Consumption Inequality Among Children: Evidence from Child Fostering in Malawi*

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Abstract

The share of household resources devoted to a child may depend on their gender, birth order, or relationship to the household head. However, it is challenging to determine whether parents favour certain children over others as consumption data is collected at the household level and goods are shared among family members. I develop a new methodology using the collective household framework to identify consumption inequality between different types of children. I apply this method to child fostering in Malawi. I find little evidence of inequality between foster and non-foster children.

Keywords: Child Fostering, Intrahousehold Resource Allocation, Cost of Children, Collective Model, Poverty

JEL Codes: D1, I32, J12, J13

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1 Introduction

Do parents favour certain types of children? Dating back to Becker (1960), economists have recognized that parents can to some degree choose the "quality" of their children through schooling decisions, health investments, and consumption allocations. While many parents treat their children equally, some parents may have a preferred type of child. Gender, birth order, prenatal endowments, and degree of kinship are all child characteristics that may impact parental treatment.

In this paper, I study intrahousehold consumption inequality. Do parents allocate a larger share of the household budget to certain types of children? This question is difficult to answer as consumption data is collected at the household level and goods are shared among family members. Existing work has used reduced-form methods to identify the existence of discrimination, but not its extent. For example, Deaton (1989) tests for gender discrimination by examining how expenditure on adult goods varies with the number of boys and girls in the household.[1] A large literature has applied this technique to a variety of different contexts (see e.g., Haddad and Reardon (1993), Kingdon (2005), and Zimmermann (2012)). In this paper, I develop a new methodology using a structural model of intrahousehold resource allocation to identify the existence *and extent* of consumption inequality among children. I rely only on standard household-level survey data and am able to identify the share of total household resources allocated to each type of child within the family. I use this method to study child fostering in Malawi, where 17 percent of households have a child who is living away from both of their biological parents.

Following Chiappori (1988, 1992), I use a collective household model, where each individual has their own utility function and the household reaches a Pareto efficient allocation of goods. I obtain a measure of individual-level consumption by identifying *resource shares*, defined as the share of the total household budget allocated to each household member. Dunbar, Lewbel and Pendakur (2013) (DLP henceforth) demonstrate that resource shares can be identified by observing how expenditure on *assignable* goods varies with household income and size, where a good is assignable if it is consumed exclusively by a particular type of person in the household (e.g., men's clothing). DLP obtain identification by comparing Engel curves for the assignable goods within the framework of a structural model.

While the DLP identification results and related studies (Bargain and Donni, 2012; Bargain et al., 2014) have allowed economists to identify inequality between men, women, and children, these existing methods are often unable to uncover inequality *among* children within the

[1] Deaton (1989) uses an approach similar to the Rothbarth method (Rothbarth, 1943). Bhalotra and Attfield (1998) develop an alternative method that also uses Engel curves to infer gender inequality.

same household. This limitation is due to the nature of consumption surveys which include expenditures on goods that can be assigned to children (clothing, shoes, toys), but not goods that can be assigned to individual children.[2] I overcome this common data limitation. I develop a framework to identify inequality among children using Engel curves for *partially assignable* goods. A good is partially assignable if the researcher can, to a limited extent, determine which individuals in the household consume it. For example, children's clothing expenditures are partially assignable to boys and girls, or foster and non-foster children.

My identification method proceeds as follows: First, I note that children's clothing expenditures can be assigned exclusively to a specific type of child if the household only contains that type of child. That is, children's clothing expenditures are assignable to boys if the household only has boys. It follows that in these households I can use the DLP methodology to identify resource shares for each type of child. I next move to households with both types of children (boys and girls, foster and non-foster children, etc.), where children's clothing expenditures are no longer assignable. The key assumption is to impose a limited similarity restriction between the clothing Engel curves in households with one type of child, which have already been identified, and households with both types of children. With these similarity restrictions resource shares can then be identified.

In my framework, I maintain several key identifying assumptions of DLP: I assume that resource shares are independent of household expenditure, and I impose one of two semi-parametric restrictions on individual preferences for clothing.[3] As in DLP, the model parameters are identified by comparing the slopes of clothing Engel curves across individuals or household sizes.

With this methodological contribution, I add to the growing literature that examines intrahousehold resource allocation using the collective household framework. This strand of research, beginning with work by Chiappori (1988, 1992), Apps and Rees (1988), and Browning et al. (1994) models households as a collection of individuals, each with their own distinct preferences. Within this field, my paper relates mostly to work on the identification of resource shares.[4] I differ from this literature in several ways. Unlike Lewbel and Pendakur (2008) and

[2] There are a limited number of surveys that include individual-level consumption data, such as the Bangladesh Integrated Household Survey and the China Health and Nutrition Survey.

[3] These two assumptions have been tested in the collective household literature and have strong empirical support. See Menon et al. (2012); DLP; Bargain et al. (2018); Lechene et al. (2019); Calvi (Forthcoming). A related issue concerns the use of clothing as the assignable good. I analyse complications due to sharing of purchased clothing, and the existence of hand-me-down clothing in Section A.2.

[4] See Lewbel and Pendakur (2008), Bargain and Donni (2012), Bargain et al. (2014), Browning et al. (2013), and DLP, for examples of other identification methods that identify the level of resource shares. A different approach places bounds on resource shares using revealed preference inequalities (Cherchye et al., 2011, 2015, 2017).

Browning et al. (2013), I am able to identify resource shares for children, and unlike Bargain and Donni (2012) and Bargain et al. (2014), I impose weaker similarity restrictions in preferences for goods across household compositions. The cost of the weaker assumptions is that I cannot identify economies of scale in consumption. The study closest to mine is DLP. Similar to the method I present, DLP require no similarity restrictions between households with and without children. The key difference is that DLP are dependent on the existence of assignable goods within the data, whereas I weaken this requirement by imposing similarity restrictions across households with one type of child, and those with both. This additional assumption is what allows me to identify inequality among children using standard household-level data.

The identification results of this paper can therefore be used to quantify inequality in variety of contexts where assignable goods often do not exist, such as inequality between boys and girls, first-born children and children of lower birth order, or inequality among children with different prenatal endowments.

In the empirical application, I study foster children in Sub-Saharan Africa (SSA). Foster children have become a population of increasing interest as economists have come to recognize the diversity of household structures that exist in certain parts of the world. Child fostering is most common in SSA where it varies from 8 percent in Burkina Faso to as high as 25 percent in Zimbabwe.[5] In Malawi, 13 percent of children are fostered and 17 percent of households have a foster child. While some of these children are orphans, the majority are children who are voluntarily sent away by their parents to live with close relatives.[6] Children are fostered for many reasons, including child labour, educational opportunities, or to share risk across households (Ainsworth, 1995; Akresh, 2009; Serra, 2009; Beck et al., 2015). Because foster children live away from their parents, they may be particularly vulnerable to unequal treatment within the household. Existing work on foster child welfare has focused on education (Case et al., 2004; Fafchamps and Wahba, 2006; Ainsworth and Filmer, 2006; Evans and Miguel, 2007; Beck et al., 2015), but much less is known about consumption.[7] I contribute to this literature by quantifying the extent of consumption inequality between foster and non-foster children.

I estimate the model using detailed consumption and expenditure data from the Malawi Integrated Household Survey. The resulting structural estimates allow me to quantify the share of the total household budget consumed by both foster and non-foster children. I find little evidence of inequality. My estimates indicate that foster children, who often live with close

[5] These figures are taken from Grant and Yeatman (2012) who use Demographic and Health Survey data to compute foster rates for 14 countries in Sub-Saharan Africa.

[6] I use “orphan" to describe a child who has lost at least one parent. This is consistent with the UNICEF and UNAIDS definition. In Malawi, 34 percent of foster children are orphans.

[7] An exception is Case et al. (2000) who study how household food expenditures vary by the fostering status of the household’s children.

relatives, are treated no differently than the household's biological children.[8] I also investigate the role of child labour and remittances as a source of heterogeneity in foster child treatment.

I examine potential policy implications by performing a poverty analysis that accounts for the unequal allocation of goods within the household. Specifically, I use the predicted resource shares to estimate foster and non-foster child poverty rates. Traditional measures of poverty implicitly assume an equal distribution of resources across household members. I move away from the traditional approach by using the predicted resource shares to determine each household member's individual consumption. I show that using household-level poverty rates understates child poverty.[9] This result is important for several reasons. First, coverage of government programs is rarely universal, and policymakers must find ways to determine who is poor. Different methods that are used to identify the poor, such as proxy-means testing, use household-level measures. I demonstrate that these methods have drawbacks, since poor individuals do not necessarily live in poor households. My results suggest that anti-poverty programs should account for both household wealth, as well as the characteristics of individuals living in the household. Finally, programs that improve the relative standing of children in the household, such as cash transfer programs that are conditional on children being enrolled in school, may at times be beneficial.

The remainder of the paper is organised as follows. Section 2 presents the collective household model. Section 3 discusses the identification results. I then apply the identification method to child fostering in Malawi in Section 4. In Section 5, I conduct a poverty analysis using the structural results. I conclude in Section 6. Additional analyses and proofs are provided in the Appendix.

2 Collective Model of the Household

This section presents a collective model of Malawian households following Chiappori (1988, 1992) and Browning et al. (2013). The household is modelled as a group of individuals, each with their own distinct preferences. The key assumption of the model is that the household is Pareto efficient in its allocation of goods.[10] The model accounts for economies of scale in

[8] The main results focus on consumption. I analyse education and child labour in Section A.1 of the Appendix.

[9] This finding is consistent with DLP, Brown et al. (2016), and Brown et al. (2018).

