and π are all strictly positive, and the maximizing values of $g_1, q_1, \dots, g_J, q_J$ in Assumption A1 are all strictly positive.

LEMMA 1. Let Assumptions A1 and A2 hold. Then there exist positive resource share functions $\eta_j(p, \pi, y, f, z)$ such that $\sum_{j=1}^J \eta_j(p, \pi, y, f, z) = 1$, and the household's demand function for goods is given by each member j solving the program

$$\max_{g_j, q_j} U_j(q_j, g_j, z) \tag{16}$$

$$\text{such that } p' A_f g_j + \pi_j q_j = \sum_{j=1}^J \eta_j(p, \pi, y, z, f) y \quad \text{and } g = A_f \sum_{j=1}^J g_j.$$

To prove Lemma 1, first observe that the values of $g_1, q_1, \dots, g_J, q_J$ that maximize equation

(10) are equivalent to the values that maximize

$$\max_{g_1, q_1, \dots, g_J, q_J} \sum_{j=1}^J U_j(q_j, g_j, z) \omega_j(p, \pi, y, f) \quad (17)$$

given the same budget constraint. because the terms in equation (10) that are not in (17) do not depend on $g_1, q_1, \dots, g_J, q_J$. 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 η_j in Lemma 1 do not depend on r , because r , including the component v , does not appear in either equation (17) or in the budget constraint, and so cannot affect 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 identification of the model, and without requiring price variation.

ASSUMPTION A3. The resource share functions $\eta_j(p, \pi, y, f, z)$ 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 $\eta_j(\pi, p, f, z)$.

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

ASSUMPTION A4. For each household member j , the direct utility function $U_j(g_j, q_j, z)$, when facing prices p and π and having the budget y , has the associated indirect utility function

$$V_j(\pi_j, p, y, z) = [\ln y - \ln S_j(\pi_j, p, z)] M_j(\pi_j, p, z) \quad (18)$$

For some functions S_j and M_j .

Assumption A4 says that household members each have utility functions in the class that

Muellbauer (1974) called PIGLOG (price independent, generalized logarithmic) preferences. As noted in the main text, this is a class of functional forms that is widely known to fit 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.¹⁴

LEMMA 2: Let Assumptions A1, A2, A3, and A4 hold. Then the value of $U_j(q_j, g_j, z)$ attained by household member j is given by

$$U_j = [\ln \eta_j(\pi, A_f p, f, z) + \ln y - \ln S_j(\pi_j, A_f p, z)] M_j(\pi_j, A_f p, z) \quad (19)$$

and the household's demand functions for the private assignable goods q_j are

$$q_j = \eta_j(\pi, A_f p, f, z) y \left(\frac{\partial \ln S_j(\pi_j, A_f p, z)}{\partial \pi_j} - \frac{\partial \ln M_j(\pi_j, A_f p, z)}{\partial \pi_j} (\ln(\eta_j(\pi, A_f p, f, z) y) - \ln S_j(\pi_j, A_f p, z)) \right) \quad (20)$$

To prove Lemma 2, observe that by Lemma 1, household member j maximizes the utility function $U_j(q_j, g_j, z)$ facing shadow prices $A'_f p$ and π_j and having the shadow budget $\eta_j(\pi, A_f p, f, z) y$. Therefore, using the definition of indirect utility, member j 's attained utility level $U_j(q_j, g_j, z)$ is given by $V_j(\pi_j, A'_f p, \eta_j(\pi, A_f p, f) y)$, which by Assumption A4 equals equation (19). Next, a property of regular indirect utility functions is that the corresponding demand functions can be obtained by Roy's identity. Equation (20) is obtained by applying Roy's identity to equation (18) for the private assignable goods q_j , and then replacing p and y in the result with $A'_f p$ and $\eta_j(\pi, A_f p, f) y$.

We could similarly obtain the demand functions for other goods g , as in BCL, but these will be more complicated due to the sharing, with Roy's identity being applied to each member to obtain each g_j demand function, and substituting the results into $g = A_f \sum_{j=1}^J g_j$. However, our empirical analyses will only make use of the private assignable goods q_j with demands given by equation (20).

