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 favor certain children over others as consumption data is collected at the household level. 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, with the exception of orphaned foster children, whose consumption is 20 percent less than non-foster children.

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

JEL Codes: D1, I32, J12, J13

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1 Introduction

Do parents favor 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); 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

[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.

the 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 new 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

[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; Calvi (2016); Bargain et al. (2018). A related issue concerns the use of clothing as the assignable good. DLP require that clothing not be shared across men, women, and children and find evidence supporting this claim. However, this assumption is more worrisome in my context where I require clothing not be shared across different types of children. I analyse this issue in Section 5.

shares.[4] I differ from this literature in several ways. Unlike Lewbel and Pendakur (2008) and 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.[5] 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.[6] In Malawi, 12 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.[7] Children are fostered for many reasons, including child labour, education, 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.[8] I contribute to this literature by quantifying the extent of consumption inequality between foster and non-foster children.

[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).

[5] The cost of the weaker assumptions is that I cannot identify economies of scale in consumption.

[6] 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.

[7] 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.

[8] An exception is Case et al. (2000) who study how household food expenditures vary by the fostering status of the household's 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 relatives, are treated no differently than the household's biological children.[9] However, this is not the case for orphaned foster children. While there is little inequality if the foster child's parents are both alive, I find that on average, orphaned foster children consume 80 percent of what non-foster children consume when both are present. The results highlight the importance of kinship networks in the wellbeing of foster children. This finding also suggests that selection may play an important role as the reason households receive foster children may affect how these children are treated.

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 dramatically understates child poverty.[10] Furthermore, I show that orphaned foster child poverty is being miscalculated at an even higher rate. In particular, I find that 59.5 percent of orphaned foster children living in *non-poor* households, are themselves poor. 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 that specifically target orphans, such as the Kenya Cash Transfer for Orphans and Vulnerable Children program, may be more effective. 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 also 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. I test the model assumptions in Section 5. In Section 6, I conduct a poverty analysis using the structural results. I conclude in Section 7.

[9] The main results focus on consumption. I analyse education and child labour in Section A.2 of the Appendix.
[10] This finding is consistent with DLP, Brown et al. (2016), and Brown et al. (2018).

2 Collective Model of the Household

This section presents a structural model of Malawian households using the collective framework of Browning et al. (2013). 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 exactly the same. I index household types by the number of foster and non-foster children within the household, denoted by the subscript s.[11] Consistent with the standard characterization of collective households, I make no assumptions about the bargaining process which determines how resources are allocated across household members, only that the ultimate allocation is Pareto efficient.[12] I account for economies of scale in consumption using a Gorman (1976) linear technology function.[13] Individuals have caring preferences in the sense that they are allowed to get utility from the utility of other household members, though not the consumption of specific goods by the other household members.

Households consume K types of goods at market prices $p = (p^1, ..., p^K)'$. Let $z_s = (z_s^1, ..., z_s^K)$ be the K - vectors of observed quantities purchased by the household. The vector of unobserved quantities consumed by individuals within the household is denoted by $x_t = (x_t^1, ..., x_t^K)$. The household-level quantities are converted into private good equivalents x_t using a linear consumption technology as follows: $z_s = A(\sigma_f x_f + \sigma_m x_m + \sigma_a x_a + \sigma_b x_b)$ where A is a $K \times K$ matrix which accounts for economies of scale in consumption,[14] 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 A takes a value of one with all off-diagonal elements in that row and column equal to zero.

Each individual member has a monotonically increasing, continuously twice differentiable strictly quasi-concave utility function over a bundle of goods. Let $U_t(x_t)$ be the utility of an

[11] I occasionally denote household type by s_{ab} to explicitly indicate the number of foster and non-foster children within the household. For example, s_{21} denotes a household with two foster children, and one non-foster child.

[12] Pareto efficiency in household consumption allocations has been analysed in many different contexts and usually cannot be rejected. Notable papers that analyse this assumption include Browning and Chiappori (1998), Bobonis (2009), and Attanasio and Lechene (2014). Pareto efficiency has at times been rejected in the context of household agricultural production decisions, especially in West Africa. See Udry (1996) for example.

[13] See Browning et al. (2013) for a detailed explanation of accounting for economies of scale and sharing in collective households.

[14] The use of private good equivalents was introduced in Browning et al. (2013). This approach differs from the Chiappori (1988, 1992) 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.

individual of type t who consumes x_t goods while living in the household. This utility function is assumed to be separable from leisure, savings, or any other goods not included in the commodity bundle. Individuals of the same type are assumed to have the same utility function.

Each household maximizes the Bergson-Samuelson social welfare function, $\tilde{U}$ where each individual's utility function is discounted by the Pareto weights $\mu_t(p/y)$ where y is total household expenditure:

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

The household then solves the following maximisation problem:

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

Solving this system results in bundles of private good equivalents. If these goods are priced at within household prices $A'p$, I obtain the *resource share* η_s^t, which is defined as the fraction of total expenditure that is allocated to each individual of type t.[15] By definition, resource shares for men, women, foster, and non-foster children sum to one. I will ultimately 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 x_t to maximize their own utility function U_t subject to the shadow budget constraint $\sum_k A_k p^k x_t^k = \eta_s^t y$. This formulation facilitates the derivation of the household-level demand functions that are necessary to identify resource shares.

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).

[15] 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.

Private assignable goods have the benefit of having relatively simple household-level demand functions. In effect, there are only two reasons that households would demand more of a private assignable good, such as men's clothing: (1) men have a strong preference for clothing, or (2) men control a large share of the budget, i.e., they have a high resource share. In contrast, there are many reasons why households purchase varying amounts of non-private goods, such as electricity. For assignable clothing, the only challenge is to separately identify resource shares from clothing preferences.

Let $W_s^t(y,p)$ 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]

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

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 $A'p$. Resource shares and the individual demand functions are not observable, and hence the system is not identified without more assumptions (for each equation there are two unknown functions).[17]

3 Identification

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 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, children's clothing in particular, 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

[16] See Section A.3 for the 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. In these types of households, the household and individual demand functions are the same.

partially assignable goods in Sections 3.2. An alternative method is provided in the Appendix in Section A.1. Throughout this discussion, I emphasize where and why I differ.

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.

For expositional reasons, I assume individuals have preferences over clothing given by a piglog indirect utility function (Deaton and Muellbauer, 1980): $V_t(p, y) = b_t(p)(\ln y - a_t(p))$. A more general functional form is used in the Appendix. Using Roy's identity, the budget share functions are written as follows:

$$w_t(p, y) = \delta_t(p) + \beta_t(p)\ln y \tag{4}$$

where $\delta_t(p)$ is a function of $a_t(p)$ and $b_t(p)$, and $\beta_t(p)$ is minus the price elasticity of $b_t(p)$ with respect to the price of person t's assignable good. Substituting Equation (4) into Equation (3) results in the system of clothing Engel curves given below:

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

where W_s^t are budget shares for the private assignable good for person type t in household s. I drop prices from Equation (5) 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.[18] Resource shares can however depend on variables highly correlated with expenditure, such as household member wages, remittances, or wealth.

[18] Menon et al. (2012) show this assumption to be quite reasonable. They rely on a household survey question 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. Lastly, resource shares need to be independent of household expenditure only at low levels of household expenditure.

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 $\beta_s^t = \beta_s$.[19]

The SAT restriction was first used in Lewbel and Pendakur (2008) and is equivalent to assuming price differences across household types can be absorbed into an income deflator. 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 housing may have an effect on each person's demand for clothing. However, under SAT, this price change can only affect the demand for clothing through a person-specific income deflator. The identification method developed in Section 3.2 builds upon this similarity assumption.[20]

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 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 goods using private partially assignable goods.

3.2 Identification with Private Partially Assignable Goods

Without private assignable goods for foster and non-foster children, I rewrite the Engel curves for foster and non-foster child clothing in System (5) as a single Engel curve for children's

[19] 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.

[20] Bargain et al. (2018) use a unique Bangladeshi data set with observable individual-level consumption to directly test the SAT restriction. Their results provide strong evidence in support of this assumption.

clothing, and I begin by imposing the SAT restriction (i.e., $\beta_s^t = \beta^t$):

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

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 (5) 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 5.1, 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.

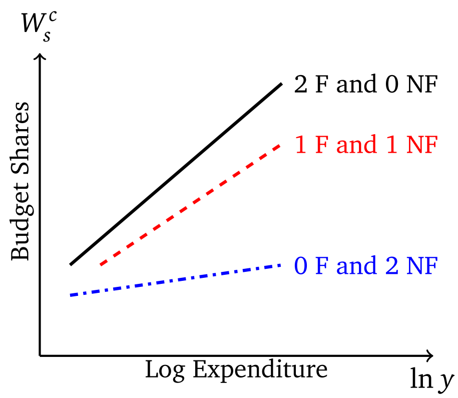
Suppose there are four one-child-type households $s \in \{s_{10}, s_{20}, s_{01}, s_{02}\}$ where, for example, s_{10} denotes a household with one foster child and no foster children.[21] I can use a simple counting exercise to show that the order condition is satisfied. With three Engel curves for 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 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.[22] 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 the one-child-type households is provided in the 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*

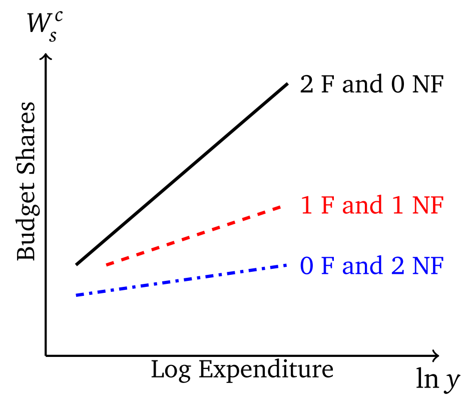
[21] In the empirical application the sample includes households with as many as five children.

[22] 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 to identify resource shares, however it is unnecessary to identify the intercept preference parameter δ_s^t and it is therefore ignored.

Figure 1: Graphical Intuition for Identification



(a)



(b)

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.

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 as their expenditure increases 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 Appendix in Section A.5. I discuss potential violations to this identification approach in Section 5.

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.

4 Application: Child Fostering in Malawi

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 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.[23] Figure 2a presents the percentage of children fostered by age in Malawi (the green solid line). Overall, 12.5 percent of children are fostered (Malawi Integrated Panel Survey 2013), and fostering rates are increasing with age. The red and blue lines show the number of children living away from their father and mother, respectively.[24] 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.

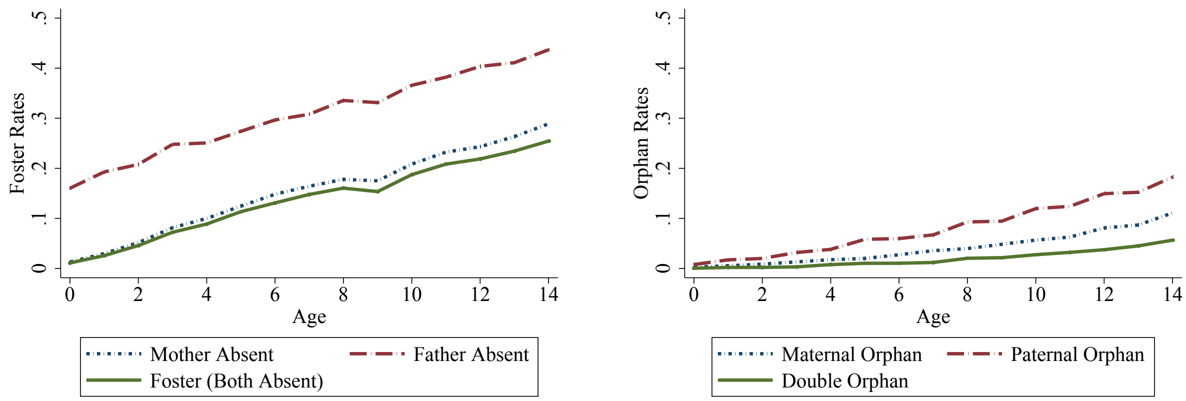
The literature divides foster children into two categories: those who are fostered for voluntary reasons, and those who are not (Serra, 2009). Non-voluntary, or crisis fostering occurs when the child is orphaned, or has parents who are ill and unable to care for their child. Non-voluntary fostering has become substantially more common as a result of the AIDS epidemic. Voluntary, or purposive child fostering occurs when the child's parents voluntarily send the child to another household. There are a myriad of reasons parents may choose to do this: to provide educational access for the child, to strengthen kinship networks, to increase fertility, to reallocate child labour across households, or due to agricultural shocks.[25] Children are also often fostered as a result of their parents divorce and subsequent remarriage (Grant and Yeatman, 2014). This is especially prevalent in Malawi as almost half of all marriages end in divorce, with remarriage rates being equally high (Reniers, 2003).