[10] Pareto efficiency in household consumption allocations has been analysed in many different contexts and usually cannot be rejected. Important papers that test this assumption include Browning and Chiappori (1998), Bobonis (2009), and Attanasio and Lechene (2014). Other evidence in favour of the collective model comes from Chiappori et al. (2002), Cherchye et al. (2009) and Dunbar et al. (2013). Some of these tests are done on nuclear households, whereas I use a sample that includes extended family households where Pareto efficiency may be a stronger assumption. Notably, however, recent work by Rangel and Thomas (2019) shows efficiency in non-nuclear households. Pareto efficiency has at times been rejected in the context of house-

consumption using a Gorman (1976) linear technology function (Browning et al., 2013). To better capture common family structures in Malawi, the model accommodates both nuclear and extended family households.

2.1 Model

The household consists of four types of individuals denoted by t: adult men (m), adult women (w), foster children (a), and non-foster children (b). Person types a and b could refer to boys and girls, or young and old children and everything that follows would be the same. I index household types by the number of foster and non-foster children within the household, denoted by the subscript s.

Households consume K types of goods at market prices $\mathbf{p} = (p^1, ..., p^K)'$. Let $\mathbf{z_s} = (z_s^1, ..., z_s^K)$ be the K - vector of observed quantities purchased by the household. The vector of unobserved quantities consumed by individuals within the household is denoted by $\mathbf{x_t} = (x_t^1, ..., x_t^K)$. The household-level quantities are converted into private good equivalents $\mathbf{x_t}$ using a linear consumption technology as follows: $\mathbf{z_s} = \mathbf{A}(\sigma_f \mathbf{x_f} + \sigma_m \mathbf{x_m} + \sigma_a \mathbf{x_a} + \sigma_b \mathbf{x_b})$ where $\mathbf{A}$ is a $K \times K$ matrix which accounts for economies of scale in consumption,[11] and σ_t denotes the number of each person type within the household. If good x^k is not shared, then what the household purchases is equal to the sum of what individuals consume, and the element in the k'th row in the k'th column of matrix $\mathbf{A}$ takes a value of one with all off-diagonal elements in that row and column equal to zero. Non-zero off diagonal elements occur when the amount a good is shared depends on the consumption of other goods.

Let $U_t(\mathbf{x_t})$ be the consumption utility of an individual of type t.[12] Individuals of the same type are required to have the same utility function, though the model can be extended to relax this assumption.[13] This utility function is assumed to be separable from leisure, savings, or anything else not included in the commodity bundle. Thus, I am not measuring welfare, but rather, material well-being. Individuals have caring preferences, with each person's total consumption utility being weakly separable over the sub-utility functions for goods. For example,

hold agricultural production decisions, especially in West Africa. See Udry (1996) for example. I assess the assumption myself in Section A.6.

[11] The use of private good equivalents was introduced in Browning et al. (2013). This approach differs from the Chiappori (1988, 1992); Browning et al. (1994) version of the collective model where goods are either purely public or purely private; here goods can be purely public, purely private, or partially shared, and is therefore a more general framework.

[12] As in Dunbar et al. (2013), children are modelled as having their own utility function. This differs from other work which treats children as a public good that is consumed by altruistic parents (see Browning et al. (2014) for examples). Dauphin et al. (2011) provide a more detailed discussion of children as decision makers.

[13] This assumption is data driven. In the estimation, I allow preferences and resource allocations to vary with certain characteristics, such as child age and gender.

the father's total utility would be given by $\tilde{U}_m = \tilde{U}_m(U_m(\mathbf{x_m}), ..., U_b(\mathbf{x_b}))$.

Each household maximizes the Bergson-Samuelson social welfare function, $\tilde{U}$:

$$\tilde{U}(U_m, U_f, U_a, U_b, \mathbf{p}/y) = \sum_{t\epsilon\{m,f,a,b\}} \mu_t(\mathbf{p}/y)U_t \tag{1}$$

where $\mu_t(\mathbf{p}/y)$ are the Pareto weights and y is household expenditure. The household then solves the following maximisation problem:

$$\begin{aligned} \max_{x_m,x_f,x_a,x_b} \tilde{U}(U_m, U_f, U_a, U_b, \mathbf{p}/y) \quad & \text{such that} \\ & \mathbf{z_s} = \mathbf{A_s}(\sigma_f \mathbf{x_f} + \sigma_m \mathbf{x_m} + \sigma_a \mathbf{x_a} + \sigma_b \mathbf{x_b}) \\ & y = \mathbf{z_s}'\mathbf{p} \end{aligned} \tag{2}$$

Solving this system results in bundles of private good equivalents. If these goods are priced at within household prices $\mathbf{A}'\mathbf{p}$, I obtain the *resource share* η_s^t, which is defined as the fraction of total household resources that are allocated to each individual of type t.[14] By definition, resource shares for men, women, foster, and non-foster children sum to one. In Section 4, I compare resource shares of foster and non-foster children to test for intrahousehold inequality.

With Pareto efficiency, I can reformulate the household's problem as a two stage process using the second welfare theorem; In the first stage, resources are optimally allocated across household members. In the second stage, each individual chooses $\mathbf{x_t}$ to maximize their own utility function U_t subject to the shadow budget constraint $\sum_k A_k p^k x_t^k = \eta_s^t y$. Using standard duality theory, the household program in Equation (2) can then be reduced to the choice of optimal resource shares subject to resource shares summing to one. The choice of optimal resource shares accounts for altruism as the model allows for caring preferences.

How should resource shares be interpreted? Resource shares are the share of the shadow budget allocated to each person type within the household. The shadow budget includes spending on public, private, and partially shared goods. Resource shares are not necessarily a measure of individual welfare though, as they do not account for differences in leisure, or health. Moreover, while resource shares allow for the existence of altruism, they do not identify the extent of altruism one feels towards others.[15] Nonetheless, higher resource shares indicate higher consumption, and therefore greater material well-being. This result holds only if the

[14] Resource shares have a one-to-one correspondence with the Pareto weights, where the Pareto weights are the marginal response of $\tilde{U}$ to U_t.

[15] The model allows for children to consume more because their mother is altruistic towards them. However, the fact that the mother receives utility from her child's consumption is not accounted for in her resource share. For this reason, resource shares are not a complete measure of welfare.

shadow price of public goods does not vary across individuals within the household (Chiappori and Meghir, 2014, 2015). However, with a linear consumption technology function (i.e., $\mathbf{z_s} = \mathbf{A_s}(\mathbf{x_a} + \mathbf{x_b} + \mathbf{x_m} + \mathbf{x_f})$), Lindahl prices will be the same across people and resource shares can be used as a measure of intrahousehold inequality (Browning et al., 2013).

2.2 Demand for Private Assignable Goods

As in DLP, I focus on demand functions for *private assignable* goods. Define a *private* good as one that is not shared across person types, and define an *assignable* good as one that is consumed by a person of known type t. Examples of private goods include food and clothing; if the father drinks a glass of milk, the mother cannot consume that same glass of milk. Unfortunately, food is not assignable as the data provides information on the total amount of food consumed by the household, but not who in the household consumed it. Clothing, however, is private and also assignable to men, women, and children (but not to different types of children).

Let $W_s^t(y, \mathbf{p})$ be the share of household expenditure y spent on person type t's private assignable good in a household of type s. Browning et al. (2013) derive the household demand functions for the private assignable goods, which can be written as follows:[16]

$$W_s^t(y, \mathbf{p}) = \sigma_t \eta_s^t w_s^t(\mathbf{A}'\mathbf{p}, \eta_s^t y) \tag{3}$$

where w_s^t is the amount of the private assignable good that a person of type t living in a household of type s would hypothetically demand had they lived alone with income $\eta_s^t y$ facing price vector $\mathbf{A}'\mathbf{p}$. Resource shares and the individual demand functions are not observable, and hence the system is not identified without additional assumptions (for each equation there are two unknown functions).[17]

3 Identification

Dunbar et al. (2013) (DLP) demonstrate how resource shares can be identified by observing how budget shares for assignable clothing vary with household expenditure and size. The key data requirement for their identification strategy is household-level expenditure on a private assignable good for each person type within the household. In this context, that would mean separately observing expenditure on foster child clothing and non-foster child clothing, neither

[16] See Section A.8 in the Online Appendix for details of the derivation.

[17] Browning et al. (2013), Bargain and Donni (2012), and Bargain et al. (2014) achieve identification by assuming w_s^t is “observed" using data from households that have only single men, or only single women.

of which are available in the data. Thus, a direct application of the DLP methodology is infeasible. I work around this data limitation by making use of expenditure on partially assignable goods. In particular, I use children's clothing, which is partially assignable to both foster and non-foster children.

I demonstrate two different sets of assumptions to identify resource shares in this context. I begin in Section 3.1 by summarizing how DLP use private assignable goods to identify resource shares. I then present a new approach to identify resource shares using expenditure on private partially assignable goods in Sections 3.2. A second method is provided in Section 3.3, as well as a discussion of the relative merits of each approach.

3.1 Identification with Private Assignable Goods

Identification with private assignable goods requires that foster and non-foster child clothing (W_s^a and W_s^b) are separately observed. In what follows, I illustrate the DLP identification method assuming that these data requirements are met.