¹⁴Most more recent alternatives, like so-called "rank three" demand systems, are used for data from countries where the distribution of y is large, and more complicated budget responses are needed to capture behavior at both low and high income levels. Other popular demand models, like the multinomial logit based models widely used in the industrial organization literature, are designed for use with discrete demand data and are unsuitable for the type of continuous consumer demand data we analyze here.

ASSUMPTION A5. Let $\ln M_j(\pi_j, A_f p, z) = m_j(A_f p, z) - \beta(z) \ln \pi_j$ for some functions m_j and β .

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 $\ln \pi_j$, and the other is that the function $\beta(z)$ 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) satisfies this restriction. Assumption A5 could be further relaxed by letting β depend on p (though not on A_f) without affecting later results.

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

ASSUMPTION A6. Let $\ln S_j(\pi_j, A_f p, z) = \ln s_j(\pi_j, p, z) - \ln \delta(A_f p, z)$ for some functions s_j and δ . Without loss of generality, let $\ln \delta(A_0 p, z) = 0$.

Assumption A6 assumes separability of the effects of π_j and f on the function S_j . Assuming $\ln \delta(A_0 p, z) = 0$ in Assumption A6 is without loss of generality, because if it does not hold then one can make it hold if one redefines δ and s_j by subtracting $\ln \delta(A_0 p, z)$ from both $\ln \delta(f, p, z)$ and $\ln s_j(\pi_j, p, z)$. 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 .¹⁵ This assumption is not vital, but will be helpful for making the cost of an inefficient choice of f identifiable

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

¹⁵For 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 π_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 example as shown in Lewbel (1991), the Translog demand system as implemented by Jorgenson, and Slesnick (1987) imposes a linear constraint on its Barten (1964) scales, that results in a restriction like this on its equivalence scales. Note that BCL refer to the diagonal elements of A_f as Barten technology parameters, due to their equivalent to Barten scales.

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

$$[\ln \eta_j(\pi, A_f p, f, z) + \ln y - \ln s_j(\pi_j, p, z) + \ln \delta(A_f p, z)] [m_j(A_f p, z) - \beta(z) \ln \pi_j] \quad (21)$$

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

$$w_j = \eta_j(\pi, A_f p, f, z) [\gamma_j(\pi_j, p, z) + \beta(z) (\ln y + \ln \eta_j(\pi, A_f p, f, z) + \ln \delta(A_f p, z))]. \quad (22)$$

where the function γ_j is defined by

$$\gamma_j(\pi_j, p, z) = \frac{\partial \ln s_j(\pi_j, p, z)}{\partial \ln \pi_j} - \beta(z) \ln s_j(\pi_j, p, z)$$

The proof of Lemma 3 consists of substituting the expressions for M_j and S_j given by Assumptions A5 and A6 into the equations given by Lemma 2, and converting the quantity q_j into the budget share w_j .

ASSUMPTION A7. Market prices p and π are the same for all households.

Our data come from a single time period, which (assuming the law of one price) justifies assuming p and π are the same across all households. This assumption makes our demand functions reduce to Engel curves. For simplicity, we abuse notation here and redefine objects that were functions of $A_f p$ as just functions of f , since with fixed 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

$$[\ln \eta_j(f, z) + \ln y - \ln s_j(z) + \ln \delta(f, z)] M_j(f, z) \quad (23)$$

and the budget share Engel curve functions $w_j = W_j(f, z, y)$ for each private assignable

good are given by

$$W_j(f, z, y) = \eta_j(f, z) [\gamma_j(z) + \beta(z) (\ln y + \ln \eta_j(f, z) + \ln \delta(f, z))]. \quad (24)$$

Lemma 4 entails a small abuse of notation, where we have absorbed the values of p and π into the definitions of all of our functions, noting that any function of $A_f p$ remains a function of f even if p is a constant. Lemma 4 is just rewriting Lemma 3 after dropping the prices.