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

[24] Fathers are more likely than mothers to live away from their children, potentially due to migration for work, or the AIDS epidemic.

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

Figure 2: Foster and Orphan Status by Age



(a) **(b)**

Notes: Malawi Integrated Panel Survey 2013. 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, and I find that this distinction matters for foster child treatment.

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 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 favor non-foster children. Unfortunately, I am unable to test this hypothesis given the available data.

4.2 Data

I use the Malawi Integrated Households Survey (IHS3) 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. Both 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.2, I use the data on education and employment to study the relationship between fostering, school enrollment, 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 10,763 households. For ease of estimation, I exclude households that have less than one or more than four men and women, or less than one or more than five 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 Appendix in Table A5.

Table 1 reports descriptive statistics for the estimation sample. Households have on average 5.27 individuals. The average age of foster children (9.26) is significantly higher than that of non-foster children (5.80). This is consistent with child labour and education being reasons households foster children. Roughly 37 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 126,580 MWK (approximately US$ 1,147).[26] Lastly, households spend a large fraction of their income on food (62 percent), which consistent with the high level of poverty in Malawi.

[26] The median per capita household expenditure is considerably lower at US$ 871.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Sample Size
Household Characteristics					
Household Size	5.273	1.712	3	13	10,763
Men	1.394	0.713	1	4	10,763
Women	1.344	0.646	1	4	10,763
Children	2.580	1.254	1	5	10,763
Non-Foster	2.305	1.370	0	5	10,763
Foster	0.275	0.696	0	5	10,763
Per Capita Total Expenditures (1000s MWK)	126.58	106.58	145.63	1,266.38	10,763
Men's Clothing Budget Shares	0.006	0.014	0	0.142	10,763
Women's Clothing Budget Shares	0.009	0.016	0	0.139	10,763
Child's Clothing Budget Shares	0.009	0.017	0	0.149	10,763
Food Budget Shares	0.625	0.137	0.077	0.963	10,763
Preference Factors					
Year=2010	0.744	0.436	0	1	10,763
Average Age Foster Children	9.255	3.343	0	14	1,933
Average Age non-Foster Children	5.803	3.397	0	14	9,864
Proportion Orphaned of Foster Children	0.376	0.467	0	1	1,933
Proportion One Parent Absent of Non-Foster Children	0.139	0.330	0	1	9,864
Proportion Female of non-Foster	0.502	0.365	0	1	9,864
Proportion Female of Foster	0.554	0.447	0	1	1,933
Average Age Women	30.560	10.831	15	99	10,763
Average Age Difference (Men-Women)	1.96	12.658	-77	60	10,763
Education Men	6.666	3.719	0	14	10,763
Education Women	5.180	3.646	0	14	10,763
Share Women Age 15-18	0.077	0.183	0	1	10,763
Share Men Age 15-18	0.114	0.247	0	1	10,763
Rural	0.804	0.397	0	1	10,763
Matrilineal Village	0.608	0.488	0	1	10,763
North	0.200	0.400	0	1	10,763
Central	0.369	0.483	0	1	10,763
South	0.431	0.495	0	1	10,763

Notes: Households with 1-4 men and women, and 1-5 children. Children are age 14 or younger. Malawi Third Integrated Household Survey and Integrated Household Panel Survey.

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. To match the data used in the empirical analysis, I now explicitly account for households with multiple men and women with σ_f and σ_m denoting the number of women and men, respectively.

$$
\begin{aligned}
W_s^m &= \sigma_m \eta_s^m \left[\delta_s^m + \beta_s^m \ln(\eta_s^m)\right] + \sigma_m \eta_s^m \beta_s^m \ln y + \epsilon_m \\
W_s^f &= \sigma_f \eta_s^f \left[\delta_s^f + \beta_s^f \ln(\eta_s^f)\right] + \sigma_f \eta_s^f \beta_s^f \ln y + \epsilon_f \\
W_s^c &= \sigma_a \eta_s^a \left[\delta_s^a + \beta_s^a \ln(\eta_s^a)\right] + \sigma_b \eta_s^b [\delta_s^b + \beta_s^b \ln(\eta_s^b)] + \\
&\quad (\sigma_a \eta_s^a \beta_s^a + \sigma_b \eta_s^b \beta_s^b) \ln y + \epsilon_c
\end{aligned}
\tag{7}
$$

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, δ_s^t, and β_s^t are all linear functions of the preference factors provided in Table 1. 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. Resource shares for foster children are then parameterized as follows:

$$
\eta_s^a = \underbrace{\Big(\sum_{i=0}^{5} \sum_{j=0}^{5} \eta_{s_{ij}}^a I\{s_{ab} = s_{ij}\} \Big)}_{\text{Household type indicators}} + X'\gamma, \qquad 1 \le i + j \le 5
$$

where the first set of terms are the indicators for household types. The vector of household characteristics is given by X. Resource shares for non-foster children are parameterized similarly. 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.[27]

To identify resource shares, I restrict the slope preference parameter to be the same across household sizes, and across composite and one-child type households. This is the key assumption discussed in Section 3.2. Moreover, I restrict the ratio of foster child resource shares in two different household types be independent of the number of non-foster children present, and vice versa: $\eta_{s_{a0}}^a / \eta_{s_{a+1,0}}^a = \eta_{s_{ab}}^a / \eta_{s_{a+1,b}}^a$ and $\eta_{s_{0b}}^b / \eta_{s_{0,b+1}}^b = \eta_{s_{ab}}^b / \eta_{s_{a,b+1}}^b$. This restriction is in line with the alternative identification approach presented in Section A.1 of the Appendix, and is imposed to ensure that the model converges. In words, this restriction requires that the ratio of foster child resource shares in households with σ_a and σ_{a+1} foster children is independent

[27] 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.

of the number of non-foster children present. The same is true in the opposite direction. I test this assumption in Section A.1, and fail to reject that the ratios hold.

Lastly, I would ideally like to estimate resource shares separately for orphaned and non-orphaned foster children. However, given the small number of orphans in the sample, this is infeasible. Instead, I include the proportion of foster children who are orphaned as a covariate of the resource share functions. Other studies have used this method to identify inequality among children by allowing the child resource share function to vary with certain characteristics such as gender and age (Bargain and Donni, 2012; Dunbar et al., 2013). However, identifying inequality among children in this fashion requires strong similarity assumptions across children in preferences and resource shares. In contrast, the identification approach I develop in this paper to identify inequality among foster and non-foster children is significantly more general. Nonetheless, I am forced to impose strong similarity assumptions across orphaned and non-orphaned foster children to identify inequality among them.[28]

4.4 Results

I begin by presenting average predicted resource shares for men, women, non-foster, and foster children (η_s^t) 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 percent of the household budget, while the average foster child consumes only 10.3 percent. This however does not imply unequal treatment because foster children tend to live in larger households, and therefore they are splitting the household budget across more individuals. This motivates comparing foster and non-foster child resource shares for a given household size.

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

[28] In some specifications I interact the proportion of foster children who are orphaned with other covariates, such as gender and an indicator for rural residence. This allows foster child resource shares to vary somewhat flexibly with the share of foster children who are orphaned.

Table 2: Predicted Resource Shares

	Observations	Mean	Median	Std. Dev.
	(1)	(2)	(3)	(4)
Men	10,763	0.368	0.404	0.118
Women	10,763	0.297	0.297	0.087
Non-Foster Children	9,864	0.110	0.099	0.040
Foster Children	1,933	0.103	0.099	0.040

Notes: Malawi Third 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 1-5 children.

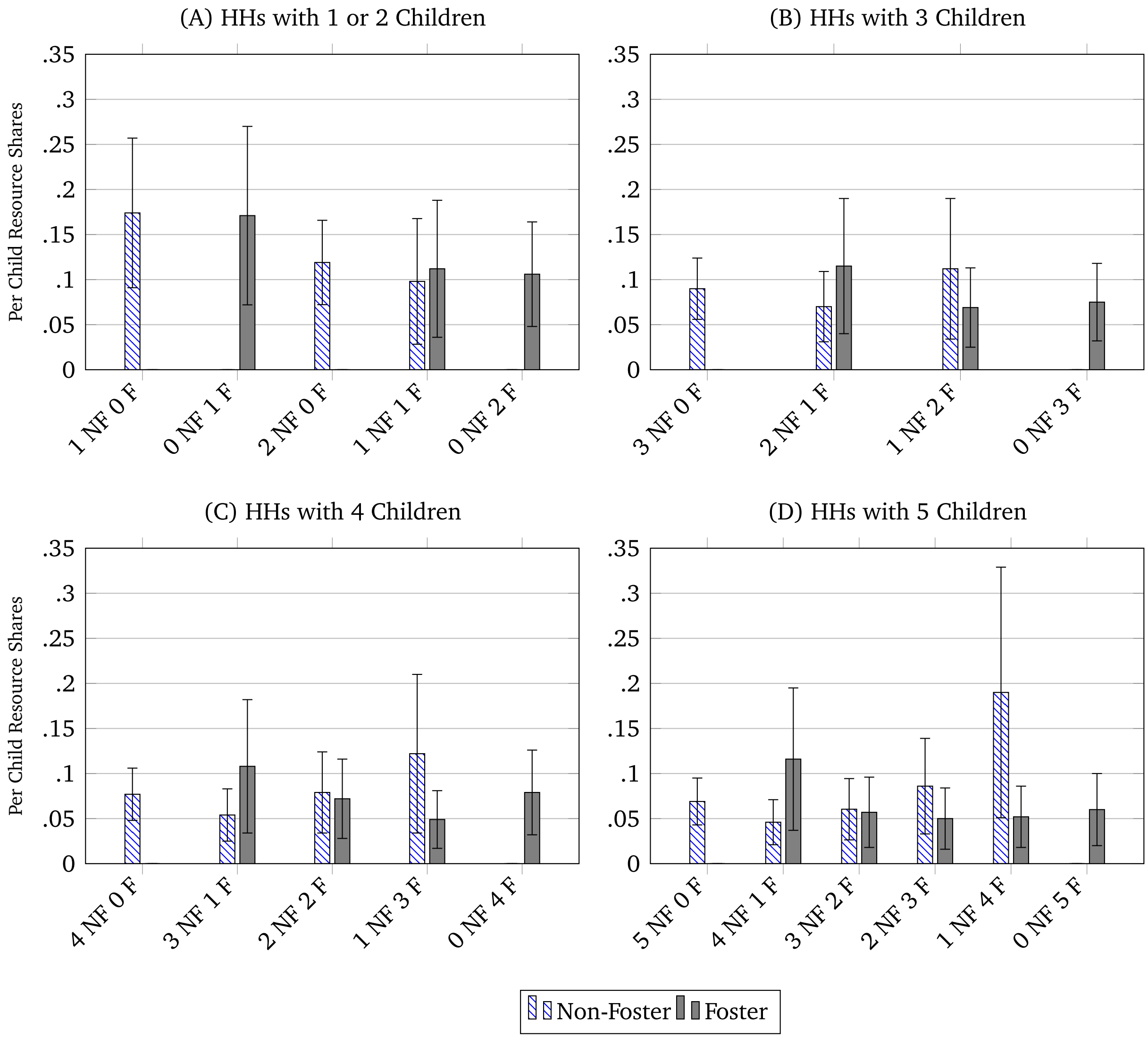
hold with one man, one woman, and all other covariates set to their median value.[29] [30] The brackets are the 95 percent confidence intervals of the predicted values.