Assume individuals have preferences given by a Piglog indirect utility function (Deaton and Muellbauer, 1980): $V_t(\mathbf{p}, y) = b_t(\mathbf{p})(\ln y - a_t(\mathbf{p}))$.[18] Using Roy's identity, the budget share functions are given by $w_t(\mathbf{p}, y) = \delta_t(\mathbf{p}) + \beta_t(\mathbf{p}) \ln y$ where $\delta_t(\mathbf{p})$ is a function of $a_t(\mathbf{p})$ and $b_t(\mathbf{p})$, and $\beta_t(\mathbf{p})$ is minus the price elasticity of $b_t(\mathbf{p})$ with respect to the price of person t's assignable good. Substituting the budget share functions into Equation (3) results in the system of clothing Engel curves given below:

$$\begin{cases} W_s^m = \eta_s^m \left[\delta_s^m + \beta_s^m \ln(\eta_s^m)\right] + \eta_s^m \beta_s^m \ln y \\ W_s^f = \eta_s^f \left[\delta_s^f + \beta_s^f \ln(\eta_s^f)\right] + \eta_s^f \beta_s^f \ln y \\ W_s^a = \sigma_a \eta_s^a \left[\delta_s^a + \beta_s^a \ln(\eta_s^a)\right] + \sigma_a \eta_s^a \beta_s^a \ln y \\ W_s^b = \sigma_b \eta_s^b \left[\delta_s^b + \beta_s^b \ln(\eta_s^b)\right] + \sigma_b \eta_s^b \beta_s^b \ln y \end{cases} \tag{4}$$

where W_s^t are budget shares for the private assignable good for person type t in household s. I drop prices from Equation (4) as Engel curves describe the relationship between budget shares and total expenditure holding prices fixed. The number of foster and non-foster children in the household is given by σ_a and σ_b, and this determines the household type given by the subscript s. To simplify notation, the household is assumed to have only one man ($\sigma_m = 1$) and one woman ($\sigma_f = 1$). To achieve identification, resource shares are assumed to be independent of household expenditure.[19]

[18] A more general functional form is used in the Online Appendix.

[19] Menon et al. (2012) show that this is a reasonable assumption. They rely on a household survey question

DLP demonstrate one of two additional assumptions are necessary for identification: (1) Preferences for the assignable good are Similar Across household Types (SAT), so $\beta_s^t = \beta^t$; or (2) Preferences for the assignable good are Similar Across People (SAP), so $\beta_s^t = \beta_s$.

The SAT restriction, first used in Lewbel and Pendakur (2008), restricts how the prices of shared goods enter each person's utility function. In effect, it restricts changes in the prices of shared goods to have a pure income effect on each person's demand for clothing.[20] Under this restriction, identification is achieved by comparing Engel curves across households of different sizes for a given individual type. To better understand what this restriction entails, consider the demand for a purely public good such as housing. As the household size increases, the shadow price of rent decreases. This change in the price of rent may have an effect on each person's demand for clothing. However, under SAT, this price change can only affect the demand for clothing in way that's independent of total expenditure. That is, changes in household size can shift the Engel curve for clothing up and down, but not change the shape of it. The identification method developed in Section 3.2 builds upon this similarity assumption.[21]

The SAP restriction is a more commonly used preference restriction in the demand literature and is a weaker version of shape-invariance (Pendakur (1999), Lewbel (2010)). Under this restriction, identification is achieved by comparing Engel curves across individuals for a given household type.

Assuming resource shares sum to one, the model parameters can then be identified by inverting the Engel curves for the assignable goods. It is important to note that the relative size of the budget shares for foster and non-foster child clothing does not necessarily determine which child type has higher resource shares. It is entirely possible for $\eta_s^b > \eta_s^a$ with $W_s^a > W_s^b$, since preferences for clothing are allowed to be different across individuals.

The key complication for my purposes is the absence of a separate private assignable good for foster and non-foster children in the data; I do not observe the budget shares for foster and non-foster child clothing, W_s^a and W_s^b, but rather their sum $W_s^c = W_s^a + W_s^b$, where W_s^c is the budget share for *child* clothing. This is a widespread data problem that is present in a

that asked Italian parents what percentage of household expenditures they allocated to children. Their answers did not vary considerably across expenditure levels. Cherchye et al. (2015) use a revealed preference approach to place bounds on resource shares and also find that they do not vary with household expenditure. Importantly, resource shares can depend on variables highly correlated with expenditure, such as individual wages, remittances, or wealth. Lastly, resource shares need to be independent of household expenditure only at low levels of household expenditure.

[20] When the household gets larger, the Lindahl prices of shared goods declines. SAT restricts how this price change affects demand for private assignable goods. See Dunbar et al. (2013) for a more detailed discussion.

[21] Bargain et al. (2018) use a unique Bangladeshi data set with observable individual-level consumption to directly test how preferences vary across household compositions. Their results provide some evidence in support of this type of assumption when using clothing as an assignable good. The results are less supportive when using other assignable goods, such as rice.

variety of settings where inequality among children is of interest; consumption surveys rarely contain data on goods that are assignable to specific types of children. To work around the lack of sufficient data, I now develop a new methodology to identify resource shares in the absence of private assignable good.

3.2 Identification with Private Partially Assignable Goods using SAT

Without private assignable goods for foster and non-foster children, I rewrite the Engel curves for foster and non-foster child clothing in System (4) as a single Engel curve for children's clothing, and I begin by imposing the SAT restriction (i.e., $\beta_s^t = \beta^t$):

$$\begin{cases} W_s^m = & \eta_s^m \left[\delta_s^m + \beta^m \ln(\eta_s^m)\right] + \eta_s^m \beta^m \ln y \\ W_s^f = & \eta_s^f \left[\delta_s^f + \beta^f \ln(\eta_s^f)\right] + \eta_s^f \beta^f \ln y \\ W_s^c = & \sigma_a \eta_s^a \left[\delta_s^a + \beta^a \ln(\eta_s^a)\right] + \sigma_b \eta_s^b \left[\delta_s^b + \beta^b \ln(\eta_s^b)\right] + \\ & (\sigma_a \eta_s^a \beta^a + \sigma_b \eta_s^b \beta^b) \ln y \end{cases} \tag{5}$$

Here, the Engel curve for children's clothing is given as the sum of the Engel curves for foster and non-foster child clothing. I have simply taken the bottom two equations from System (4) and summed them together. The key assumption underlying this action is that foster and non-foster children do not share purchased clothing. The validity of this assumption is analysed in detail in Section A.2, where I also address concerns related to hand-me-down clothing.

The identification proof proceeds in two steps. First, I demonstrate that resource shares are identified in *one-child-type* households, that is, households with only foster children or only non-foster children. This follows directly from DLP as children's clothing expenditures are fully assignable in these households. I then move to the *composite* households, or households with both foster and non-foster children, where children's clothing expenditures are not assignable. The key new assumption is to impose some similarity between the one-child-type households and the composite households.

Suppose there are four one-child-type households $s \in \{s_{10}, s_{20}, s_{01}, s_{02}\}$ where, for example, s_{10} denotes a household with one foster child and no foster children.[22] I can use a simple counting exercise to show that the order condition is satisfied. With three Engel curves for each household type, and four household types, there are twelve Engel curves. Moreover, for each of the four household types resource shares must sum to one. This results in a system of sixteen equations in total. In terms of the number of unknowns, each Engel curve has one

[22] In the empirical application the sample includes households with as many as four children.

resource share η_s^t that needs to be identified (twelve total) and there are four shape parameters β^t that need to be identified.[23] This leads to sixteen unknowns, and with sixteen equations the order condition for identification is satisfied. A formal proof that the rank condition holds for one-child-type households is provided in the Online Appendix.

I next move to the composite households which is where the main contribution of this paper lies. With SAT, preferences for clothing are similar across household sizes. I modify this restriction by assuming that preferences are both similar across households sizes *and across household compositions*; that is, preferences for clothing are similar across one-child-type and composite households. In words, the foster child's marginal propensity to consume clothing is independent of the number of non-foster children present in the household, and vice versa. I take β^t from the one-child-type households and assume it is the same in the composite households. It follows that the resource shares for men and women can be immediately recovered since the slope coefficients for their Engel curves ($\beta^m \eta_s^m$ and $\beta^f \eta_s^f$) are identified by a simple OLS-type regression of the budget shares on log expenditure. Furthermore, the slope coefficient on the Engel curve for children's clothing ($\beta^a \eta_s^a + \beta^b \eta_s^b$) is identified. This coefficient contains two unknowns. I can then use that resource shares sum to one to identify the resource shares for foster and non-foster children. A formal proof for composite households is provided in the Online Appendix in Section A.11. I discuss potential violations to this identification approach in Sections A.2, A.3, and A.4 of the Online Appendix.

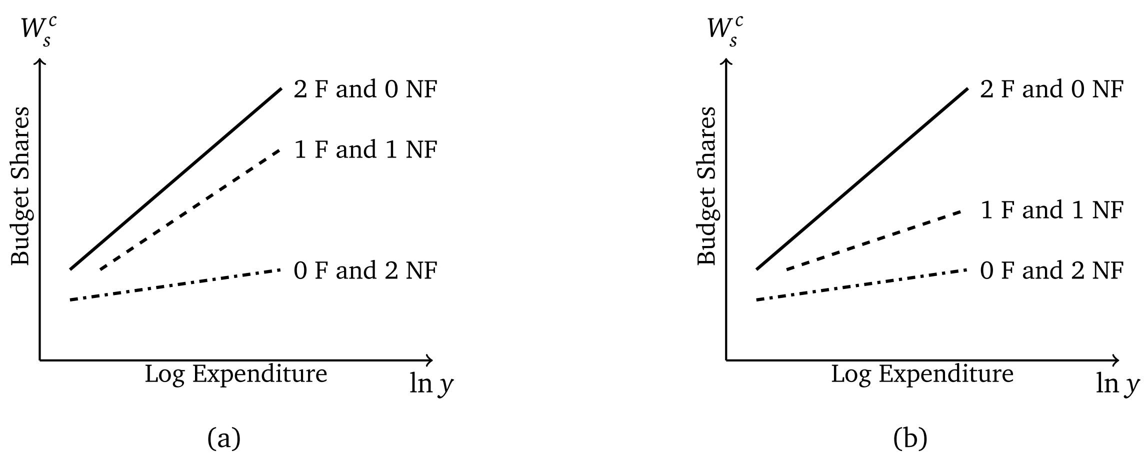
A graphical representation of the intuition is provided in Figure 1. Each graph plots the children's clothing Engel curve for three different household compositions. If the *slope* of the children's clothing Engel curve in the composite household (1 F and 1 NF) is more similar to the slope of the Engel curve in the foster-only household (2 F and 0 NF) relative to the non-foster only household (0 F and 2 NF), then this suggests that the parents in the composite household are placing more weight on the foster child's clothing preferences, and therefore are allocating a larger share of the budget to the foster child. This situation is presented in Figure 1a. In Figure 1b, the non-foster child in the composite household is allocated a larger share of the budget as the slope is more similar to his or her Engel curve.