LEMMA 5: Let Assumptions A1 to A7 hold. Let $W_j(f, z, y)$ be defined by equation (24) for $j = 1, \dots, J$. Given functions $W_j(f, z, y)$, the functions $\eta_j(f, z)$, $\delta(f, z)$, $\gamma_j(z)$, and $\beta(z)$ are identified.

To prove Lemma 5, observe first by equation (24) that $\eta_j(f, z) \beta(z) = \partial W_j(f, z, y) / \partial \ln y$. Next, since resource shares sum to one, we can identify $\beta(z)$ and $\eta_j(f, z)$ by

$$\beta(z) = \sum_{j=1}^J \frac{\partial W_j(f, z, y)}{\partial \ln y} \quad \text{and} \quad \eta_j(f, z) = \frac{1}{\beta(z)} \frac{\partial W_j(f, z, y)}{\partial \ln y}$$

Next, define $\rho_j(f, z, y)$ by

$$\rho_j(f, z, y) = \frac{W_j(f, z, y)}{\eta_j(f, z)} - \beta(z) (\ln y + \ln \eta_j(f, z))$$

The function $\rho_j(f, z, y)$ is identified because it is defined entirely in terms of identified functions. By equation (24), $\rho_j(f, z, y) = \gamma_j(z) - \beta(z) \ln \delta(f, z)$. It follows from Assumption A6 that $\ln \delta(0, z) = 0$, so $\gamma_j(z)$ and $\delta(f, z)$ are identified by

$$\gamma_j(z) = \rho_j(0, z, y) \quad \text{and} \quad \ln \delta(f, z) = \frac{\rho_j(f, z, y) - \rho_j(0, z, y)}{\beta(z)}$$

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 $\eta_j(f, z)$ are identified, so our model, like DLP, overcomes the problem in the earlier collective

household literature of (the levels of) resource shares not being identified. Lemma 5 also shows identification of the preference related functions $\gamma_j(z)$ and $\beta(z)$, and identification of our new cost of inefficiency function $\delta(f, z)$.

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

$$R_j(f, y, v, z) = (\ln \eta_j(f, z) + \ln y - \ln s_j(z) + \ln \delta(f, z)) M_j(f, z) + u_j(f, v, z)$$

The proof of Lemma 6 is then that, by equation (23) and the definition 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 tractable form, replace the function $\ln S_j(\pi_j, A_f p, z)$ with $\ln S_j(\pi_j, A_f p, z) - \tilde{\varepsilon}_j$ where $\tilde{\varepsilon}_j$ is a random utility parameter representing unobserved variation in preferences for goods. This means that $\tilde{\varepsilon}_j$ appears in member j 's utility function U_j . We assume these taste parameters vary randomly across households, so $E(\tilde{\varepsilon}_j | r, z) = 0$. Similarly, replace $u_j(f, r, z)$ with $u_j(f, r, z) + \tilde{e}_{jf}$ where \tilde{e}_{jf} represents variation in the utility or disutility associated with the choice of f . The errors \tilde{e}_{jf} and $\tilde{\varepsilon}_j$ can be correlated with each other and across household members.

Substituting these definitions into the above equations, we get

$$w_j = \eta_j(f, z) [\gamma_j(z) + \beta(z) (\ln y + \ln \eta_j(f, z) + \ln \delta(f, z)) + \varepsilon_j] \quad (25)$$

where $\varepsilon_j = \beta(z) \tilde{\varepsilon}_j$ so $E(\varepsilon_j | r, z) = 0$, and f is now determined by

$$f = \arg \max \Psi(\tilde{R}_{1f}, \dots, \tilde{R}_{Jf}), \text{ where } \tilde{R}_{jf} = R_j(f, y, r, z) + (M_j(f, z) / \beta(z)) \varepsilon_j + \tilde{e}_{jf} \quad (26)$$

We will want to estimate the Engel curve equations (25) for $j = 1, \dots, J$. Equation (26)

shows that f is an endogenous regressor in these equations, because f depends on both ε_j and $\tilde{\varepsilon}_{jf}$. As discussed in the main text, we do not try to empirically identify or estimate equation (26), because both the functions R_j and errors $\tilde{\varepsilon}_{1f}$ depend on u_j , and there may be important determinants 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 suffer from measurement error. We will therefore require instruments for y . Our current collective household model is static. This is justified by a standard two stage budgeting (time separability) assumption, in which households first 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 (10). These means that variables associated with household income and wealth will correlate with y and so are potential instruments for y .