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 17.4 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 17.1 percent of the household budget. This provides little evidence of discrimination. Panels B, C, and D present the results for households with three, four, and five total children respectively, and again, the results do not demonstrate a systematic pattern of unequalt treatment towards foster children. It should be emphasized that this lack of unequal treatment is for households with all covariates at their median value, and that the median foster child is non-orphaned. I therefore examine how heterogeneity in these covariates, such as orphanhood, relate to foster child treatment.

Tables A6 and A7 in the Appendix present the parameter estimates of the resource share functions for foster and non-foster children. Table A6 focuses on the preference factors (i.e., the demographic characteristics of the household) whereas Table A7 displays the household type indicators.[31] Most of the preference factors are insignificant suggesting that household composition is what matters in how resources are allocated within the household.[32] One exception is the proportion of foster children who are orphaned. I find that orphaned foster children

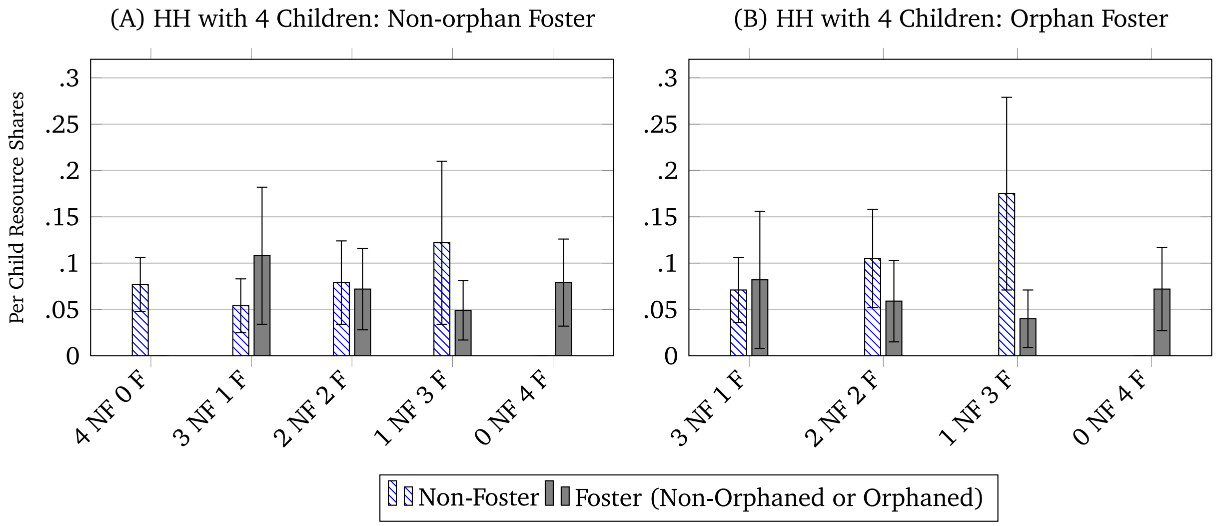
[29] Instead of using the median value for foster and non-foster child age, I set both to seven to make the predicted resource shares more comparable.
[30] Using mean values for the predictions instead of median values does not meaningfully affect the results.
[31] Because most of the covariates are demeaned, the indicators for the household type variables are largely similar to the predicted values found in Figure 3.
[32] This is consistent with the findings of Brown et al. (2018) in Bangladesh.

Figure 3: Predicted Resource Shares: Reference Household



Note: Malawi Third 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.

Figure 4: Predicted Resource Shares by Presence of Orphans



Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. Robust standard errors. The brackets are the 95 percent confidence intervals. Panels A and B present predicted foster and non-foster child resource shares for households with four children. In Panel A, all covariates are set to the median value of households with no orphaned foster children present. Panel B sets all covariates to the median value of households with orphaned foster children present. Predicted values are computed assuming households have one man and one woman. Comparing panel A with panel B demonstrates differences in treatment for foster children by orphan status.

consume 79.6 percent of what non-foster children consume when both are present.

To better illustrate the importance of orphanhood in foster child treatment, Figure 4 presents the predicted resource shares for households where the foster children are orphaned. The earlier predicted resource shares in Figure 3 were for households with non-orphaned foster children, as the median foster child is non-orphaned. To facilitate a comparison between non-orphaned and orphaned foster children, I reproduce the results from Figure 3 for households with four children in panel (A) while in panel (B), I present the predicted resource shares for non-foster and orphaned foster children. The results illustrate a clear pattern of unequal treatment of orphaned foster children relative to non-fostered children. For example, focusing on households with two non-foster children and two foster children ("2 NF 2 F"), when the foster children are non-orphaned, the predicted per child resource shares for non-foster and foster children are 7.9 and 7.1 percent, respectively. However, when the foster children are orphaned, the predicted per child resource shares are now 10.5 and 5.9 percent for non-foster and foster children. Similar differences are found across the different household types.

I estimate several other specifications. First, I estimate a more flexible model that allows for the relationship between orphanhood and foster child treatment to vary with both gender and rural residence. These results are provided in Table A8. For conciseness, I again limit the parameter estimates displayed in the table to several preference factors and household type indicators. Columns (2a) and (2b) present the results for non-foster and foster children respectively, whereas columns (1a) and (1b) reproduce the main results as a point of comparison. The number of interactions make a clean interpretation of the relationship between orphanhood and foster child treatment difficult, however, the results still suggest the extent of unequal treatment between foster and non-foster children increases with the presence of orphaned foster children. I next limit the sample to only nuclear households with one man and one woman who are married.[33] Columns (3a) and (3b) or Table A8 display these results. While several parameter estimates differ in magnitude, none are statistically different.

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 vera (the ratio restrictions discussed briefly in Section 4.3 and more thoroughly in Section A.1). 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). 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. Lastly, in column (4) I impose every restriction. Columns (1a) - (4a) present the results for non-foster children, and columns (1b) - (4b) do the same for 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 large standard errors. Moreover, using this approach requires dropping several household types in order for the system to converge. Across specifications, none of the parameter estimates on the household type indicators are statistically different, and overall are quite 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 different across people), while simultaneously having standard errors that are significantly more precise than the results presented in columns (1a) and (1b).

[33] Only 54.7 percent of the estimation sample households consist of a single married couple with no other adult men or women present. Because of the much smaller sample size I limit the number of preference factors and household types, but the results are quantitatively similar.

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	0.260***	0.280***	0.271***	0.238***				
	(0.0939)	(0.080)	(0.067)	(0.072)				
1 Non-Foster 1 Foster	0.121	0.139**	0.129**	0.134**	0.135	0.109*	0.143**	0.135*
	(0.104)	(0.063)	(0.055)	(0.064)	(0.121)	(0.060)	(0.061)	(0.071)
0 Non-Foster 2 Foster					0.225*	0.211***	0.297***	0.238***
					(0.134)	(0.082)	(0.078)	(0.085)
3 Non-Foster 0 Foster	0.303***	0.313***	0.311***	0.279***				
	(0.0992)	(0.085)	(0.068)	(0.074)				
2 Non-Foster 1 Foster	0.153	0.180**	0.177***	0.192***	0.154	0.112*	0.139**	0.117*
	(0.130)	(0.071)	(0.062)	(0.070)	(0.121)	(0.059)	(0.058)	(0.067)
1 Non-Foster 2 Foster	0.135**	0.152**	0.135**	0.123*	0.210	0.136**	0.194**	0.192**
	(0.056)	(0.066)	(0.056)	(0.064)	(0.136)	(0.067)	(0.070)	(0.080)
0 Non-Foster 3 Foster					0.274*	0.222**	0.347***	0.279***
					(0.152)	(0.089)	(0.087)	(0.097)
Covariates								
Average Age non-Foster	1.887**	-0.125	2.089**	0.838	0.0720	-0.287	-0.623	-0.041
	(0.914)	(0.830)	(0.848)	(0.926)	(1.227)	(0.813)	(0.935)	(0.986)
Average Age non-Foster^2	-0.0622	0.046	-0.104	-0.038	0.00257	0.042	0.058	0.014
	(0.0642)	(0.061)	(0.065)	(0.070)	(0.0859)	(0.059)	(0.068)	(0.070)
Average Age Foster	-2.347	-2.240	-1.316	-0.712	2.822	0.969	2.590	1.985
	(3.138)	(1.791)	(2.245)	(2.830)	(1.937)	(1.201)	(3.141)	(8.010)
Average Age Foster^2	0.124	0.129	0.088	0.043	-0.118	-0.035	-0.138	-0.100
	(0.170)	(0.103)	(0.128)	(0.161)	(0.120)	(0.069)	(0.175)	(0.425)
Matrilineal Village	0.00551	0.016	0.007	0.010	0.0295	0.026	0.025	0.017
	(0.0184)	(0.017)	(0.016)	(0.016)	(0.0227)	(0.017)	(0.016)	(0.016)
Proportion of	0.0462	0.052*	0.054	0.042	-0.0451	-0.025	-0.018	-0.021
Fostered Orphaned	(0.0412)	(0.029)	(0.034)	(0.037)	(0.0418)	(0.019)	(0.036)	(0.039)
N	10,433	10,763	10,763	10,763	10,433	10,763	10,763	10,763
Log Likelihood	88,450	92,402	92,323	92,332	88,450	92,402	92,323	92,332

Notes: The sample includes all households with 1-4 men and women, and 1-5 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

Moreover, this estimation has the highest log likelihood.

5 Robustness

5.1 Is Clothing a Private Good?

The model requires that clothing is not shared across person types. This assumption means that foster children cannot share clothing with non-foster children, and vice versa.[34] Hand-me-down clothing is a separate issue that is discussed shortly. While this assumption may at first seem worrisome, there are several reasons it is not of too great a concern. First, clothing includes shoes and school uniforms, both of which are difficult to share. Second, foster children are typically different ages than the non-foster children within the household; Fostering is often used to balance the demographic structure of the household in order to maximize household production (Akresh, 2009). As a result, it is somewhat rare to have a foster and non-foster child of the same age and gender in a given household.

To examine the merit of this assumption, I drop all households with both foster and non-foster children in any of the following age groups: 0-3, 4-7, 8-11, and 12-14, and re-estimate the model. Since foster and non-foster children in different age groups are unlikely to share clothing, I can confidently assume clothing is private in this restricted sample. Table A9 in the Appendix presents the results. In the age-restricted sample, resource shares for the both foster and non-foster children are not statistically different from the unrestricted results, but they are slightly larger in magnitude. This small increase could be due to sharing. Note, however, that resource shares increase by a similar amount for both foster and non-foster children, suggesting that inequality across child types is not affected by the sharing of clothes.