3.3 Identification with Partially Assignable Goods using SAP

Without private assignable goods for foster and non-foster children, I again rewrite the Engel curves for foster and non-foster child clothing in System (4) as a single Engel curve for

[23] With Piglog preferences, identification is achieved using the first derivative of the Engel curve with respect to log expenditure. It is therefore necessary to identify the slope preference parameter β^t, but not the intercept preference parameter δ_s^t.

Figure 1: Graphical Intuition for Identification



Notes: The above figures present hypothetical children's clothing Engel curves by household composition. In Figure 1a, the slope of the children's Engel curve in the composite household (1 F 1 NF) is more similar to the foster only household (2 F 0 NF) which suggests that in the composite household, the foster child is allocated more of the budget. The opposite is true in Figure 1b.

children's clothing, and assume SAP (i.e., $\beta_s^t = \beta_s$):

$$\begin{cases} W_s^m = & \eta_s^m \left[\delta_s^m + \beta_s \ln(\eta_s^m)\right] + \eta_s^m \beta_s \ln y \\ W_s^f = & \eta_s^f \left[\delta_s^f + \beta_s \ln(\eta_s^f)\right] + \eta_s^f \beta_s \ln y \\ W_s^c = & \sigma_a \eta_s^a \left[\delta_s^a + \beta_s \ln(\eta_s^a)\right] + \sigma_b \eta_s^b \left[\delta_s^b + \beta_s \ln(\eta_s^b)\right] + \\ & (\sigma_a \eta_s^a \beta_s + \sigma_b \eta_s^b \beta_s) \ln y \end{cases} \tag{6}$$

This system of equations is identical to System (5) except now the shape parameter β is allowed to vary with the household type s, but not the person type t. Resource shares are identified in the one-child-type households following DLP. To see how the order condition is satisfied, note that for each household type there are three resource shares (η_s^m, η_s^f, and either η_s^a or η_s^b) and a single preference parameter β_s that need to be identified. Moreover, there are four equations: three Engel curves slopes, and the restriction that resource shares sum to one. With four equations and four unknowns, resource shares are identified for each one-child-type household.

Moving to the composite households, it is easy to see how identification fails. For each household type, there are five unknowns; four resource shares (both η_s^a and η_s^b are now non-zero) and again a single preference parameter β_s. However, the number of equations is still four, so the order condition is no longer satisfied. It is important understand why the SAP restriction fails here, but the SAT restriction does not. With the SAT restriction, as the number of household types increases, the number of preference parameters β^t does not change. However, with the SAP restriction, there is a different β_s for each household type, and therefore as the number of household types increases, so too does the number of preference parameters that need to be identified.

To overcome this problem, I add structure to the model by introducing additional restrictions which limit how foster and non-foster child resource shares vary by household size. In short, *resource shares must decline in a consistent way as household size increases*. Ratio Restriction 1 is given below:

$$\frac{\eta^a_{s_{a0}}}{\eta^a_{s_{a+1,0}}} = \frac{\eta^a_{s_{ab}}}{\eta^a_{s_{a+1,b}}} \text{ and } \frac{\eta^b_{s_{0b}}}{\eta^b_{s_{0,b+1}}} = \frac{\eta^b_{s_{ab}}}{\eta^b_{s_{a,b+1}}} \tag{7}$$

where the household type is now given as s_{ab} to explicitly indicate the number of foster and non-foster children present. If non-foster children consume 25 percent less per-child in households with two non-foster children instead of one, then this percent decline must hold regardless of the number of foster children present in the household. I provide a numerical example of this restriction in Section A.7 of the Online Appendix.

More generally, this restriction requires that (1) the ratio of foster child resource shares in households with σ_a and σ_{a+1} foster children is independent of the number of non-foster children present; and (2) the ratio of non-foster child resource shares in households with σ_b and σ_{b+1} non-foster children is independent of the number of foster children present. For both equations, the left-hand-side is identified from the one-child-type households, which are used to identify the composite households on the right-hand-side of the equality.

Next, I make an additional assumption, Ratio Restriction 2, relating to composite households with one of each child type:

$$\frac{\eta^a_{s_{10}}}{\eta^b_{s_{01}}} = \frac{\eta^a_{s_{11}}}{\eta^b_{s_{11}}} \tag{8}$$

This restriction states that the degree of unequal treatment *within* a household with one of each child type is proportional to the degree of unequal treatment *across* households with one foster child or one non-foster child. With both restrictions, I identify how resource shares vary across household sizes in the one-child-type households, and assume resource shares behave in a similar way in the composite households. The additional restrictions ensure the order condition holds. A formal proof is provided in Section A.11 of the Online Appendix.

Which set of identification assumptions should be used? The answer depends on the empirical context. For example, if preferences for the assignable good are likely to be different across child types, then SAP should not be assumed (as appears to be the case in this context). However, preferences do not seem to vary substantially across household size, meaning the identification method discussed in Section 3.2 is preferred. This makes sense; SAT may be more restrictive when public goods comprise a larger share of the budget, which is less likely to hold in Malawi where private expenditures constitute 76 percent of household expenditure on average. In other settings, estimation based on the method discussed in Section 3.3 may be more attractive. To shed more light on this, I test the validity of both approaches in Section A.4 of the Online Appendix.

4 Application: Child Fostering in Malawi

In this section, I apply the identification methods developed in Section 3 to child fostering in Malawi. I begin by discussing child fostering as a cultural institution and the reasons households practice this custom. I then discuss the data, estimation, and results.

4.1 Background

Child fostering, or kinship care, is the practice of sending one's biological children to live with close relatives. I use a broader definition of foster children to include all individuals age 14 and under who are living in households away from both of their biological parents. This definition includes children in kinship care, but also orphans and adopted children. Child fostering rates vary by country and are highest in West African societies (Grant and Yeatman, 2012). In Malawi, fostering is also quite common with 17 percent of households having a foster child.[24] Figure 2a presents the percentage of children fostered by age in Malawi (the solid line). Overall, 13.1 percent of children are fostered (Malawi Integrated Household Survey 2016), and fostering rates are increasing with age. The dashed lines show the number of children living away from their father and mother, respectively.[25] Figure 2b displays orphan rates by age. I use the UNICEF definition of "orphan", defined as any child who has lost at least one parent. A double orphan is a child who has lost both parents, and a maternal or paternal orphan is a child who has lost either their mother or father. By definition, double orphans are foster children. Comparing Figure 2a with Figure 2b demonstrates that the majority of foster children are not double orphans, suggesting orphanhood is not the primary cause of fostering.

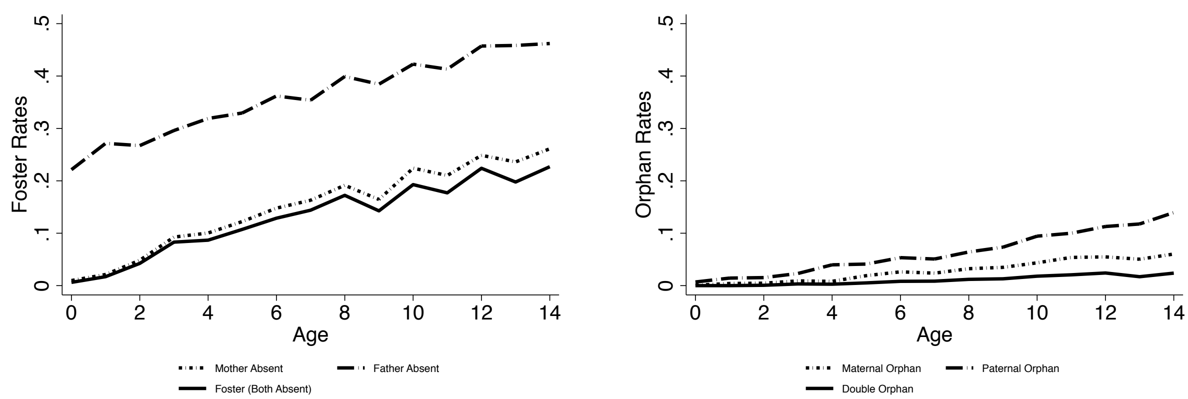
The literature commonly divides foster children into two categories: those who are fostered for voluntary reasons, and those who are not (Serra, 2009). Non-voluntary, or crisis fostering occurs when the child is orphaned, or has parents who are ill and unable to care for their child. Non-voluntary fostering has become substantially more common as a result of the AIDS epidemic. Voluntary, or purposive child fostering occurs when the child's parents voluntarily send

[24] Grant and Yeatman (2012) use DHS data to examine the prevalence of fostering and orphanhood across sub-Saharan African countries.

[25] Fathers are more likely than mothers to live away from their children, potentially due to migration for work.

the child to another household. There are a myriad of reasons parents may choose to do this: parents may want to provide better educational access for their child, to strengthen kinship networks, to increase their own fertility, to reallocate child labour across households, agricultural shocks, or to facilitate adult labour (by reducing parenting responsibilities).[26] Finally, children are also often fostered as a result of their parents divorce and subsequent remarriage (Grant and Yeatman, 2014). This cause is especially prevalent in Malawi as almost half of all marriages end in divorce, with remarriage rates being equally high (Reniers, 2003; Cherchye et al., 2018).