This time separability applies to the utility functions over goods, $U_j(q_j, g_j, z)$ for each 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 \tilde{r} denote a vector of potential instruments for y . These are measures related to income or wealth that are not already included in v .

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 Ψ . Then it follows from equation (26) that f varies with v , so v can serve as an instrument for f . Similarly, assume that $\ln y$ correlates with \tilde{r} , which can serve as instruments for $\ln y$ (elements of v could also be instruments for y). Based on equation (25), we then have conditional moments

$$E \left[\left(\frac{w_j}{\eta_j(f, z)} - \gamma_j(z) - \beta(z) (\ln y + \ln \eta_j(f, z) + \ln \delta(f, z)) \right) \mid \tilde{r}, v, z \right] = 0 \quad (27)$$

Later in this Appendix we consider nonparametric identification of the functions in this expression based on these moments, but for now consider using these moments parametric-

ally. If we parameterize each of the unknown functions using a parameter vector θ , then equation (27) implies unconditional moments

$$E \left[\left(\frac{w_j}{\eta_j(f, z, \theta)} - \gamma_j(z, \theta) - \beta(z, \theta) (\ln y + \ln \eta_j(f, z, \theta) + \ln \delta(f, z, \theta)) \right) \phi(\tilde{r}, v, z) \right] = 0 \quad (28)$$

for any suitably bounded functions $\phi(\tilde{r}, v, z)$. Our actual estimator will consist of parameterizing the unknown functions in this expression, choosing a set of functions $\phi(\tilde{r}, v, z)$, and estimating the parameters by GMM (the generalized method of moments) based on these moments. At the end of this Appendix we discuss choice of the ϕ functions.

Equation (28) can suffice for parametric identification and estimation, but is it still possible to nonparametrically identify the functions in this model in the presence of unobserved heterogeneity? The following Theorem shows that the answer is yes, if we make some additional assumptions. Theorem 1 shows these additional assumptions are sufficient for nonparametric identification of these functions, These additional assumptions, which are not required for parametric identification, are listed in Assumption A8.

ASSUMPTION A8. Add unobservable heterogeneity terms $\tilde{\varepsilon}_j$ and \tilde{e}_{jf} to the model by replacing the function $\ln S_j(\pi_j, A_{fp}, z)$ with $\ln S_j(\pi_j, A_{fp}, z) - \tilde{\varepsilon}_j$ and $u_j(f, v, z)$ with $u_j(f, v, z) + \tilde{e}_{jf}$, for $j = 1, \dots, J$. Assume f is determined by maximizing Ψ , where Ψ is linear, so $\Psi(\tilde{R}_{1f}, \dots, \tilde{R}_{Jf}) = \sum_{j=1}^J \tilde{c}_j \tilde{R}_{jf}$ for some constants $\tilde{c}_1, \dots, \tilde{c}_J$. Let $\tilde{e} = \sum_{j=1}^J \tilde{c}_j (\tilde{e}_{j1} - \tilde{e}_{j0})$. Define $\tilde{y}(\tilde{r}, v, z)$ by $\ln \tilde{y}(\tilde{r}, v, z) = E(\ln y | \tilde{r}, v, z)$. Assume the following: The function $\tilde{y}(\tilde{r}, v, z)$ is differentiable in a scalar \tilde{r} with a nonzero derivative. The error \tilde{e} is independent of y, \tilde{r}, v, z and $(\varepsilon_j, \tilde{e})$ is independent of \tilde{r} conditional on (v, z) . $E(\varepsilon_j | \tilde{r}, v, z) = 0$. The functions $M_j(f, z)$ do not depend on f . There exist values v_1 and v_0 of v such that $\sum_{j=1}^J \tilde{c}_j u_j(f, v_1, z) \neq \sum_{j=1}^J \tilde{c}_j u_j(f, v_0, z)$.