Given the age difference of foster and non-foster children, one might further be concerned about hand-me-down clothing. Specifically, the amount of hand-me-down clothing in composite households may differ from the amount in one-child-type households, and therefore assuming any similarity in clothing Engel curves across household types is unrealistic. In the model and estimation, I define children's clothing expenditures to be the amount the household spends on children's clothing within the past year (i.e., purchased clothing). For the identification assumptions to be violated, the relationship between hand-me-down clothing and purchased clothing would have to be different in composite and one-child-type households in such a way that is correlated with total expenditure. To see why, first note that preferences

[34] If I instead studied inequality between boys and girls, this issue of sharing becomes significantly less problematic as clothing is often gender-specific. Thus, any concerns about sharing are partly due to the nature of child fostering, and less so with the identification method in general.

for purchased clothing do not have to be identical across composite and one-child-type households. Preferences just have to be similar; Preferences for purchased clothing can differ across composite and one-child-type households in the intercept preference parameter δ_s^t, but not the slope parameter β^t of Equation (6). As a result, if foster or non-foster children consume a large amount of hand-me-down clothing, then they would have a lower δ_s^t in the Engel curve for purchased clothing. This is allowed. A violation could occur if the existence of hand-me-down clothing affects the marginal propensity for foster or non-foster children to consume purchased clothing (i.e., β^t).

5.2 Are the Restrictions Valid?

In Section 3.2, I impose some similarity in the clothing Engel curves across households with only foster or non-foster children, and those with both. So I first ask, are one-child-type and composite households similar? To answer this question, I compute sample means of different household characteristics for one-child-type and composite households. If households with only foster (or non-foster) children differ from composite households over observable characteristics, that may suggest they differ in unobservable ways, which may limit the validity of the restrictions. Table A12 presents sample means for several household characteristics by the different household compositions.

The results are mostly positive; encouragingly, foster and non-foster child characteristics, such as age and gender, do not seem to vary much between one-child-type and composite households. Unfortunately, adult characteristics, such as age and education, differ across one-child-type foster households and the composite households. The underlying reason for this is that households that have only foster children tend to be households where the foster children are cared for by grandparents, while in composite households foster children are typically cared for by their aunt and uncle, who have their own non-foster (biological) children. Table A13 presents the percentage of foster children cared for by different relatives in households with only foster children, and in households with both foster and non-foster children.

Since one-child-type and composite households do seem to differ in some ways across the entire sample, I next examine if there is overlap among subsamples of the different household types. To do this, I select two subsamples of one-child-type households (foster only and non-foster only) that are most similar to the composite households using a propensity score matching procedure.[35] The results are presented in Table A14. Columns (1) and (2) compare

[35] I use nearest neighbour propensity score matching, where households are selected based on the covariates listed in Table 1. In comparing non-foster one-child-type households with composite households, I drop one-child-type households and match them with the full sample of composite households. When I compare foster

households with only non-foster children to households with both non-foster and foster children. I do the same for foster one-child-type households in columns (3) and (4). None of the estimated means are statistically different across the matched subsamples. Then since the model does allow for observable heterogeneity in the resource share parameters, concerns regarding potential violations due to differences in composite and one-child-type households are likely minimal.

Lastly, it is useful to note that in principle, these restrictions are testable with additional data. If I observed assignable goods for foster and non-foster children, I could analyse how preferences vary across household types. I leave that for future work.

5.3 Is There Selection Bias?

Foster and non-foster children are not randomly assigned into households. The decision to foster one's children, and the decision to receive a foster child is a complicated process. Furthermore, households that decide to accept a foster child may be different from households without foster children in unobservable ways that are correlated with the treatment of foster and non-foster children. For example, a household with non-foster children that refuses to take in a foster child may do so because they prefer to devote more resources to their own biological children.

In this paper, I do not model the fostering decision as others have done (Ainsworth, 1995; Akresh, 2009; Serra, 2009), but instead analyse child welfare conditional on being in a given household. In other words, I do not analyse the causal effect of living in a foster household on child treatment. I am more interested in a descriptive analyses of the wellbeing of children currently being fostered. Nevertheless, I briefly examine whether or not selection of children into different household types affects foster and non-foster child treatment. The primary concern is that there is a subset of one-child-type, non-foster households who are driving the results, and that these households are different in unobservable ways from the composite households. If this were true, imposing any similarity between these different household types may be problematic. To determine the severity of this concern, I attempt to drop these "problem" households. I conduct a matching exercise to select a subsample of one-child-type, non-foster households that are most similar to the composite households using nearest neighbour propensity score matching.[36] I estimate the model on the subsample of one-child-type households and compare these results to the main results from Section 4.4 in Table A15. Columns (1) and (2)

one-child-type households with composite households, I select a subsample of similar one-child-type foster households and composite households.

[36] See Table A14 columns (1) and (2).

display the predicted per non-foster child resource shares for a reference household. Column (1) presents the results for the full sample, while column (2) does the same for the restricted sample. Overall, there are no statistical differences between the results, suggesting that for non-foster children, selection bias is not too great of a concern.[37]

6 Poverty Analysis

6.1 Household vs. Individual Poverty Rates

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 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. In a setting where intrahousehold inequality is likely, accounting for an unequal distribution of resources is essential, and highly relevant for accurately targeting anti-poverty programs.

I classify adults as poor using a US $1.90 a day poverty line.[38] 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.[39] 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 US $0.95 a day. The choice of poverty line is arbitrary, however the results are still somewhat comparable to DLP as the average child poverty line across all ages is roughly 60 percent of the adult poverty line, which is the child poverty line used by DLP for children of all ages.

As a point of comparison, I calculate household-level poverty rates where I assume an equal

[37] I lack a sufficient number of households to proceed with a similar analysis of one-child-type foster households.
[38] This is the World Bank 2011 extreme poverty line.
[39] 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.

distribution of resources within the household. The household-level poverty measures 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 US $1.90 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 individuals, rather than levels of poverty.[40]

Table 4 presents poverty rates for individuals by household size, defined by the number of children in the household. Columns (1) - (5) provide individual poverty rates computed using the predicted resource shares. Column (6) presents the household-level poverty rates.[41] Comparing column (6) 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 DLP and recent work on using health measures to analyse the ability of household-level measures to capture individual-level poverty (Brown et al., 2016). Moving to the individual poverty rates, I separate orphaned from non-orphaned foster children to emphasize differences in foster child treatment by orphan status. This choice is motivated by the results in Section 4.4, and as expected, orphaned foster child poverty rates are greater than non-orphaned foster child poverty. For example, comparing households with either one non-orphaned foster child, or one orphaned foster child, I find that 33.7 percent of non-orphaned foster children are poor, whereas 53.0 percent of orphaned foster children are poor.

Comparing columns (1) - (3) of Table 4 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), and selection into wealthier households likely occurs more frequently for non-orphaned children as they are *purposively* fostered. On the other hand, orphans are more likely to be involuntarily fostered into a household that may not have the means to care for them.

Motivated by existence of inequality both across and within households, I present the results in a different way. I plot individual poverty rates for non-foster, orphaned foster, and non-orphaned foster children by percentiles of the per-adult equivalent household expendi-

[40] 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.

[41] Using a per-capita poverty line as opposed to a per-adult equivalent one results in a household-level poverty rate of 37.3 percent across all household sizes, which is significantly above the per-adult equivalent measure.

Table 4: Estimated Poverty Rates by Household Size

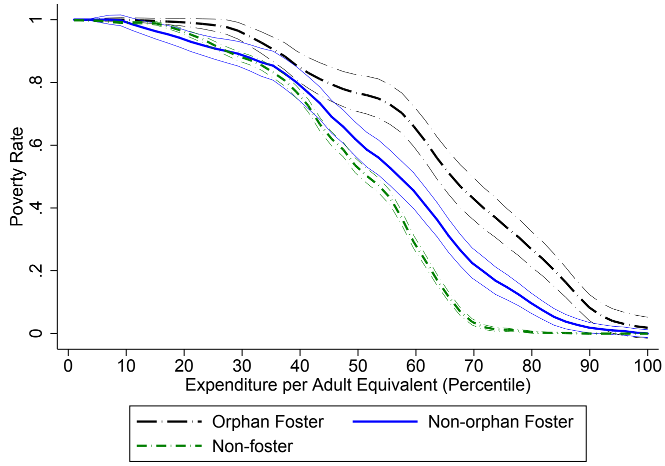
Number of Children	Sample Size: # Households	Individual Poverty Rates					Assuming Equal Distribution
		Foster		Non-Foster	Men	Women	
		Non-Orphaned (1)	Orphaned (2)	(3)	(4)	(5)	(6)
1	2,639	0.337	0.530	0.188	0.153	0.237	0.090
2	2,840	0.489	0.576	0.350	0.142	0.275	0.119
3	2,595	0.540	0.664	0.520	0.162	0.301	0.167
4	1,777	0.513	0.742	0.642	0.199	0.318	0.225
5	912	0.640	0.864	0.692	0.204	0.344	0.261
	10,763	0.500	0.672	0.524	0.165	0.286	0.167

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. A household is poor if per adult equivalent expenditures are less than $1.90 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.

ture distribution. These results are displayed in Figure 5. As expected, individual poverty rates decline as household expenditure increases. However, for certain levels of household expenditure, orphaned foster child poverty (the blue dashed line) is significantly higher than non-foster child poverty (the green solid line). This result suggests that orphaned foster children often live below the poverty line, despite living in households that are not considered poor. In effect, household-level measures of poverty are likely to misclassify orphaned foster children as non-poor more frequently than both non-foster and non-orphaned foster children. Specifically, 59.5 percent of orphaned foster children living in non-poor households are themselves poor. For non-orphaned and non-foster children, the rate of misclassification is 43.2 percent and 41.7 percent, respectively. These results demonstrate the importance of accounting for intrahousehold inequality when designing policy. To efficiently target anti-poverty programs, it is essential to accurately identify poor individuals, not just poor households.

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.

Figure 5: Individual Poverty Rates by Household Expenditure Percentile



Notes: The graph shows the proportion of different child types 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.

6.2 Why are Orphans Treated Worse?

The above poverty rates suggest that orphaned foster children are somewhat disadvantaged in terms of intrahousehold consumption allocations. I next examine one potential explanation for this unequal treatment: non-orphaned foster children have a better outside option.[42] More specifically, since both of their biological parents are alive, non-orphaned foster children can potentially return to live with their parents. Foster children who have lost at least one parent, on the other hand, do not have that same advantage. From the perspective of Nash bargaining, non-orphaned foster children have a higher threat point. To determine the plausibility of this hypothesis, I take advantage of the panel structure of the data and compute the probability of a foster child in 2010 being in the same household in 2013. If orphaned foster children are more likely to still be present, that suggests their outside option is worse, as they are forced to remain in their current household. I assign children into four mutually exclusive groups: non-orphaned non-foster (g=1); orphaned non-foster (g=2); non-orphaned foster (g=3); orphaned foster (g=4). I then estimate the following probit regression:

$$Y_{ihsg} = \alpha + \gamma_1 O_i + \gamma_2 F_i + \gamma_3 (O_i \times F_i) + \psi_s + X_{ih}\delta + \epsilon_{ihsg} \quad (8)$$

[42] Another potential explanation is due to differences in child labour, i.e., children who work more require more resources, and orphans work less as they are physically unable to participate in certain strenuous occupations (e.g., agriculture). I investigate this in Section A.2 in the Appendix. However, the results do not indicate any large differences in activity levels across children.

where Y_{ihsg} is an indicator for whether child i in household h in region s in orphan-foster group g was present in the same household in 2013 as they were in 2010. F_i and O_i are indicators for foster and orphan status respectively. I include a vector of individual and household characteristics X_{ih} that includes child age, age squared, gender, household expenditure, residence in a rural area, and the number of men, women, male, and female siblings.