Figure 2: Foster and Orphan Status by Age



(a) *(b)*

Notes: Malawi Integrated Household Survey 2016. The sample includes all children age 14 and under. Foster children are individuals living in households away from both of their biological parents. Figure 2a presents the mean number of children fostered by age. Figure 2b presents the mean number of children orphaned by age.

Data limitations prevent me from examining in detail the reasons households foster children, as I only observe the receiving household. With additional data, I would be able to analyse both how foster children are treated within the household, *and* whether the reason for fostering affects foster child treatment. I can however differentiate between children who are fostered due to orphanhood and those who are not. Overall, foster children are not randomly allocated to households. I therefore discuss the role of selection and how it may affect the results in Section A.5.

There are several reasons why foster children may be treated worse than non-foster children. First, parents are likely to be more altruistic towards their own biological children. This

[26] See Ainsworth (1995), Akresh (2009), Serra (2009), and Beck et al. (2015) for a detailed analysis of why households foster children.

theory, known as Hamilton's Rule (Hamilton, 1964), hypothesizes that altruism is increasing in relatedness; parents care more for their children relative to their nephews and nieces, and they care more about their nephews and nieces than their neighbour's children. This theory has a basis in evolutionary biology and is sometimes referred to as inclusive fitness. Hamilton's Rule has direct implications in the context of child fostering since children who are more closely related to their caregivers should experience better access to education, lower levels of child labour, and a higher share of household consumption. The second reason for unequal treatment is related to the parent's expectation of old age care. Specifically, parents may invest more in children that they believe will care for them in old age (Becker, 1992). If adult children primarily support their biological parents, then parents may be inclined to favour non-foster children. Unfortunately, I am unable to test this hypothesis given the available data.

There is, however, reason to believe that there will be no inequality. Child fostering often functions as a transaction between willing households within the same kinship network. Foster caretakers have an incentive to treat foster children well, as they themselves may send their children to the foster child's parents in the future (Akresh, 2005; Beck et al., 2015). In short, there is reciprocity. Foster children can stay with their foster caregivers for multiple years, and therefore are akin to family members. Further evidence supporting this hypothesis is the nature of inheritance in Malawi. In matrilineal societies (like parts of Malawi), children tend to be nearly as close to their maternal uncles as their fathers (Sear, 2008; Lyngdoh and Nongkynrih, 2016). Inheritance is done through the men on the maternal side of the family (Lowes, 2017), and uncles have a substantial role in the lives of their sister's children. As a result, it is intuitive that foster children living with their aunts and uncles are treated well. This intuition is consistent with the empirical results of the paper.

4.2 Data

I use the Malawi Integrated Households Survey (IHS3 and IHS4) and the Malawi Integrated Panel Survey (IHPS). The IHS3 and IHPS together consist of 12,288 households surveyed in 2010, of which, 4,000 were resurveyed in 2013. The IHS4 consists of 12,480 households that were surveyed in 2016. The IHS3, IHS4 and IHPS are nationally representative household surveys and contain detailed information on individual education, employment, migration, health, and other demographic characteristics as well as household-level expenditure data. I rely primarily on the expenditure module in the estimation of the structural model. In Section A.1 in the Online Appendix, I use the data on education and employment to study the relationship between fostering, school enrolment, and child labour.

From the survey, I can determine whether or not each child's parents are present in the household, and if not, whether their parents are living or dead. This allows me to identify both foster children and orphans.

Identifying resource shares requires expenditure data for assignable clothing. In both surveys, households are asked their expenditure on different categories (shirts, shoes, pants, etc.) of men's, women's, children's clothing, which I use to construct the corresponding budget shares. I account for heterogeneity across households using data on the age, orphan status, education, and gender of the households men, women, foster, and non-foster children. Other household-level variables include an indicator for whether the household is located in an urban or rural area, an indicator for residence in a matrilineal village, and region indicators.

From the data, I select a sample of 17,203 households. For ease of estimation, I exclude households that have less than one or more than four men, women, or children. I also exclude households that are in the top or bottom percentile of expenditure to eliminate outliers. Households are dropped if they are missing information on any of the covariates listed in Table 1. Sample sizes for each household type are provided in the Online Appendix in Table A16.

Table 1 reports descriptive statistics for the estimation sample. Households have on average 5 individuals. The average age of foster children (9.36) is significantly higher than that of non-foster children (5.90). This is consistent with child labour and education being reasons households foster children. Roughly 33 percent of foster children have lost at least one parent. Households in Malawi are very poor, with the average real annual per capita household expenditure equal to 920,000 MWK (approximately US$ 1,200 in 2016).[27] Lastly, households spend a large fraction of their income on food (62.5 percent), which consistent with the high level of poverty in Malawi.

4.3 Estimation

To estimate the model, I add an error term to the clothing Engel curves for men, women, and children. Since the error terms of the Engel curves are likely to be correlated across equations, the system is estimated using Non-linear Seemingly Unrelated Regression.[28] To match the data used in the empirical analysis, I now account for households with multiple men and women

[27] The median per capita household expenditure is considerably lower at US$ 932.

[28] Household expenditure may suffer from measurement error. As a result, I instrument for expenditure using the log value of total household assets. These results are very similar to the main estimation results and are available upon request.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Sample Size
Household Characteristics					
Household Size	4.997	1.502	3	12	17,203
Men	1.364	0.680	1	4	17,203
Women	1.327	0.628	1	4	17,203
non-Foster	2.055	1.184	0	4	17,203
Foster	0.251	0.628	0	4	17,203
Log Real Total Expenditures	13.519	0.627	12.035	15.716	17,203
Men's Clothing Budget Shares	0.005	0.013	0	0	17,203
Women's Clothing Budget Shares	0.009	0.015	0	0	17,203
Child's Clothing Budget Shares	0.009	0.015	0	0	17,203
Food Budget Shares	0.625	0.131	0	1	17,203
Preference Factors					
Year=2010	0.425	0.494	0	1	17,203
Year=2013	0.148	0.355	0	1	17,203
Year=2016	0.427	0.495	0	1	17,203
Foster Child Age	9.356	3.277	0	14	2,990
Non-Foster Child Age	5.904	3.549	0	14	15,654
Proportion Orphaned of Foster Children	0.333	0.455	0	1	2,990
Proportion Female of non-Foster	0.501	0.378	0	1	15,654
Proportion Female of Foster	0.554	0.452	0	1	2,990
Average Age Women	31.871	11.192	15	75	17,203
Average Age Difference	1.770	12.827	-60	60	17,203
Education Women	1.029	0.616	0	3	17,203
Education Men	1.254	0.637	0	3	17,203
Rural	0.805	0.396	0	1	17,203
Share of Women Age 15-18	0.115	0.251	0	1	17,203
Share of Men Age 15-18	0.075	0.182	0	1	17,203
Matrilineal Village	0.539	0.499	0	1	17,203
North	0.203	0.403	0	1	17,203
Central	0.362	0.481	0	1	17,203
South	0.435	0.496	0	1	17,203

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. Households with 1-4 men and women, and 1-4 children. Children are defined as individuals age 14 or younger.

with σ_m denoting the number of men, and σ_f denoting the number of women.

$$\begin{cases} W_s^m = & \sigma_m \eta_s^m(\mathbf{z})\ [\delta_s^m(\mathbf{z}) + \beta_s^m \ln(\eta_s^m(\mathbf{z}))] + \sigma_m \eta_s^m(\mathbf{z})\beta_s^m \ln y + \epsilon_m \\ W_s^f = & \sigma_f \eta_s^f(\mathbf{z})\ \ [\delta_s^f(\mathbf{z}) + \beta_s^f \ln(\eta_s^f(\mathbf{z}))]\ + \sigma_f \eta_s^f(\mathbf{z})\beta_s^f \ln y + \epsilon_f \\ W_s^c = & \sigma_a \eta_s^a(\mathbf{z})\ \ [\delta_s^a(\mathbf{z}) + \beta_s^a \ln(\eta_s^a(\mathbf{z}))]\ \ + \sigma_b \eta_s^b(\mathbf{z})[\delta_s^b(\mathbf{z}) + \beta_s^b \ln(\eta_s^b(\mathbf{z}))] + \\ & (\sigma_a \eta_s^a(\mathbf{z})\beta_s^a + \sigma_b \eta_s^b(\mathbf{z})\beta_s^b) \ln y + \epsilon_c \end{cases} \tag{9}$$

The objects of interest are the resource shares for foster and non-foster children, given by η_s^a and η_s^b, respectively. The estimation allows for considerable heterogeneity as η_s^t and δ_s^t, and are all linear functions of the preference factors **z** provided in Table 1.[29] To estimate how resource shares differ by household composition, I include indicator variables for household types in the parameterization of the foster and non-foster child resource share functions. I therefore omit constant terms, as those are already captured by the household type indicators.

For men and women, I assume that their resource shares increase linearly in the number of men, women, foster, and non-foster children in the household.[30]

For the main estimation results, I restrict the slope preference parameter to be the same across household sizes, and across composite and one-child type households (i.e., $\beta_s^t = \beta^t$).[31] This is the key assumption discussed in Section 3.2. Moreover, I impose the ratio restrictions provided in Equations (7) and (8). This restriction is not necessary for identification, but it improves the estimation as fewer parameters need to be identified. As a robustness check, I estimate the model with different combinations of identification assumptions (see Table 3 in Section 4.4)). This includes a specification allowing β to vary across household sizes, but not people (i.e., $\beta_s^t = \beta_s$).