THEOREM 1: Let Assumptions A1 to A8 hold. Then the functions $\eta_j(f, z)$, $\delta(f, z)$, $\gamma_j(z)$, and $\beta(z)$ are identified.

To prove Theorem 1, first observe that, with f binary, it follows from equation (26) that $f = 1$ if $\sum_{j=1}^J \tilde{c}_j [R_j(1, y, r, z) + (M_j(1, z) / \beta(z)) \varepsilon_j + \tilde{e}_{j1}]$ is greater than $\sum_{j=1}^J \tilde{c}_j [R_j(0, y, r, z) + (M_j(0, z) / \beta(z)) \varepsilon_j + \tilde{e}_{j0}]$ where the function R_j is given by Lemma 6. Taking the difference 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

$$\sum_{j=1}^J \tilde{c}_j [(\ln \eta_j(1, z) + \ln \delta(1, z)) M_j(z) + \mu_j(1, v, z) - (\ln \eta_j(0, z) + \ln \delta(0, z)) M_j(z) - \mu_j(0, v, z)] + \tilde{e}$$

is positive. This means that $f = \tilde{f}(v, z, \tilde{e})$ 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 $-\tilde{e}$, otherwise f is zero.

Now, again exploiting that f is binary,

$$\begin{aligned} E(w_j | \tilde{r}, v, z, y) &= E[W_j(f, z, y) + \beta(z) \ln \delta(f, z) \tilde{\varepsilon}_j | \tilde{r}, v, z, y] \\ &= E[W_j(1, z, y) f + \beta(z) \ln \delta(1, z) f \tilde{\varepsilon}_j + W_j(0, z, y) (1 - f) + \beta(z) \ln \delta(0, z) (1 - f) \tilde{\varepsilon}_j | \tilde{r}, v, z, y] \\ &= W_j(0, z, y) + [W_j(1, z, y) - W_j(0, z, y)] E(f | \tilde{r}, v, z, y) \\ &\quad + \beta(z) [\ln \delta(1, z) - \ln \delta(0, z)] E(f \tilde{\varepsilon}_j | \tilde{r}, v, z, y). \end{aligned}$$

Next, observe that, since $W_j(f, z, y)$ is linear in $\ln y$, $E[W_j(0, z, y) | \tilde{r}, v, z] = W_j(0, z, \tilde{y})$ and $E[W_j(1, z, y) | \tilde{r}, v, z] = W_j(1, z, \tilde{y})$ where $\tilde{y} = \tilde{y}(\tilde{r}, v, z)$. Averaging the above expression over y , and noting that $f = \tilde{f}(v, z, \tilde{e}_1)$, we get

$$\begin{aligned} E(w_j | \tilde{r}, v, z) &= W_j(0, z, \tilde{y}) + [W_j(1, z, \tilde{y}) - W_j(0, z, \tilde{y})] E(f | \tilde{r}, v, z) \\ &\quad + \beta(z) [\ln \delta(1, z) - \ln \delta(0, z)] E(f \tilde{\varepsilon}_j | \tilde{r}, v, z). \end{aligned}$$

and by the conditional independence assumptions regarding $\tilde{\varepsilon}_j$ and \tilde{e}_1 ,

$$\begin{aligned} E(w_j | \tilde{r}, v, z) &= W_j(0, z, \tilde{y}) + [W_j(1, z, \tilde{y}) - W_j(0, z, \tilde{y})] E(f | v, z) \\ &\quad + \beta(z) [\ln \delta(1, z) - \ln \delta(0, z)] E(f \tilde{\varepsilon}_j | v, z). \end{aligned}$$

Now the functions $E(w_j | \tilde{r}, v, z)$ and $\tilde{y}(\tilde{r}, v, z)$ (the latter defined by $\ln \tilde{y}(\tilde{r}, v, z) =$