Table 5: Probability of Staying in Same HH by Foster and Orphan Status

	Foster Child Sample		Full Sample	
	(1)	(2)	(3)	(4)
Orphaned Foster	0.0189	0.0244***	0.0370**	0.0453***
	(0.020)	(0.009)	(0.012)	(0.017)
Non-Orphaned Non-Foster			0.0708***	0.0713***
			(0.014)	(0.017)
Orphaned Non-Foster			0.0237	0.0285
			(0.016)	(0.283)
Mean Dependent Variable	0.871	0.871	0.915	0.915
Sample Size	746	746	6,076	6,076
Region Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes		Yes

Notes: The sample includes all children age 0-11 in 2010. The dependent variable is an indicator for whether or not the child in the 2010 sample was still in the same household in 2013. The omitted category are non-orphaned foster children. Standard errors are clustered at the region level. Individual controls include age age^2, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and whether or not the household is in a rural area. * p<0.1, ** p<0.05, *** p<0.01

Table 5 presents the marginal effects of a probit regression of Equation (8). The omitted category in each specification is group 3: non-orphaned foster children.[43] In columns (1) and (2) the sample is restricted to only foster children, while columns (3) and (4) include both foster and non-foster children. If orphaned foster children are more likely than non-orphaned foster children to remain in the same household throughout the sample period, then γ_3 should be positive. I limit the sample to children age eleven and under in 2010.[44] Column (1) shows no difference in the probability of remaining in the same household, however once variation in household characteristics is accounted for, the results suggest orphaned foster children are

[43] Equation (8) is modified so that this is the case.

[44] The consumption analysis defines children as anyone fourteen and under. Therefore I restrict the sample to children age fourteen and under in 2013, or eleven and under in 2010. Using different age thresholds does not meaningfully affect the results.

2.44 percentage points more likely than non-orphaned foster children to stay. Including non-foster children in the analysis in columns (3) and (4) yields qualitatively similar estimates. Table A11 in the Appendix further divides orphaned foster children by whether they are single orphans (maternal or paternal) or double orphans. As expected, the probability of remaining in the same household is significantly higher in magnitude for double orphans. This finding suggests that double orphans have the worst outside option of all children, which may weaken their standing within the household.

7 Conclusion

The household is in many ways a black box to economists. Understanding the inner workings of households is difficult and measuring the treatment of children within the household is far from straightforward. I build upon recent work by DLP to demonstrate how resource shares can be identified using expenditure on partially assignable clothing. Like DLP, 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 children and that extended family members are capable caretakers. However, the results suggest *orphaned* foster children are disadvantaged. I find orphaned foster child poverty is being substantially 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 also orphaned children, regardless of the poverty level of the household. Future work should connect the findings of this paper with past research on *why* children are fostered (Ainsworth, 1995; Akresh, 2009). Bridging these two areas of study will help determine the underlying mechanisms that influence foster children treatment, and ultimately allow for better policy design.

The weaknesses of the unitary household framework are well known (Attanasio and Lechene, 2002; Duflo, 2003; Bobonis, 2009). This study adds to the growing literature that stresses the importance of thinking about individuals within the household, as opposed to the household as a single economic agent. This distinction is even more relevant where intrahousehold inequality may be present, as the results of this paper demonstrate in regards to child fostering. This project identifies a second, less emphasized, limitation of household-level studies, in that they typically ignore kinship networks. Individuals within a kinship network interact along many dimensions, with child fostering being a central component. The finding that non-orphaned foster children are treated better than orphaned foster children suggests kinship networks play a role in child welfare; having living parents in another household influences how foster children are treated. Recognising the role of extended families in child welfare is therefore critical to designing policies that help children. Future work should analyse in more depth the relationship between different types of kinship systems (matrilineal vs. patrilineal), as well as the role of different types of relatives (grandparents vs. aunts and uncles) in foster and non-foster child treatment.

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A Appendix

The Appendix is organised as follows: In Section A.1, I present an alternative identification method that identifies resource shares with partially assignable goods using the SAP restriction of DLP. I then build upon the consumption results be analysing education and child labour differences across foster and non-foster children in Section A.2. I specify the full model in Section A.3. Section A.4 provides additional tables. Finally, I present the identification theorems in Section A.5.

A.1 Identification with Partially Assignable Goods Using SAP

Without private assignable goods for foster and non-foster children, I rewrite the Engel curves for foster and non-foster child clothing in System (5) as a single Engel curve for children's clothing, and assume SAP (i.e., $\beta_s^t = \beta_s$):

$$\begin{aligned} W_s^m &= \eta_s^m \left[\delta_s^m + \beta_s \ln(\eta_s^m)\right] + \eta_s^m \beta_s \ln y \\ W_s^f &= \eta_s^f \left[\delta_s^f + \beta_s \ln(\eta_s^f)\right] + \eta_s^f \beta_s \ln y \\ W_s^c &= \sigma_a \eta_s^a \left[\delta_s^a + \beta_s \ln(\eta_s^a)\right] + \sigma_b \eta_s^b \left[\delta_s^b + \beta_s \ln(\eta_s^b)\right] + \\ &\quad (\sigma_a \eta_s^a \beta_s + \sigma_b \eta_s^b \beta_s) \ln y \end{aligned} \tag{A1}$$

This system of equations is identical to System (6) 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 (these equations originate from taking the first derivative with respect to log expenditure), 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 nonzero) 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.

I now introduce several new model assumptions to make the SAP restriction employable. To do this, I add structure to the model by introducing additional restrictions which limit how foster and non-foster child resource shares vary by household type. Ratio Restriction 1 is given below:

$$\frac{\eta^a_{s_{a0}}}{\eta^a_{s_{a+1,0}}} = \frac{\eta^a_{s_{ab}}}{\eta^a_{s_{a+1,b}}} \text{ and } \frac{\eta^b_{s_{0b}}}{\eta^b_{s_{0,b+1}}} = \frac{\eta^b_{s_{ab}}}{\eta^b_{s_{a,b+1}}} \tag{A2}$$

where the household type is now given as s_{ab} to explicitly indicate the number of foster and non-foster children present. In words, 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.

I do not restrict the levels of foster child resource shares to be a specific value, only that the ratio of foster child resource shares in two different household types be independent of the number of non-foster children present. This ratio is assumed to be the same whether or not there are zero, one, or two, non-foster children are present, which greatly reduces the number of parameters that need to be identified.

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

$$\frac{\eta^a_{s_{10}}}{\eta^a_{s_{11}}} = \frac{\eta^b_{s_{01}}}{\eta^b_{s_{11}}} \tag{A3}$$

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.

With these additional model restrictions, resource shares are now identified in the composite households. I limit my attention to the following household types: $s \in \{s_{11}, s_{21}, s_{12}, s_{22}\}$. To see that the order condition is satisfied, note that with three Engel curves for each household type and four household types, there are twelve Engel curve slopes in total. And again, for each household type resource shares sum to one. This results in four additional equations. Finally, Ratio Restriction 1 generates four additional equations and Ratio Restriction 2 leads to one additional equation, resulting in a system of twenty-one equations in total. In terms of unknowns, with four household types, and four resource shares for each household type, there are sixteen resource shares that need to be identified. For each household type, there is a preference parameter β_s that needs to be identified (four total). This results in twenty unknowns, so the order condition is satisfied.[45] A proof of the rank condition is provided in Section A.6.2.

Are Ratio Restrictions 1 and 2 Valid? To test the validity of the above restrictions, I estimate the model assuming preferences are *similar across household types* (SAT), and test whether or not the estimated resource shares are consistent with Ratio Restriction's 1 and 2. As discussed in Section 3.2, if I make the SAT restriction, I do not need to restrict how resource shares vary across household types. This allows for a direct test of the second approach to identification. Specifically, I test the following null hypotheses which are assumed to hold by Restriction 1: $\eta_{21}^a = \frac{\eta_{11}^a \eta_{20}^a}{\eta_{10}^a}$, $\eta_{31}^a = \frac{\eta_{11}^a \eta_{30}^a}{\eta_{10}^a}$, $\eta_{12}^b = \frac{\eta_{11}^b \eta_{02}^b}{\eta_{01}^b}$; and Restriction 2: $\eta_{11}^b = \frac{\eta_{11}^a \eta_{01}^b}{\eta_{10}^a}$. I omit several household types because they have too few observations.[46] Overall, I consistently fail to reject the hypothesis that the restrictions hold. While the resource shares are not estimated that precisely and therefore the hypotheses are difficult to reject, the restrictions are still largely consistent with the estimated resource shares. The estimation results are presented in Table A10.[47]

A.2 School Enrollment and Child Labour

To provide context to the consumption results, I examine intrahousehold inequality among foster and non-foster children along two other dimensions of welfare: education and child labour. As discussed in Section 4.1, education and child labour are centrally linked to why parents foster their children. In terms of education, if the household does not live close to a school, or if the nearby school is low quality, parents may send their children to live with a relative who lives in a village with better educational access. Moreover, households may be more amenable to accepting foster children if the foster children work. For example, a household with a newborn child benefits from fostering in a young teenage girl who can care for the newborn. Alterna-

[45] For the household type s_{22}, I restrict both $\eta_{22}^a = \frac{\eta_{20}^a \times \eta_{12}^a}{\eta_{10}^a}$ and $\eta_{22}^b = \frac{\eta_{02}^b \times \eta_{21}^b}{\eta_{01}^b}$, however only one of these two ratios needs to be assumed for identification.

[46] This is one reason why identification with the SAT assumption without Ratio Restrictions 1 and 2 is less than satisfactory in this context.

[47] Other results from this estimation were presented previously in Table 3, columns (1) and (5).

tively, if a household has a stronger than normal harvest, they may foster in children to help with the farm work. This suggests child labour may be higher among foster children.

Empirical Strategy: Unlike consumption, both school enrollment and work hours are observable at the individual level using standard household-level survey data. This facilitates a direct comparison of enrollment rates and child labour between foster and non-foster children. I begin by assigning children to two mutually exclusive groups: both biological parents absent (g=1); at least one parent present (g=2). Children in group 1 are foster children, while children in group 2 are non-foster children.

For a child i age 6-14 living in household h, living in region r in year t, I estimate the following regression,

$$Y_{ihst} = \alpha + \gamma F_i + \pi_h + \psi_{st} + X_i\delta + \epsilon_{ihst} \tag{A4}$$

where Y_{ihst} is an indicator for school enrollment and F_i is an indicator variable equal to one if the child is fostered. In other specifications, Y_{ihst} is hours worked. Since this variable is censored at zero, I use a Tobit model and the system is estimated via maximum likelihood. The parameter of interest is γ, which captures the effect of the absence of a child's parents on the various outcomes of interest. The omitted category is children with at least one biological parent present. In some specifications I include household fixed effects to control for any unobserved heterogeneity that does not vary over time. Household fixed effects allow for the direct examination of unequal treatment between foster and non-foster children, as I am relying only on within-household variation. Lastly, I include region-year fixed effects to account for any region specific year effects that are common across foster status and households. I cluster standard errors at the region-year level.

The consumption results suggest orphanhood is an important factor in how children are treated. I modify the above estimation to account for orphan status in order to examine whether a similar pattern emerges here. I now assign children into four mutually exclusive groups consistent with the consumption analysis: non-orphaned non-foster (g=1); orphaned non-foster (g=2); non-orphaned foster (g=3); orphaned foster (g=4). I estimate the following specification:

$$Y_{ihstg} = \alpha + \gamma_1 O_i + \gamma_2 F_i + \gamma_3 (O_i \times F_i) + \pi_h + \psi_{st} + X_i\delta + \epsilon_{ihstg} \tag{A5}$$

where F_i and O_i are indicators for foster and orphan status respectively. The parameters of interest are now γ_g, which captures the differential effects of the child's foster and orphan status on school enrollment or child labour. The omitted category is non-orphaned children with at least one biological parent present. I again use the Malawi Integrated Households Survey (IHS3) 2010 and the Malawi Integrated Panel Survey 2013. Descriptive statistics are presented in Table A16 in the Appendix.