4.4 Results

I begin by presenting average predicted resource shares for men, women, non-foster, and foster children in Table 2. These are the average *per-person* resource shares across all household compositions. The results suggest that the average non-foster child consumes 11.2 percent of the household budget, while the average foster child consumes only 14.8 percent. This, however, does not imply unequal treatment because foster children are on average nearly four years older than non-foster children, and it's reasonable to assume that older children consume more goods (especially when food is such a large component of expenditures). Moreover, foster children tend to live in smaller households where resource shares will be mechanically larger. This motivates comparing foster and non-foster child resource shares for a given household size and household characteristics.

Figure 3 presents estimates for the predicted resource shares for foster and non-foster chil-

[29] The slope preference parameter β_s^t is modelled as a constant and does not vary across household characteristics aside from household size in certain specifications.

[30] This assumption is for computational reasons. Determining household types by the number of men and women in the household, in addition to the number of foster and non-foster children, would result in a significant increase in the number of parameters needed to be estimated. For robustness, I include indicators for the number of men and women in the parametrization of men's and women's resource shares and the results are unaffected. To further improve precision I restrict $\beta^f = \beta^m$. I fail to reject the hypothesis that these parameters are equal.

[31] Tommasi and Wolf (2016) demonstrate that "flat" Engel curves result in unstable resource share estimates when estimating DLP. This is fortunately not the case in the data. Table A17 in the Online Appendix presents parameter estimates for the slope preference parameter β for each of the main specifications.

Table 2: Predicted Resource Shares

	Observations	Mean	Median	Std. Dev.
	(1)	(2)	(3)	(4)
Men	17,203	0.355	0.389	0.114
Women	17,203	0.293	0.324	0.090
Non-Foster	15,654	0.112	0.104	0.032
Foster	2,990	0.148	0.143	0.043

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The predicted resource shares are per person, and therefore do not need to sum to one. The sample includes all households with 1-4 men and women, and 1-4 children.

dren by household composition. The resource shares are per child. The solid bars denote foster child resource shares, and the line-patterned bars denote non-foster child resource shares. Each quadrant corresponds to a different household size, defined by the number of children in the household. Within each quadrant, predicted resource shares for foster and non-foster children are given by household composition, which is determined by the number foster and non-foster children present, where for example, “1 NF 0 F" indicates a household with 1 non-foster child and 0 foster children. The motivation for this grouping of the results is that, if all children are treated equally, then foster and non-foster child resource shares should not vary for a given household size. The predictions are made for a reference household, which I define as a household with one man, one woman, and all other covariates (except for age) set to their median value.[32] Instead of using the median value for foster and non-foster child age, I set both to seven to make the predicted resource shares more comparable. The brackets are the 95 percent confidence intervals of the predicted values. By assumption, resources are assumed to be allocated equally within a person type. For example, if together two foster children consume 30 percent of the household budget, I assume each child consumes 15 percent, all else equal.

Panel A of Figure 3 provides the predicted resource shares for reference households with one or two children. For households with one non-foster child, and zero foster children (“1 NF 0 F"), the non-foster child consumes 19.7 percent of the household budget. Similarly, for households with one foster child, and zero non-foster children (“0 NF 1 F"), the foster child is allocated roughly 20.5 percent of the household budget. This provides little evidence of discrimination. Panels B, C, and D present the results for households with two, three, and four total children respectively, and again, the results do not demonstrate a systematic pattern of

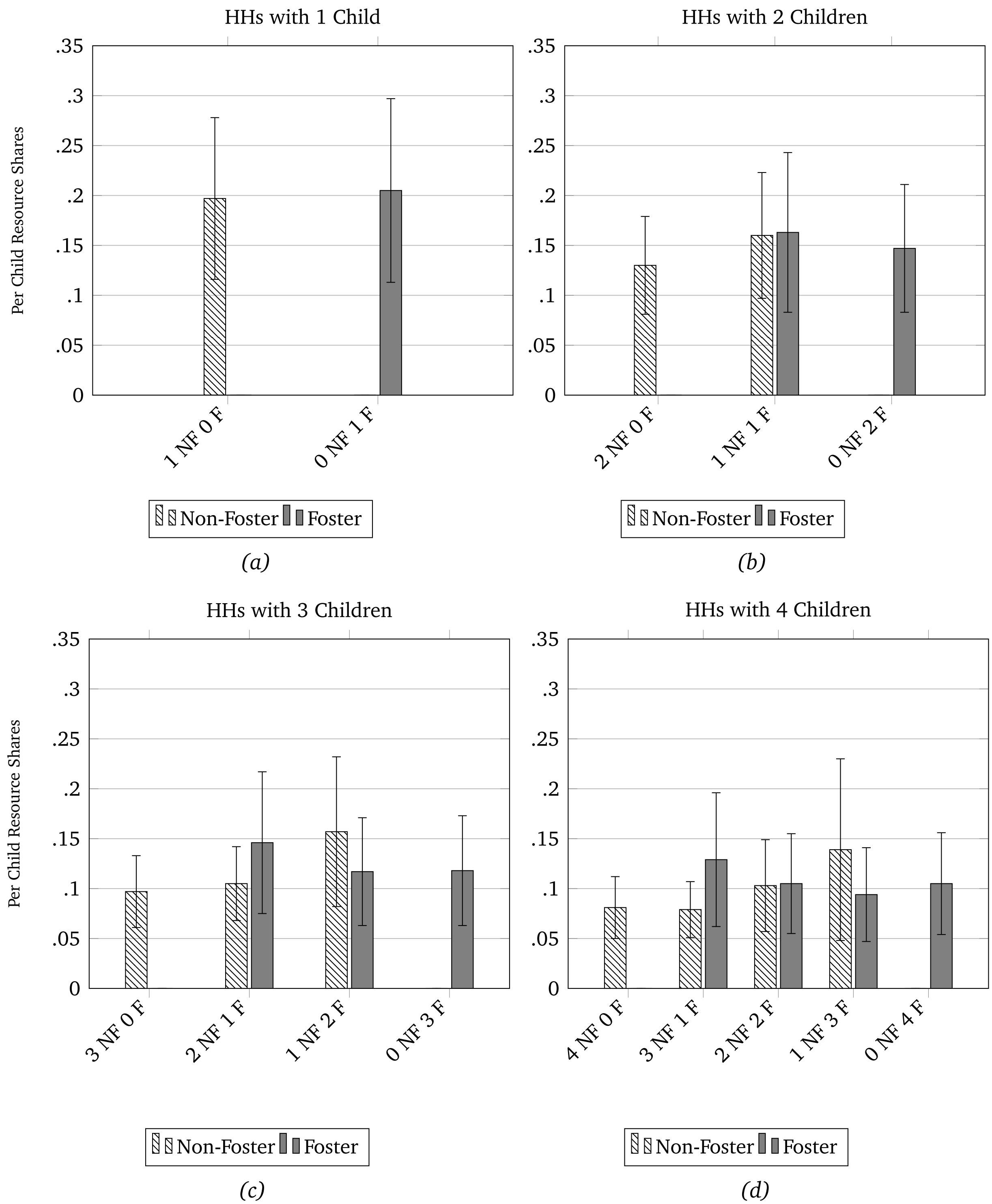
[32] Using mean instead of media values for the predictions does not meaningfully affect the results.

unequal treatment towards foster children.

Tables A18 and A19 in the Online Appendix present the parameter estimates of the resource share functions for foster and non-foster children. The parameter estimates in these tables are used to construct Figure 3. Table A18 focuses on the preference factors (i.e., the demographic characteristics of the household) whereas Table A19 displays the household type indicators.[33] Notably, child age is an important factor in resource shares for both foster and non-foster children. Figure A2 plots predicted resource shares for different foster and non-foster child ages. For all predictions, foster and non-foster children are assumed to be the same age. As implied by the parameter estimates, there is a larger age gradient for foster children. Most other preference factors are insignificant suggesting that household composition is the main factor in determining how resources are allocated within the household.

[33] Because most of the covariates are demeaned, the indicators for the household type variables are similar to the predicted values found in Figure 3.

Figure 3: Predicted Resource Shares: Reference Household



Note: Malawi Integrated Household Survey and Integrated Household Panel Survey. Robust standard errors. The brackets are the 95 percent confidence intervals. Each quadrant presents non-foster and foster child resource shares for a different household size defined by the number of children. Within each quadrant, foster, and non-foster child resource shares are presented by household type which is defined by the number of foster and non-foster children, respectively. A reference household is a household with 1 man, 1 woman, and all other covariates at their median value, excluding foster and non-foster child age, which are both set to 7.

I next exclude several alternative types of households where the assumptions of the collective model may be less likely to hold. Specifically, households with multiple adult men or women, or households where the household head has multiple wives may not necessarily bargain in a cooperative way. As I result, I first exclude any non-nuclear household from the sample, where a nuclear household is defined as having one man and one woman who are married.[34] Columns (2a) and (2b) of Table A20 display these results. While several parameter estimates differ in magnitude, none are statistically different. I next exclude polygamous households. In the main estimation sample, only 8 percent of household heads are part of a polygamous marriage. The results are presented in columns (3a) and (3b) of Table A20, and are again similar in magnitude to the main estimation results.

Alternative Identification Assumptions: The above results are estimated assuming preferences for assignable clothing are similar across households types, including across one-child-type and composite households. I also impose that the way in which resource shares for foster children vary across household types is independent of the number of non-foster children present, and vice versa (the ratio restrictions discussed in Section 3.3). To examine the robustness of these results, I estimate the model using several alternative identification assumptions. Table 3 presents the results of each different specification. In the interest of conciseness, I limit the displayed parameter estimates to several key household characteristics and household type indicators (full results are available upon request). The approach developed in Section 3 modifies the SAT restriction by assuming that preferences for clothing in one-child-type and composite households are similar, and is presented in column (1). Recall that the SAT ("Similar Across Household Types") restriction, introduced by Dunbar et al. (2013), assumes preferences for clothing are similar across household sizes. Moving to column (2), I additionally impose the ratio restrictions (the main results use this specification). In column (3), I assume SAP and the ratio restrictions, where SAP requires preferences for clothing be similar across person types (i.e., "Similar Across People"). Lastly, in column (4) I impose every restriction. Columns (1a) - (4a) present the results for foster children, and columns (1b) - (4b) do the same for non-foster children.