$E(\ln y \mid \tilde{r}, v, z)$ 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{r} are identified. This means that the following expression is identified.

$$\frac{\partial E(w_j \mid \tilde{r}, v, z)}{\partial \ln \tilde{r}} / \frac{\partial \ln \tilde{y}(\tilde{r}, v, z)}{\partial \ln \tilde{r}} = \frac{\partial W_j(0, z, \tilde{y})}{\partial \ln \tilde{y}} + \frac{\partial [W_j(1, z, \tilde{y}) - W_j(0, z, \tilde{y})]}{\partial \ln \tilde{y}} E(f \mid v, z) \quad (29)$$

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 (29) 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 show that the functions $\beta(z)$, $\eta_j(f, z)$, $\gamma_j(z)$, and $\delta(f, z)$ are identified.

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Tables

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 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).

Variable	Mean	Std Dev	Min	Max
$\ln y$, log-expenditure	0.100	0.556	-1.681	2.764
w_m , male food share	0.161	0.070	0.014	0.514
w_f , female food share	0.145	0.065	0.013	0.534
w_c , children food share	0.130	0.080	0.001	0.488
average age of males/10	0.176	1.189	-2.258	6.042
average age of females/10	0.377	0.937	-1.322	5.878
average education of men/10	0.338	3.537	-3.500	6.500
average education of women/10	-0.359	3.186	-4.366	5.634
average age of children/10	0.045	0.359	-0.709	0.691
fraction girl children	-0.028	0.414	-0.500	0.500
log of marital wealth	-0.416	3.368	-8.742	5.630
f , cooperation indicator	0.585	0.493	0.000	1.000
log of household wealth	0.088	2.684	-9.403	4.356
village-average of f	0.585	0.261	0.000	1.000

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). Village-average of f is the leave-one-out average (for each household, the average of f of other households in the village).

Table 2: "First Stage"

		cooperation, f			log-budget, $\ln y$		
		est	<i>std err</i>	t	est	<i>std err</i>	t
Constant		0.178	<i>0.042</i>	4.24	0.039	<i>0.039</i>	1.00
Covariates	average age of males/10	0.002	<i>0.008</i>	0.25	-0.005	<i>0.007</i>	-0.72
	average age of females/10	-0.022	<i>0.012</i>	-1.92	0.016	<i>0.011</i>	1.43
	average education of men/10	-0.006	<i>0.003</i>	-2.21	0.025	<i>0.003</i>	9.55
	average education of women/10	0.011	<i>0.003</i>	3.31	0.032	<i>0.003</i>	10.18
	average age of children/10	0.067	<i>0.025</i>	2.68	0.116	<i>0.024</i>	4.92
	fraction girl children	-0.020	<i>0.020</i>	-0.98	0.038	<i>0.019</i>	2.05
	log of marital wealth	0.002	<i>0.003</i>	0.61	0.004	<i>0.002</i>	1.62
Composition	m1_f1_c1	-0.018	<i>0.025</i>	-0.72	-0.139	<i>0.024</i>	-5.87
	m1_f1_c3	0.059	<i>0.031</i>	1.93	0.052	<i>0.029</i>	1.82
	m1_f1_c4	0.005	<i>0.051</i>	0.10	0.119	<i>0.047</i>	2.51
	m1_f2_c1	-0.106	<i>0.033</i>	-3.17	0.111	<i>0.031</i>	3.54
	m1_f2_c2	-0.028	<i>0.034</i>	-0.83	0.162	<i>0.032</i>	5.10
	m2_f1_c1	-0.052	<i>0.036</i>	-1.47	0.056	<i>0.033</i>	1.68
	m2_f1_c2	0.035	<i>0.040</i>	0.87	0.189	<i>0.037</i>	5.07
	m2_f2_c1	-0.097	<i>0.036</i>	-2.68	0.284	<i>0.034</i>	8.42
	m2_f2_c2	-0.098	<i>0.042</i>	-2.31	0.265	<i>0.040</i>	6.69
budget instruments	ln real wealth	-0.005	<i>0.010</i>	-0.47	0.095	<i>0.009</i>	10.19
	squared	0.000	<i>0.004</i>	-0.03	0.037	<i>0.003</i>	11.20
	cubed	-0.001	<i>0.001</i>	-1.07	0.005	<i>0.001</i>	4.50
	quartic	0.000	<i>0.000</i>	-1.01	0.000	<i>0.000</i>	1.99
cooperation instruments	village-average f	0.614	<i>0.536</i>	1.15	-0.555	<i>0.501</i>	-1.11
	squared	1.133	<i>2.190</i>	0.52	0.099	<i>2.048</i>	0.05
	cubed	-1.675	<i>3.227</i>	-0.52	0.936	<i>3.018</i>	0.31
	quartic	0.582	<i>1.560</i>	0.37	-0.686	<i>1.459</i>	-0.47
R^2		0.17			0.43		
F -stats	cooperation	121.4			9.3		
	budget	1.7			186.2		
	all	62.1			100.7		