Results: I begin by analyzing the difference in school enrollment rates between foster and non-foster children. I estimate Equation (A4) and present the results in Table A1. The coefficient of interest γ describes the difference in treatment for foster and non-foster children. Column 1 provides an estimate of differences in means by foster status, controlling for child age and gender. This specification ignores any household characteristics that may be associated with both school enrollment rates and the types of households that foster in children. Columns 2 and 3 attempt to uncover evidence of intrahousehold discrimination of foster children. In column 2, I account for observable household characteristics, including the education, age, and gender of the household head, household composition measures, and log per capita household expenditure. In column 3, I include household fixed effects, which accounts for any unobservable household characteristics that do not vary across time. The results provide evidence that foster children are enrolled in school at lower rates than non-foster children.

Table A1: School Enrollment by Foster Status

	LPM			Probit
	(1)	(2)	(3)	(4)
Foster Child	-0.028***	-0.013	-0.047***	-0.015
	(0.009)	(0.010)	(0.017)	(0.009)
Sample Size	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes	Yes
Household Fixed Effects			Yes	

Notes: The sample includes all children age 6-14. The omitted fostering category are children with at least one biological parent present. Robust standard errors. Columns 1-3 provide estimates for a linear probability model. Column 4 presents marginal effects for a probit specification. Individual controls include age fixed effects, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head. * p<0.1, ** p<0.05, *** p<0.01

The consumption results imply orphans are particularly mistreated within the household. To examine whether this pattern holds for education, I estimate Equation (A5) with four foster categories that account for orphanhood. The results are presented in Table A2. Columns 1-3 present results from a limited probability model with increasing controls moving left to right. The findings largely show that orphaned and non-orphaned foster children are less likely to be enrolled in school than non-foster children. The preferred specification is provided in column 4, where the model is estimated via a probit model. The displayed parameter gives the marginal effects, and suggest that orphaned foster children are 2.6 percentage points less likely to be enrolled in school than non-orphaned non-foster children.

Table A2: School Enrollment by Foster Status (Detailed Categories)

	LPM			Probit
	(1)	(2)	(3)	(4)
Fostering Categories				
Non-Orphaned Foster	-0.024**	-0.009	-0.053**	-0.012
	(0.011)	(0.012)	(0.020)	(0.064)
Orphaned Foster	-0.040***	-0.022	-0.034	-0.026*
	(0.013)	(0.014)	(0.021)	(0.014)
Orphaned Non-Foster	-0.022	-0.007	0.016	-0.008
	(0.013)	(0.014)	(0.027)	(0.072)
Sample Size	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes	Yes
Household Fixed Effects			Yes	

Notes: The sample includes all children age 6-14. The omitted fostering category are non-orphaned children with at least one biological parent present. Robust standard errors. Columns 1-3 provide estimates for a linear probability model. Column 4 presents marginal effects for a probit specification. Individual controls include age fixed effects, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head. * p<0.1, ** p<0.05, *** p<0.01

Table A3 provides the child labour results. In columns 1 and 2, I examine the relationship between foster status and hours worked doing chores,[48] while columns 3 and 4 focus on hours worked for a household farm, household enterprise, or wage work outside the household in the previous week.[49] I add controls moving from left to right. The results again provide little evidence that work around the house differs substantially between foster and non-foster children, which is contrary to what the literature suggests (Serra, 2009). This lack of any effect is partially due to the limited definition of chores (only fetching wood and water), and possible measurement error in the data, as parents may be unwilling to reveal that their children work. The same lack of an association is apparent in examining the relationship foster status on work hours in columns 4 to 6. Table A4 accounts for orphanhood when examining the effect of foster status on child labour. The results provide some evidence that orphans are work more than

[48] Chores include fetching wood and fetching water.

[49] The survey includes hours worked in agriculture during the most recent wet and dry seasons. Using that measure of child labour is consistent with the 7-day recall and those results are available upon request.

non-foster children. The results in column (2) which account for differences in household characteristics, suggest that orphaned-foster children spend 0.25 more hours per week on chores than non-foster children. This effect goes away when household fixed effects are included. A similar pattern emerges when looking at work outside the household.

Table A3: Weekly Hours Worked by Fostering Status

	Chores		Work Outside HH	
	(1)	(2)	(3)	(4)
Foster Child	0.280	0.061	0.374	-0.884
	(0.240)	(0.265)	(0.564)	(0.617)
Sample Size	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes	

Notes: The sample includes all children age 6-14. The omitted fostering category are children with both biological parents present. Robust standard errors. Individual controls include age fixed effects, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head. * p<0.1, ** p<0.05, *** p<0.01

Table A4: Weekly Hours Worked by Fostering Status

	Chores		Work Outside HH	
	(1)	(2)	(3)	(4)
Orphaned Non-Foster	0.282	0.314	0.722	-0.307
	(0.336)	(0.357)	(0.812)	(0.842)
Non-Orphaned Foster	0.035	-0.240	0.095	-1.329*
	(0.299)	(0.324)	(0.703)	(0.752)
Orphaned Foster	0.705*	0.594	0.972	-0.352
	(0.360)	(0.373)	(0.842)	(0.870)
Sample Size	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes		Yes

Notes: The sample includes all children age 6-14. The omitted fostering category are children with both biological parents present. Robust standard errors. Individual controls include age fixed effects, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head. * p<0.1, ** p<0.05, *** p<0.01

A.3 Fully Specified Model

The estimation in this study identifies resource shares from Engel curves for assignable clothing. In this section, I follow DLP and write a fully specified household demand model consistent with the restrictions contained in the clothing Engel curves. In particular, Engel curves for clothing are required to be linear in log expenditure, and resource shares must be independent of household expenditure.

Let y be household expenditure, and $\tilde{p}$ be the price vector of all goods aside from men's, women's, and children's clothing, which is denoted by p. While more general formulations are possible, I start with assuming individuals have subutility over clothing given by the Price Independent Generalized Logarithmic (piglog) functional form (Deaton and Muellbauer, 1980).

$$\ln V_t(p, y) = \ln[\ln(\frac{y}{G^t(p_t, \tilde{p})})] + p_t e^{-a' \ln \tilde{p}} \tag{A6}$$

where G^t is some function that is nonzero, differentiable, and homogeneous of degree one, and some constant vector a with elements a_k summing to one. Each member of the same type is assumed to have the same utility function. This assumption could be dropped with a data set that has goods that are assignable at a more detailed level.

The household weights individual utilities using the following Bergson-Samuelson social welfare function:

$$\tilde{U}_s(U_f, U_m, U_a U_b, p/y) = \sum_{t\epsilon\{m,f,a,b\}} \omega_t(p)[U_t + \rho_t(p)] \tag{A7}$$

where $\omega_t(p)$ are the Pareto weight functions and $\rho_t(p)$ are the externality functions. Individuals are allowed to receive utility from another person's utility, but not from another person's consumption of a specific good. This can be considered a form of restricted altruism.

The household's problem is to maximize the social welfare function subject to a budget constraint, and a consumption technology constraint.

$$\begin{aligned} \max_{x_m, x_f, x_a, x_b, z_s} \quad & \omega(p) + \sum_{t\epsilon\{m,f,a,b\}} \omega_t(p) U_t \\ & \text{s.t} \quad y = z_s' p \ \text{ and} \\ & z_s^k = A_s^k (x_m^k + x_f^k + \sigma_a x_a^k + \sigma_b x_b^k) \ \text{ for each good } \ k \end{aligned}$$

where the household type is given by s, or the number of foster and non-foster children present in the household and $\omega(p) = \sum_{t\epsilon\{m,f,a,b\}} \omega_t(p)\rho_t(p)$. Matrix A_s is the consumption technology function. It is a $k \times k$ diagonal matrix and determines the relative publicness or privateness of good k. If good k is private, then the k,k'th element is equal to one, and what the household purchases is exactly equal to individual consumption.

By Pareto efficiency, the household maximisation can be decomposed into two step process; In the first stage, resource shares are optimally allocated, and in the second stage, each individual maximizes their individual utility subject to the budget constraint $A_s^k p^k x_t^k = \eta_s^t y$. Resource shares can then be defined as $\eta_s^t = x^t A_s p / y = \sum_k A_s^k p^k x_t^k / y$ evaluated at the optimized level of expenditures x_t. The optimal utility level is given by the individual's indirect utility function V^t evaluated at Lindahl prices, $V_t(A_s' p, \eta_s^t, y)$.

Using the functional form assumptions regarding individual indirect utility functions, the household problem can again be rewritten:

$$\begin{aligned} \max_{\eta_s^m, \eta_s^f, \eta_s^a, \eta_s^b} \quad & \omega(p) + \sum_{t\epsilon\{m,f,a,b\}} \tilde{\omega}_s^t(p) \ln\left(\frac{\eta_s^t y}{G^t(A_s' p)}\right) \\ & \text{s.t} \quad \eta_s^m + \eta_s^f + \sigma_a \eta_s^a + \sigma_b \eta_s^b = 1 \end{aligned} \tag{A8}$$

where $\tilde{\omega}(p) = \omega_t \exp(A_t p_t e^{-a'(\ln \tilde{p} + \ln \tilde{A}_s)})$

The first order conditions from this maximisation problem are as follows:

$$\frac{\tilde{\omega}_s^m(p)}{\eta_s^m} = \frac{\tilde{\omega}_s^f(p)}{\eta_s^f} = \frac{\tilde{\omega}_s^a(p)}{\sigma_a \eta_s^a} = \frac{\tilde{\omega}_s^b(p)}{\sigma_b \eta_s^b}, \text{ and } \sum_{t \epsilon \{m,f,a,b\}} \sigma_t \eta_s^t = 1 \tag{A9}$$

Solving for person specific resource shares gives the following equations:

$$\eta_s^t(p) = \frac{\tilde{\omega}_s^t(p)}{\tilde{\omega}_s^m + \tilde{\omega}_s^f + \tilde{\omega}_s^a + \tilde{\omega}_s^b} \text{for } t \ \epsilon \ \{m, f\} \tag{A10}$$

$$\eta_s^t(p) = \frac{\tilde{\omega}_s^t(p)/\sigma_t}{\tilde{\omega}_s^m + \tilde{\omega}_s^f + \tilde{\omega}_s^a + \tilde{\omega}_s^b} \text{for } t \ \epsilon \ \{a, b\} \tag{A11}$$

With each person now allocated their share of household resources, each person can then maximize there own utility, subject to their own personal budget constraint. In particular, individuals choose x_t to maximize $U_t(x_t)$ subject to $\eta_s^t y = \sum_k A_s^k p_k x_t^k$. Individual demand functions can be derived using Roy's Identify on the indirect utility functions given in Equation (A22), where individual income is used $\eta_s^t y$ and individuals face the Lindahl price vector $A_s p$.

$$h_t^k(\eta_s^t y, A_s p) = \frac{\eta_s^t y}{G^t} \frac{\partial G^t}{\partial A_s p^k} - \frac{\partial (A p^k e^{-a' \ln \tilde{p}})}{\partial A p^k} [\ln \eta_s^t y - \ln G^t] \eta_s^t y \tag{A12}$$

for any good k for person of type t. This can be written more concisely:

$$h_t^k(\eta_s^t y, A_s' p) = \tilde{\delta}_t^k(A_s' p) \eta_s^t y - \psi_t^k(A_s' p) \eta_s^t y \ln(\eta_s^t y) \tag{A13}$$

Using the individual demand functions, household demand for good k is written in general terms as follows accounting for the consumption technology function:

$$z_s^k = A_s \sum_{t \epsilon \{m,f,a,b\}} h_t^k(A_s' p, \eta_s^t(p) y) \tag{A14}$$

Dividing the individual demand functions by income produces the budget share equations:

$$\frac{h_t^k(\eta_s^t y, A_s' p)}{y} = \tilde{\delta}_t^k(A_s' p) \eta_s^t - \psi_t^k(A_s' p) \eta_s^t \ln(\eta_s^t y) \tag{A15}$$

The analysis in this paper uses Engel curves for private goods, which simplifies the above equation even further. First, Engel curves demonstrate how budget shares vary with income holding prices constant. Thus prices can be dropped from the above equation. Secondly, the consumption technology drops out for private goods, as the element in the A matrix takes a value of 1 for private goods. The Engel curves are then written as follows:

$$W_s^t(y) = \frac{h_s^t(y)}{y} = \eta_s^t \delta_s^t + \eta_s^t \beta_s^t (\ln y + \ln \eta_s^t) \tag{A16}$$

A.4 Additional Tables

Table A5: Household Structure

		# Foster					
		0	1	2	3	4	5
# Non-Foster	0	0	480	234	107	55	23
	1	2,159	283	79	22	18	0
	2	2,323	242	57	23	0	0
	3	2,167	170	41	0	0	0
	4	1,473	99	0	0	0	0
	5	708	0	0	0	0	0

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. Households with 1-4 men and women, and 1-5 children.