The results are reassuringly similar across identification assumptions. As expected, estimating the model assuming only SAT and that preferences are similar across one-child-type and composite households leads to larger standard errors. Across specifications, none of the parameter estimates on the household type indicators are statistically different, and overall are quite

[34] In the main estimation sample, only 55.8 percent of households are nuclear. Because foster children tend to live in extended-family households, the main analysis includes non-nuclear households.

Table 3: Resource Share Estimates by Identification Assumptions

	Non-Foster Children				Foster Children			
Preference Restriction:	SAT	SAT	SAP	SAP+SAT	SAT	SAT	SAP	SAP+SAT
One-Child-Type and Composite Similarity:	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Ratio Restrictions:	No	Yes	Yes	Yes	No	Yes	Yes	Yes
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)
Household Type Indicators								
2 Non-Foster 0 Foster	0.247***	0.251***	0.324***	0.307***				
	(0.0525)	(0.0484)	(0.0276)	(0.0283)				
1 Non-Foster 1 Foster	0.113**	0.151***	0.187***	0.180***	0.200***	0.171***	0.174***	0.174***
	(0.0511)	(0.0313)	(0.0243)	(0.0242)	(0.0580)	(0.0355)	(0.0277)	(0.0249)
0 Non-Foster 2 Foster					0.286***	0.301***	0.312***	0.302***
					(0.0673)	(0.0637)	(0.0488)	(0.0414)
3 Non-Foster 0 Foster	0.283***	0.285***	0.371***	0.352***				
	(0.0596)	(0.0548)	(0.0287)	(0.0297)				
2 Non-Foster 1 Foster	0.169**	0.201***	0.247***	0.241***	0.175***	0.154***	0.162***	0.155***
	(0.0686)	(0.0381)	(0.0273)	(0.0271)	(0.0616)	(0.0342)	(0.0281)	(0.0256)
1 Non-Foster 2 Foster	0.0855	0.148***	0.191***	0.178***	0.283***	0.241***	0.238***	0.236***
	(0.0557)	(0.0381)	(0.0346)	(0.0327)	(0.0674)	(0.0530)	(0.0402)	(0.0348)
0 Non-Foster 3 Foster					0.346***	0.363***	0.369***	0.352***
					(0.0881)	(0.0839)	(0.0648)	(0.0527)
Covariates								
Average Age non-Foster	1.181**	1.435**	2.227***	1.562**	-0.330	-0.227	-0.270	-0.110
	(0.601)	(0.586)	(0.640)	(0.685)	(0.753)	(0.771)	(0.768)	(0.743)
Average Age non-Foster^2	-0.0656	-0.0811*	-0.120**	-0.0841*	0.0269	0.0186	0.0222	0.0103
	(0.0430)	(0.0418)	(0.0485)	(0.0508)	(0.0540)	(0.0546)	(0.0545)	(0.0528)
Average Age Foster	-0.204	-0.545	-0.629	-0.615	1.828	2.428	2.440	2.476**
	(2.207)	(1.888)	(2.134)	(1.870)	(1.705)	(1.609)	(1.991)	(1.021)
Average Age Foster^2	0.0242	0.0435	0.0468	0.0470	-0.0890	-0.120	-0.116	-0.126
	(0.124)	(0.107)	(0.122)	(0.108)	(0.106)	(0.102)	(0.117)	(0.0771)
Matrilineal Village	0.00812	0.00777	0.00227	0.00787	0.0175	0.0180	0.0180	0.0176
	(0.00960)	(0.00948)	(0.0114)	(0.0118)	(0.0122)	(0.0118)	(0.0123)	(0.0115)
Proportion of	0.0296	0.0265	0.0254	0.0287	-0.0238	-0.0190	-0.0131	-0.0196
Fostered Orphaned	(0.0235)	(0.0259)	(0.0319)	(0.0269)	(0.0299)	(0.0289)	(0.0293)	(0.0200)
Sample Size	17,203	17,203	17,203	17,203	17,203	17,203	17,203	17,203
Log Likelihood	150,454	150,467	150,487	150,453	150,454	150,467	150,487	150,453

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-4 children. Robust standard errors in parentheses. Coefficients on the household type are not per child. Age variables are divided by 100 to ease computation. Estimates for certain household types and preferences factors are omitted for conciseness. Columns (1a-4a) and (1b-4b) differ by identification assumptions. * p<0.1, ** p<0.05, *** p<0.01

similar to each other. Looking at the household characteristics, the results are again for the most part consistent. The preferred results are presented in columns (2a) and (2b) of Table 3. This combination of assumptions has the advantage being relatively flexible (preferences are allowed to be entirely different across people), while simultaneously having standard errors that are significantly more precise than the results presented in columns (1a) and (1b).

Another key assumption is that resource shares are independent of household expenditure. This assumption is potentially concerning in this context as foster children tend to be sent to higher-consumption households. However, Dunbar et al. (2013) note that resource shares can still depend on certain measures that are highly correlated with household expenditure, such as household wealth or individual wages. Since the data includes the value of total household assets, I include that in the resource share functions as a proxy for household wealth. Resource shares now only have to be independent of household expenditure, *conditional on household wealth*. These results are presented in Table A21 in the Online Appendix. The results are statistically similar to the main estimation results and log total assets do not have a statistically significant relationship with child resource shares.

The results being similar across specifications is not by itself suggestive that the results are robust; the results could, in theory, be incorrect in a similar way across specifications. How concerning is this? While the data used in this paper is not suitable to fully test every aspect of the model, recent work by Bargain et al. (2018) and Brown et al. (2018) have provided support for several of the model assumptions. These studies use unique data sets containing either individual-level consumption data, assignable food consumption, or individual-level health data to test the validity of Dunbar et al. (2013) and recent extensions.

Heterogeneity in Foster Child Treatment: The above results suggest that foster and non-foster children are treated equally. While this may simply suggest that foster caretakers are equally altruistic towards their own biological (non-foster) children and their foster children, I next investigate some alternative explanations: child labour and remittances. First, children who work more may be compensated for their contribution to household income. The literature on fostering suggests that labour is one reason children are fostered (Akresh, 2009), and one would potentially expect that it is a factor in how foster children are treated.

I analyse the importance of child labour in two ways. First, I allow foster child resource

Table 4: Determinants of Foster Child Treatment: Child Labour and Remittances

	Child Labour			Remittances		
	Work in Resource Share Function (1)	Foster Child Working (2)	No Foster Child Working (3)	Remittances in Resource Share Function (4)	Foster HH Received Remittances (5)	Foster HH No Remittances (6)
Household Type Indicators						
1 Non-Foster 1 Foster	0.169***	0.171***	0.179***	0.170***	0.168***	0.171***
	(0.0364)	(0.0396)	(0.0532)	(0.0358)	(0.0602)	(0.0409)
0 Non-Foster 2 Foster	0.294***	0.298***	0.344***	0.300***	0.276**	0.316***
	(0.0622)	(0.0708)	(0.0915)	(0.0633)	(0.113)	(0.0712)
2 Non-Foster 1 Foster	0.152***	0.160***	0.149***	0.153***	0.157***	0.153***
	(0.0343)	(0.0389)	(0.0565)	(0.0341)	(0.0603)	(0.0396)
1 Non-Foster 2 Foster	0.240***	0.241***	0.254***	0.240***	0.217***	0.258***
	(0.0523)	(0.0596)	(0.0826)	(0.0529)	(0.0919)	(0.0625)
0 Non-Foster 3 Foster	0.352***	0.357***	0.400***	0.361***	0.310**	0.394***
	(0.0834)	(0.0934)	(0.121)	(0.0837)	(0.145)	(0.0961)
Covariates						
Foster Child Working	0.0390					
	(0.0405)					
Remittances/Expenditure				0.0301		
				(0.0528)		
Average Age non-Foster	-0.258	-0.0837	-1.313	-0.218	-0.690	0.262
	(0.777)	(0.870)	(1.374)	(0.771)	(1.070)	(0.943)
Average Age non-Foster^2	0.0212	0.0126	0.0774	0.0178	0.0501	-0.0182
	(0.0553)	(0.0605)	(0.101)	(0.0546)	(0.0735)	(0.0667)
Average Age Foster	2.434	2.092	1.704	2.385	2.507	1.400
	(5.233)	(1.839)	(8.137)	(3.184)	(2.079)	(1.948)
Average Age Foster^2	-0.125	-0.0930	-0.149	-0.118	-0.123	-0.0434
	(0.292)	(0.119)	(0.387)	(0.182)	(0.138)	(0.137)
Matrilineal Village	0.0176	0.0135	0.0413	0.0180	0.0189	0.0145
	(0.0129)	(0.0137)	(0.0276)	(0.0121)	(0.0180)	(0.0145)
Proportion of Fostered Orphaned	-0.0210	-0.0186	-0.0289	-0.0184	-0.0173	-0.0293
	(0.0294)	(0.0340)	(0.0493)	(0.0290)	(0.0375)	(0.0354)
Sample Size	17,203	14,777	16,639	17,203	15,891	15,525
Log Likelihood	150,471	145,435	128,623	150,468	135,568	138,468

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-4 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. Estimates for certain household types and preferences factors are omitted for conciseness. The parameters on the household type indicators are not per child, but the total allocation to all foster or non-foster children within the household. * p<0.1, ** p<0.05, *** p<0.01

shares to vary with whether any foster children worked in the previous week.[35] The parameter does not have a causal interpretation, but it allows me to determine if working more is associated with greater foster child consumption. These results are presented in column (1) of Table 4 and show no difference. I test this a different way by splitting the sample by whether foster children are working. In column (2), I exclude households with foster children that do not work from the sample, while column (3) restricts the sample to foster households where none of these children worked. Here, the results suggest that labour may matter in a limited way.