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 OLS estimates, with standard errors are clustered at the village level.

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

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 $\ln \delta$, resource shares η and money-metric welfare Δ_j . Unconditional moments are defined by instruments multiplied by each of the 3 equations, where instruments are $(1, r_{1h}, z_h) \times (1, r_{2h})$. 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), β is a constant; in column (3) β is a linear index in z .

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

We report 2-step GMM estimates, with standard errors are clustered at the village level, of the marginal effects of f on efficiency $\ln \delta$, resource shares η and money-metric welfare Δ_j . Unconditional moments are defined by instruments multiplied by each of the 3 equations, where instruments are $(1, r_{1h}, z_h) \times (1, r_{2h})$,

where r_{1h} and r_{2h} are the first four powers of village-average f and log-wealth, respectively. Compared to the baseline sample: in column (4), the cooperation factor f equals 1 if consumption decisions concerning housing are made jointly, 0 otherwise; in column (5), f equals 1 if the husband and wife spend any time doing the same shareable consumption activity at the same time during the 24 hours time-use diary, 0 otherwise; in column (6) f equals 1 if they spend any time doing the same non-private activity at the same time, 0 otherwise.

function	person	variable	(7) Food Zeroes		(8) Restrict Sample		(9) Nuclear Families	
			Estimate	<i>Std Err</i>	Estimate	<i>Std Err</i>	Estimate	<i>Std Err</i>
$\ln \delta$	all	constant	0.135	<i>0.039</i>	0.173	<i>0.040</i>	0.078	<i>0.040</i>
resource shares	men, η_m	constant	0.280	<i>0.013</i>	0.289	<i>0.012</i>	0.301	<i>0.011</i>
		f	0.033	<i>0.006</i>	0.039	<i>0.006</i>	0.020	<i>0.005</i>
	women, η_f	constant	0.347	<i>0.015</i>	0.337	<i>0.013</i>	0.328	<i>0.015</i>
		f	-0.003	<i>0.005</i>	0.014	<i>0.007</i>	0.007	<i>0.006</i>
	children, η_c	constant	0.373	<i>0.018</i>	0.374	<i>0.014</i>	0.371	<i>0.017</i>
		f	-0.030	<i>0.007</i>	-0.053	<i>0.008</i>	-0.028	<i>0.008</i>
Change in Welfare	men		0.278	<i>0.059</i>	0.351	<i>0.059</i>	0.154	<i>0.054</i>
	women		0.135	<i>0.047</i>	0.237	<i>0.061</i>	0.105	<i>0.047</i>
	children		0.054	<i>0.045</i>	0.019	<i>0.042</i>	0.000	<i>0.045</i>
N			3238		2698		1675	
J-stat	val [df] p		204.6 [192]	<i>0.25</i>	196.3 [190]	<i>0.36</i>	161.9 [163]	<i>0.51</i>

We report 2-step GMM estimates, with standard errors are clustered at the village level, of the marginal effects of f on efficiency $\ln \delta$, resource shares η and money-metric welfare Δ_j . Unconditional moments are defined by instruments multiplied by each of the 3 equations, where instruments are $(1, r_{1h}, z_h) \times (1, r_{2h})$, where r_{1h} and r_{2h} are the first four powers of village-average f and log-wealth, respectively. Compared to the baseline sample, in column (7) we add 328 households with zero food spending for at least 1 member; in column (8), we drop 302 observations where either the female respondent is unmarried, reported wealth is zero, or expenditure is an outlier; in column (9), we drop non-nuclear households.