Table A6: Determinants of Resource Shares: Preference Factors

	Non-Foster Children (1) NLSUR	Foster Children (2) NLSUR
North	0.024	0.032
	(0.023)	(0.023)
Central	0.008	0.008
	(0.015)	(0.015)
Year=2010	-0.020	-0.011
	(0.016)	(0.013)
Average Age non-Foster	-0.125	-0.287
	(0.830)	(0.813)
Average Age non-Foster^2	0.046	0.042
	(0.061)	(0.059)
Average Age Foster	-2.240	0.969
	(1.791)	(1.201)
Average Age Foster^2	0.129	-0.035
	(0.103)	(0.069)
Proportion of Fostered Orphaned	0.052*	-0.025
	(0.029)	(0.019)
Fraction Female non-Foster	-0.023	0.009
	(0.019)	(0.018)
Fraction Female Foster	-0.002	0.030
	(0.029)	(0.029)
Average Age Women	0.428	-0.119
	(0.345)	(0.308)
Average Age Women^2	-0.005	-0.000
	(0.004)	(0.003)
(Average Age Men - Average Age Women)	0.073	0.024
	(0.083)	(0.067)
(Average Age Men - Average Age Women)^2	0.001	-0.000
	(0.003)	(0.002)
Average Education Men	0.014	-0.000
	(0.012)	(0.014)
Average Education Women	-0.017	-0.007
	(0.014)	(0.012)
Rural	0.001	-0.011
	(0.018)	(0.013)
Share of Adult Women Age 15-18	0.090*	-0.023
	(0.054)	(0.039)
Share of Adult Men Age 15-18	-0.005	-0.001
	(0.032)	(0.026)
Matrilineal Village	0.016	0.026
	(0.017)	(0.017)
N	10,763	
Log Likelihood	92,402	

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-5 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. The education and age variables are demeaned. South Malawi is the omitted region. Coefficients on the household composition indicators are omitted for conciseness. * p<0.1, ** p<0.05, *** p<0.01

Table A7: Determinants of Resource Shares: Household Type Indicators

	Non-Foster Children (1) NLSUR	Foster Children (2) NLSUR
1 non-Foster 0 Foster	0.215***	
	(0.076)	
2 non-Foster 0 Foster	0.280***	
	(0.080)	
3 non-Foster 0 Foster	0.313***	
	(0.085)	
4 non-Foster 0 Foster	0.349***	
	(0.090)	
5 non-Foster 0 Foster	0.389***	
	(0.096)	
0 non-Foster 1 Foster		0.168**
		(0.075)
1 non-Foster 1 Foster	0.139**	0.109*
	(0.063)	(0.060)
2 non-Foster 1 Foster	0.180**	0.112*
	(0.071)	(0.059)
3 non-Foster 1 Foster	0.202***	0.105*
	(0.076)	(0.060)
4 non-Foster 1 Foster	0.225***	0.113*
	(0.082)	(0.061)
0 non-Foster 2 Foster		0.211***
		(0.082)
1 non-Foster 2 Foster	0.152**	0.136**
	(0.066)	(0.067)
2 non-Foster 2 Foster	0.198***	0.141*
	(0.074)	(0.066)
3 non-Foster 2 Foster	0.222***	0.110*
	(0.080)	(0.063)
0 non-Foster 3 Foster		0.222**
		(0.089)
1 non-Foster 3 Foster	0.164**	0.143**
	(0.069)	(0.072)
2 non-Foster 3 Foster	0.213**	0.148*
	(0.078)	(0.072)
0 non-Foster 4 Foster		0.313***
		(0.112)
1 non-Foster 4 Foster	0.231***	0.202**
	(0.088)	(0.092)
0 non-Foster 5 Foster		0.298**
		(0.117)
No. Men	0.001	-0.008
	(0.009)	(0.009)
No. Women	-0.019	-0.004
	(0.012)	(0.010)
N	10,763	
Log Likelihood	92,402	

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-5 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. The education and age variables are demeaned. Coefficients on the covariates (age, education, etc.) are omitted for conciseness. The parameter estimates are not per child, but rather the total resources allocated to foster or non-foster children. * p<0.1, ** p<0.05, *** p<0.01

Table A8: Determinants of Resource Shares: Orphan Interactions and Nuclear Households

	Non-Foster Children			Foster Children		
	Main Results (1a)	Orphan Interactions (2a)	Nuclear Households (3a)	Main Results (1b)	Orphan Interactions (2b)	Nuclear Households (3b)
Household Type Indicators						
2 Non-Foster 0 Foster	0.280***	0.291***	0.221***			
	(0.080)	(0.0562)	(0.0468)			
1 Non-Foster 1 Foster	0.139**	0.150***	0.101***	0.109*	0.134***	0.098**
	(0.063)	(0.0392)	(0.0313)	(0.060)	(0.0408)	(0.0341)
0 Non-Foster 2 Foster				0.211***	0.271***	0.220***
				(0.082)	(0.0692)	(0.0807)
3 Non-Foster 0 Foster	0.313***	0.332***	0.255***			
	(0.085)	(0.0609)	(0.0522)			
2 Non-Foster 1 Foster	0.180**	0.199***	0.158***	0.112*	0.130***	0.0690*
	(0.071)	(0.0454)	(0.0403)	(0.059)	(0.0399)	(0.0404)
1 Non-Foster 2 Foster	0.152**	0.176***	0.0923***	0.136**	0.186***	0.157***
	(0.066)	(0.0454)	(0.0350)	(0.067)	(0.0502)	(0.0588)
0 Non-Foster 3 Foster				0.222**	0.306***	0.281***
				(0.089)	(0.0825)	(0.106)
Covariates						
Average Age non-Foster	-0.125	0.517	2.230***	-0.287	0.0727	1.462
	(0.830)	(0.771)	(0.760)	(0.813)	(0.936)	(1.104)
Average Age non-Foster^2	0.046	0.0251	-0.135**	0.042	0.0131	-0.0624
	(0.061)	(0.0541)	(0.0527)	(0.059)	(0.0674)	(0.0822)
Average Age Foster	-2.240	-1.522	-1.501	0.969	2.858	1.478
	(1.791)	(1.855)	(2.142)	(1.201)	(1.769)	(1.852)
Average Age Foster^2	0.129	0.0989	0.0765	-0.035	-0.143	-0.0619
	(0.103)	(0.103)	(0.117)	(0.069)	(0.102)	(0.105)
Proportion Non-Foster Female	-0.023	-0.0294	0.0254	0.009	0.0244	-0.0224
	(0.019)	(0.0183)	(0.0180)	(0.018)	(0.0208)	(0.0250)
Proportion Foster Female	-0.002	0.00522	0.00863	0.030	-0.0178	0.0155
	(0.029)	(0.0342)	(0.0300)	(0.029)	(0.0411)	(0.0331)
Rural	0.001	-0.0123	-0.0388*	-0.011	-0.0123	0.00627
	(0.018)	(0.0181)	(0.0229)	(0.013)	(0.0181)	(0.0187)
Matrilineal Village	0.016	0.0134	0.0119	0.026	0.0306*	0.0235
	(0.017)	(0.0158)	(0.0171)	(0.017)	(0.0180)	(0.0200)
Proportion of	0.052*	0.0401	0.0276	-0.025	-0.0567	-0.0601*
Fostered Orphaned	(0.029)	(0.0600)	(0.0349)	(0.019)	(0.0441)	(0.0341)
Proportion of Fostered Orphaned ×		0.000358			0.0462	
Fraction Female Foster		(0.0621)			(0.0484)	
Proportion of Fostered Orphaned ×		-0.0178			0.00520	
Rural		(0.0459)			(0.0349)	
N	10,763	10,763	5,850	10,763	10,763	5,850
Log Likelihood	92,402	92,378	49,077	92,402	92,378	49,077

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-5 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

Table A9: Determinants of Resource Shares: Age-Restricted Sample

	Non-Foster Children		Foster Children	
	Estimation Sample (1a)	Age-Restricted Sample (2a)	Estimation Sample (1b)	Age-Restricted Sample (2b)
Household Type Indicators				
2 Non-Foster 0 Foster	0.280***	0.300***		
	(0.080)	(0.093)		
1 Non-Foster 1 Foster	0.139**	0.169**	0.109*	0.127*
	(0.063)	(0.079)	(0.060)	(0.075)
0 Non-Foster 2 Foster			0.211***	0.241**
			(0.082)	(0.098)
3 Non-Foster 0 Foster	0.313***	0.346***		
	(0.085)	(0.098)		
2 Non-Foster 1 Foster	0.180**	0.233***	0.112*	0.112
	(0.071)	(0.087)	(0.059)	(0.073)
1 Non-Foster 2 Foster	0.152**	0.170**	0.136**	0.187**
	(0.066)	(0.083)	(0.067)	(0.089)
0 Non-Foster 3 Foster			0.222**	0.297***
			(0.089)	(0.111)
Covariates				
Average Age non-Foster	-0.125	0.066	-0.287	0.084
	(0.830)	(0.991)	(0.813)	(0.852)
Average Age non-Foster^2	0.046	0.028	0.042	0.017
	(0.061)	(0.072)	(0.059)	(0.061)
Average Age Foster	-2.240	-2.927	0.969	3.138**
	(1.791)	(2.125)	(1.201)	(1.506)
Average Age Foster^2	0.129	0.201	-0.035	-0.169*
	(0.103)	(0.124)	(0.069)	(0.094)
Rural	0.001	0.009	-0.011	0.011
	(0.018)	(0.021)	(0.013)	(0.014)
Matrilineal Village	0.016	0.014	0.026	0.023
	(0.017)	(0.020)	(0.017)	(0.019)
Proportion of Fostered Orphaned	0.052*	0.028	-0.025	-0.015
	(0.029)	(0.030)	(0.019)	(0.024)
N	10,763	10,368	10,763	10,368
Log Likelihood	92,402	88,779	92,402	88,779

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-5 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. The Age-Restricted Sample drops households with both foster and non-foster children in any of the following age groups: 0-3, 4-7, 8-11, and 12-14. * p<0.1, ** p<0.05, *** p<0.01

Table A10: Determinants of Resource Shares: Estimation with SAT Restriction

	Non-Foster Children (1) NLSUR	Foster Children (2) NLSUR
1 non-Foster 0 Foster	0.185**	
	(0.0863)	
2 non-Foster 0 Foster	0.260***	
	(0.0939)	
3 non-Foster 0 Foster	0.303***	
	(0.0992)	
4 non-Foster 0 Foster	0.345***	
	(0.105)	
5 non-Foster 0 Foster	0.388***	
	(0.110)	
0 non-Foster 1 Foster		0.162
		(0.117)
1 non-Foster 1 Foster	0.121	0.135
	(0.104)	(0.121)
2 non-Foster 1 Foster	0.153	0.154
	(0.130)	(0.121)
3 non-Foster 1 Foster	0.221*	0.139
	(0.127)	(0.121)
0 non-Foster 2 Foster		0.225*
		(0.134)
1 non-Foster 2 Foster	0.135**	0.210
	(0.056)	(0.136)
0 non-Foster 3 Foster		0.274*
		(0.152)
No. Men	-0.00590	0.00274
	(0.0124)	(0.0136)
No. Women	-0.00253	0.00840
	(0.0190)	(0.0235)
N	10,443	
Log Likelihood	88,450	