Foster children may also be treated better if their biological parents transfer money or goods (i.e., send remittances) to the household in which the foster child currently resides. In the data I observe the amount of remittances a household receives, but unfortunately I do not observe the source, nor the intended use of the money. Nonetheless, I examine whether foster children that reside in households that receive remittances are treated better. First, I include log remittances as a covariate in the foster child's resource share function. These results are presented in column (4) of Table 4. The results are not statistically different from zero. I then split the sample based on whether the foster-child's household received any remittances and present these results in columns (5) and (6). There does not appear to be a large difference in results across samples.

Robustness: I conduct several robustness checks in the Online Appendix. In Section A.2, I examine whether clothing is shared across foster and non-foster children. In Section A.3, I analyse the extent to which in-kind transfers to foster children may bias the foster child resource shares downward. I discuss the validity of the identification restrictions in Section A.4. Finally, I examine the impact of non-random selection of foster children into certain households has on the results in Section A.5.

5 Poverty Analysis

Resource shares are a desirable object to identify in part because they allow for the estimation of individual-level consumption. I can therefore use the predicted resource shares to estimate foster and non-foster child poverty rates that account for the unequal distribution of goods

[35] Child labour in Malawi is typically either for a household enterprise or farm, or short-term agricultural work on non-household farms known as *ganyu labour* (Dimova et al., 2015). In 2016, only 2 foster children in the sample had a long-term wage job. In Table 4, work includes the following activities: work for a household farm or enterprise, wage work, apprenticeships, and ganyu labour. It excludes household chores, such as fetching wood or water.

within the household. Importantly, everyone in the household may not be poor; it is possible for the adults to be living above the poverty line, but the children below it. Moreover, not all children need to be poor; non-foster children may be above the poverty line with the foster children below it, and vice versa. This analysis therefore differs from the more traditional approach to estimating poverty which relies on household-level measures that ignore intrahousehold inequality.

I classify adults as poor using a 76.89 MWK a day poverty line. This is the poverty line the World Bank uses for the 2016 Malawi Integrated Household Survey. For children, I use several different poverty lines based on the average age of foster or non-foster children in the household. Setting a single poverty line for children abstracts from potential inequality, as older children require more resources than younger children to maintain the same standard of living, and foster children tend to be significantly older than non-foster children. To determine these age-specific poverty lines, I assume that the child poverty line is proportional to the calorie requirements for children of that age relative to adults.[36] So if a six-year-old child requires half as many calories as an adult, then their poverty line would be half of the adult poverty line, or 38.44 MWK a day.

As a point of comparison, I calculate household-level poverty rates where I assume an equal distribution of resources within the household. The household-level poverty rates use the OECD adult equivalent scale, where the number of adult equivalents in the household is given by $1+0.5\times N_c+0.7\times(N_a-1)$, where N_c is the number of children and N_a is the number of adults. A household is poor if per adult equivalent consumption is less than 76.89 MWK a day. Since the OECD equivalence scale is somewhat arbitrary, the main focus of the poverty analysis is to examine relative levels of poverty across person types, rather than levels of poverty.[37]

Table 5 presents poverty rates for individuals by household size, defined by the number of children in the household. Columns (1) - (4) provide individual poverty rates computed using the predicted resource shares. I assume that consumption is allocated equally within a person type. As a result, poverty rates do not vary within a person type in a given household. Column (5) presents the household-level poverty rates. Comparing column (5) to the individual-level poverty rates clearly illustrates that traditional household-level measures fail to identify individuals who are poor, particularly women and children. This result is consistent with Dunbar et

[36] I use the United States Department of Health and Human Services estimated daily calorie needs by age. I abstract from gender differences for children and assume adults require 2400 calories per day.

[37] Adult equivalence scales are used to account for economies of scale in household consumption. Without estimating the consumption technology function (the A - Matrix in Section 2), the individual type-specific poverty estimates cannot account for economies of scale. While the consumption technology function can in principle be identified, as in Browning et al. (2013), I lack sufficient price data to estimate it. As a result the household and individual levels of poverty are not directly comparable.

Table 5: Estimated Poverty Rates by Household Size

Number of Children	Sample Size: # Households	Individual Poverty Rates				Assuming Equal Distribution
		Foster	Non-Foster	Men	Women	
		(1)	(2)	(3)	(4)	(5)
1	2,181	0.401	0.191	0.311	0.330	0.146
2	2,266	0.485	0.352	0.322	0.400	0.192
3	1,875	0.520	0.535	0.342	0.414	0.244
4	1,030	0.613	0.693	0.425	0.455	0.334
All Households		0.485	0.499	0.339	0.391	

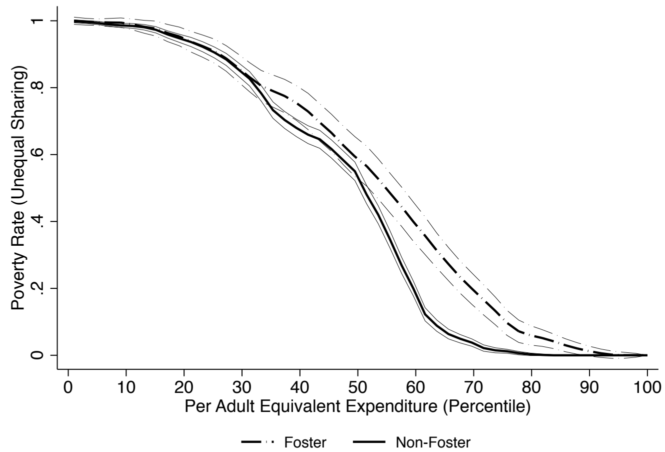
Notes: Malawi Fourth Integrated Household Survey (2016 only). A household is poor if per adult equivalent expenditures are less than 76.89 MWK a day. Individual poverty rates measure consumption as the product of predicted resource shares and total expenditure. The child poverty line is less than the adult poverty line and is determined based on the average age of foster or non-foster children in the household. The exact child poverty line is proportional to the calorie requirements for children of a given age relative to adults.

al. (2013) and recent work on using health measures to analyse the ability of household-level measures to capture individual-level poverty (Brown et al., 2016).

Comparing columns (1) - (2) of Table 5 alone does not suggest unequal treatment within the household. Poverty is determined by both inequality within the household, but also inequality across households. And importantly, household-level expenditure is correlated with both individual poverty rates and the presence of foster children; Children who are voluntarily fostered tend to live in households with the financial means to take care of additional children (Akresh, 2009).

Motivated by existence of inequality both across and within households, I present the results in a different way. I plot individual poverty rates for foster and non-foster children by percentiles of the per-adult equivalent household expenditure distribution. These results are displayed in Figure 4. As expected, individual poverty rates decline as household expenditure increases. For certain levels of household expenditure, foster child poverty (the black dashed line) is higher than non-foster child poverty (the blue solid line), and vice-versa. Again, there is no clear evidence of unequal treatment between foster and non-foster children. Household-level measures of poverty are similarly likely to misclassify foster and non-foster children as non-poor. Specifically, 32.8 percent of foster children living in non-poor households are themselves poor. For non-foster children, the rate of misclassification is 38.3 percent. Nonetheless, these results demonstrate the importance of accounting for intrahousehold inequality when designing policy as there are poor individuals living in non-poor households. To efficiently target anti-poverty programs, it is essential to accurately identify poor individuals, not just poor households.[38]

Figure 4: Individual Poverty Rates by Household Expenditure Percentile



Notes: The graph shows the proportion of different child types in 2016 who are poor at each per-adult equivalent household expenditure percentile. A lowess regression is used to fit the line. The 95% confidence intervals are provided.

6 Conclusion

The household is in many ways a black box to economists. Understanding the inner workings of the household is difficult and measuring the treatment of children within the household is far from straightforward. I build upon recent work by Dunbar et al. (2013) to demonstrate how resource shares can be identified using expenditure on partially assignable clothing. Like Dunbar et al. (2013), I rely on observing how clothing budget shares vary with household expenditure to identify resource shares. I differ in that I weaken the data requirements necessary for identification. Future work can use this methodology in other contexts where intrahousehold inequality is of interest, but assignable goods are not present in the data.

I use this new approach to measure inequality among children. While the unequal treatment of children is present in a variety of contexts, I focus on foster children in Malawi who live in situations that may leave them particularly susceptible to impoverishment. The findings of this paper demonstrate that for the most part, foster children are treated the same as other

[38] It is important to note that I am not making welfare statements about child fostering as an institution. Even if foster children sometimes receive a smaller share of household resources relative to other household members, the counterfactual of staying with their biological parents may result in a higher resource share, but lower total resources due to a smaller household budget.

children and that extended family members are capable caretakers. Nonetheless, I find that child poverty is being understated by poverty measures that rely on household-level measures of consumption. This result emphasizes the importance of designing government programs that target not just poor households, but specifically poor individuals. Household-level poverty rates may underestimate poverty rates for certain individual who have less power within the household, such as children. Future work should investigate heterogeneity in foster child treatment, which would benefit from connecting the findings of this paper with past research on *why* children are fostered (Ainsworth, 1995; Akresh, 2009; Beck et al., 2015). Bridging these two areas of study will help determine the underlying mechanisms that influence foster children treatment, and ultimately allow for better policy design.

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