Table 6: Estimated Efficiency and Resource Shares, Varying δ specifications

			ln δ equals		(11) $a_0 + a_1 \ln \frac{n}{4}$		(12) $a_0 + a'_1 (\ln \frac{n}{4} z)$	
function	person	variable	(10) 0 Estimate	<i>Std Err</i>	Estimate	<i>Std Err</i>	Estimate	<i>Std Err</i>
ln δ	all	constant			0.100	<i>0.033</i>	0.157	<i>0.050</i>
		$\ln \frac{n}{4}$			0.501	<i>0.178</i>	0.627	<i>0.242</i>
resource shares	men, η_m	constant	0.310	<i>0.012</i>	0.309	<i>0.012</i>	0.301	<i>0.012</i>
		f	0.023	<i>0.004</i>	0.025	<i>0.005</i>	0.022	<i>0.005</i>
	women, η_f	constant	0.326	<i>0.015</i>	0.332	<i>0.015</i>	0.361	<i>0.018</i>
		f	-0.004	<i>0.005</i>	-0.006	<i>0.004</i>	-0.017	<i>0.005</i>
	children, η_c	constant	0.364	<i>0.020</i>	0.360	<i>0.020</i>	0.338	<i>0.020</i>
		f	-0.019	<i>0.007</i>	-0.019	<i>0.006</i>	-0.005	<i>0.005</i>
composition								
Change in Welfare	men	m1_fl_c2	0.023	<i>0.004</i>	0.195	<i>0.051</i>	0.257	<i>0.069</i>
	women	(4 people)	-0.004	<i>0.005</i>	0.085	<i>0.040</i>	0.115	<i>0.055</i>
Change in Welfare	children		-0.019	<i>0.007</i>	0.045	<i>0.033</i>	0.152	<i>0.061</i>
	men	m1_fl_c4	0.023	<i>0.004</i>	0.466	<i>0.109</i>	0.604	<i>0.162</i>
	women	(6 people)	-0.004	<i>0.005</i>	0.317	<i>0.103</i>	0.419	<i>0.139</i>
	children		-0.019	<i>0.007</i>	0.299	<i>0.093</i>	0.487	<i>0.153</i>
N			3000		3000		3000	
J-stat	val [df] p		205.8 [193]	<i>0.25</i>	206.4 [191]	<i>0.21</i>	185.6 [184]	<i>0.45</i>

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 $\ln \delta$, resource shares η and money-metric welfare Δ_j . The effect on money-metric welfare is reported for nuclear households with 2 and 4 children. Unconditional moments are defined by instruments multiplied by each of the 3 equations, where instruments are $(1, r_{1h}, z_h) \times (1, r_{2h})$ where r_{1h} and r_{2h} are the first four powers of village-average f and log-wealth, respectively. In column (10), $\ln \delta$ is set to 0; in column (11) $\ln \delta$ is a constant plus a coefficient times $\ln \frac{n}{4}$; in column (12), $\ln \delta$ is a linear index in $\ln \frac{n}{4}$ and z .

Appendix Table 1: Estimated Efficiency and Resource Shares, Adding Covariates

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

Same as Table 3, column (1) but adding elements to the covariate list z . In column (1), instruments are as in the baseline; in columns (2) and (3) we replace log-wealth with log-income in the instrument list.

Appendix Table 2: Full Baseline GMM Estimates

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.
η_m			η_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
γ_m			γ_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
β			γ_c		
one	-0.1679	0.0041	one	0.1675	0.0179
$\ln \delta$			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

Same sample and specification as Table 3, column (1).