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-5 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. Coefficients on the covariates (age, education, etc.) are omitted for conciseness. Several household types are dropped from the sample due to too few observations. The parameter estimates are not per child, but rather the total resources allocated to foster or non-foster children. Restrictions 1 and 2 are NOT imposed in the estimation. * p<0.1, ** p<0.05, *** p<0.01

Table A11: Probability of Staying in Same HH by Foster and Orphan Status (Double vs. Single)

	Foster Child Sample		Full Sample	
	(1)	(2)	(3)	(4)
Double-Orphaned Foster	0.0307*	0.0309***	0.0573***	0.0622***
	(0.0167)	(0.009)	(0.006)	(0.016)
Single-Orphaned Foster	0.0118	0.0201	0.0254	0.0355**
	(0.025)	(0.015)	(0.016)	(0.016)
Non-Orphaned Non-Foster			0.0708***	0.0713***
			(0.014)	(0.017)
Orphaned Non-Foster			0.0237	0.0285
			(0.016)	(0.283)
Mean Dependent Variable	0.871	0.871	0.915	0.915
Sample Size	746	746	6,076	6,076
Region Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes		Yes

Notes: The sample includes all children age 0-11 in 2010. The dependent variable is an indicator for whether or not the child in the 2010 sample was still in the same household in 2013. The omitted category are non-orphaned foster children. Standard errors are clustered at the region level. Individual controls include age age^2, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and whether or not the household is in a rural area. * p<0.1, ** p<0.05, *** p<0.01

Table A12: Sample Means by Household Composition

	One-Child-Type		Composite
	Only Non-Foster	Only Foster	
	(1)	(2)	(3)
Men	1.353	1.527	1.621
Women	1.303	1.474	1.578
Non-Foster	2.575		2.007
Foster		1.784	1.310
Log Expenditure per Person	11.490	11.607	11.572
North	0.194	0.192	0.255
Central	0.375	0.326	0.362
Year=2010	0.753	0.720	0.691
Average Age Non-Foster	5.721		6.506
Average Age Foster		9.228	9.282
Proportion Female Non-Foster	0.504		0.487
Proportion Female Foster		0.552	0.555
Proportion Orphaned Foster		0.339	0.409
Average Age Women	28.789	47.126	31.327
Average Age Men	31.744	40.582	32.070
Average Education Women	5.216	3.749	6.094
Average Education Men	6.642	5.939	7.491
Rural	0.813	0.806	0.730
Proportion Female Adults Age 15-18	0.071	0.102	0.107
Proportion Male Adults Age 15-18	0.098	0.209	0.163
Matrilineal Village	0.608	0.640	0.574
Sample Size	8,830	899	1,034

Notes: Out of all households with 1-4 men and women, and 1-5 children. Malawi Third Integrated Household Survey and Integrated Household Panel Survey. One-child-type households contain either only non-foster children or only foster children. Composite households contain both foster and non-foster children.

Table A13: Distribution of Foster Caretakers by Household Composition

	All Foster Households	Households With Both Foster and Non-Foster Children	Households With Only Foster Children
	(1)	(2)	(3)
Foster Caretaker			
Grandparent(s) and Uncle/Aunt	34.27	37.71	31.12
Uncle/Aunt Only	14.16	21.38	7.55
Grandparent(s) Only	25.26	5.72	43.14
Adopted	14.00	16.50	11.71
Other*	12.31	18.69	6.47
Sample Size	1,243	594	649

Notes: Malawi Integrated Household Panel Survey 2013. The sample includes all foster children. *Other includes children living with an older sibling, other relatives, or other non-relatives.

Table A14: Sample Means by Household Composition

	Matched Sample		Matched Sample	
	Non-Foster Only (1)	Composite (2)	Foster Only (3)	Composite (4)
Men	1.625	1.621	1.648	1.634
Women	1.572	1.578	1.661	1.691
Non-Foster	1.979	2.007		1.763
Foster		1.310	1.528	1.544
Log Expenditure per Person	11.590	11.572	11.631	11.706
North	0.248	0.255	0.219	0.252
Central	0.349	0.362	0.323	0.325
Year=2010	0.693	0.691	0.706	0.685
Average Age Non-Foster	6.518	6.506		7.919
Average Age Foster		9.282	8.929	8.920
Proportion Female Non-Foster	0.495	0.487		0.483
Proportion Female Foster		0.555	0.532	0.546
Proportion Orphaned Foster		0.409	0.334	0.324
Average Age Women	31.031	31.327	37.741	37.756
Average Age Men	31.963	32.070	35.822	35.786
Average Education Women	6.181	6.094	5.131	5.246
Average Education Men	7.614	7.491	6.933	6.915
Rural	0.727	0.730	0.744	0.726
Proportion Female Adults Age 15-18	0.116	0.107	0.138	0.143
Proportion Male Adults Age 15-18	0.157	0.163	0.198	0.195
Matrilineal Village	0.571	0.574	0.607	0.595
Sample Size	1,034	1,034	489	489

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. One-child-type households contain either only non-foster children or only foster children. Composite households contain both foster and non-foster children. Matched samples are selected using propensity score matching. In total, there are 1,034 composite households that are matched with a corresponding one-child-type non-foster household. There are 899 households with only foster children, and out of those households I select 489 to match with the most similar composite households. None of the variables are statistically different at the 5% level across one-child-type and composite households.

Table A15: Predicted Resource Shares: Households with Only Non-Foster Children

Household Type	Full Sample (1)	Restricted Sample (2)
1 non-Foster 0 Foster	0.174***	0.188**
	(0.0420)	(0.0878)
2 non-Foster 0 Foster	0.119***	0.124***
	(0.0240)	(0.0510)
3 non-Foster 0 Foster	0.089***	0.099***
	(0.0174)	(0.0384)
4 non-Foster 0 Foster	0.077***	0.091***
	(0.0147)	(0.0333)
5 non-Foster 0 Foster	0.070***	0.088***
	(0.0132)	(0.0315)
N	10,763	1,034
Log Likelihood	92,402	8,919

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. The full sample includes all households with 1-4 men and women, and 1-5 children. The restricted sample is selected using nearest neighbor propensity score matching. In total, there are 1,034 composite households which are matched with one-child-type non-foster households. These matched households comprise the restricted sample. Robust standard errors in parentheses. The predicted resource shares are per-child. * p<0.1, ** p<0.05, *** p<0.01

Table A16: Descriptive Statistics: Education and Child Labour

	Mean	Std. Dev.	Min	Max	Sample Size
Foster Status					
Both Parents Present	0.622	0.485	0	1	20371
Father Present Mother Absent and Alive	0.013	0.115	0	1	20371
Father Present Maternal Orphan	0.009	0.092	0	1	20371
Mother Present Father Absent and Alive	0.116	0.320	0	1	20371
Mother Present Paternal Orphan	0.058	0.234	0	1	20371
Both Absent and Alive	0.107	0.309	0	1	20371
Double Orphan	0.027	0.163	0	1	20371
Both Absent Paternal Orphan	0.026	0.158	0	1	20371
Both Absent Maternal Orphan	0.022	0.146	0	1	20371
Individual and Household Characteristics					
Enrolled in School	0.880	0.325	0	1	20371
Hours Worked in Chores Past Week	1.825	5.674	0	96	20371
Hours Worked (Excluding Chores) Past Week	2.166	4.021	0	49	20371
Expenditure per Capita (1000s MWK)	115.992	136.494	6.896	2,976.659	20371
Remmitances Per Capita (1000s MWK)	1.943	15.409	0	1,751.6	20371
North	0.207	0.405	0	1	20371
Central	0.362	0.481	0	1	20371
South	0.432	0.495	0	1	20371
Year = 2010	0.739	0.439	0	1	20371
Male Sibling Age 0-6	0.613	0.762	0	5	20371
Female Siblings Age 0-6	0.621	0.759	0	4	20371
Male Siblings Age 7-14	0.656	0.784	0	6	20371
Female Siblings Age 7-14	0.662	0.788	0	6	20371
Men in HH	1.370	0.958	0	9	20371
Women in HH	1.485	0.810	0	7	20371
Age	9.694	2.596	6	14	20371
Female	0.508	0.500	0	1	20371
Rural	0.825	0.380	0	1	20371
Age Household Head	44.032	12.999	16	104	20371
Female Household Head	0.174	0.379	0	1	20371
Education of Household Head	5.530	4.123	0	14	20371

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. All children age 6-14.

A.5 Identification Theorems

What follows are extended versions of the identification theorems in DLP. Theorem 1 demonstrates how resource shares can be identified using the SAT restriction, while Theorem 2 does the same using the SAP restriction. Parts of both theorems and their respective proofs are similar to what is found in DLP, and I will therefore point out the parts where I differ.

Let $h_t^k(p,y)$ be the Marshallian demand function for good k and let the utility function of person t be defined as $U_t(x_t)$. Individual t chooses x_t to maximize $U_t(x_t)$ under the budget constraint $p'x_t = y$ with $x_t = h_t(p,y)$ for all goods k. Define the indirect utility function $V_t(p,y) = U_t(h_t(p,y))$ where $h_t(p,y)$ is the vector of demand functions for all goods k.

The household solves the following maximisation problem where each individual person type has their own utility function:[50]

$$\begin{aligned}\max_{x_m,x_f,x_a,x_b} \tilde{U}_{s_{ab}}[U_m(x_m), U_f(x_f), U_a(x_a), U_b(x_b), p/y] \text{ such that}\\ z_{s_{ab}} = A_{s_{ab}}[x_m + x_f + \sigma_a x_a + \sigma_b x_b] \text{ and}\\ y = z'p\end{aligned} \tag{A17}$$

The household demand functions are given by $H^k_{s_{ab}}(p,y)$. Let $A^k_{s_{ab}}$ be the row vector given by the k'th row of the linear technology function $A_{s_{ab}}$. Each individual faces the shadow budget constraint defined by the Lindahl price vector $A'_{s_{ab}}p$ and individual income $\eta^t_{s_{ab}}y$. Then household demand can be written as follows:

$$z^k_{s_{ab}} = H^k_{s_{ab}}(p,y) = A^k_{s_{ab}}\Big[\sum_{t\epsilon\{m,f,a,b\}} \sigma_t h_t(A'_{s_{ab}}p, \eta^t_{s_{ab}}y)\Big] \tag{A18}$$

where $\eta^t_{s_{ab}}$ are the resource shares of person t in a household with σ_a foster children and σ_b non-foster children. Resource shares by construction must sum to one.

$$\eta^m_{s_{ab}} + \eta^f_{s_{ab}} + \sigma_a\eta^a_{s_{ab}} + \sigma_b\eta^b_{s_{ab}} = 1 \tag{A19}$$

ASSUMPTION A1: Equations (A17), (A18), and (A19) hold with resource shares $\eta^t_{s_{ab}}$ that do not depend on y.

Resource shares being independent of household expenditure is the key identifying assumption. Resource shares can still depend on other variables correlated with household expenditure such as the individual wages for men and women.

[50] For simplicity, I have assumed there are one man and one woman in each household.

DEFINITION: A good k is a *private* good if, for any household size s_{ab}, the matrix $A_{s_{ab}}$, has a one in position k, k and has all other elements in row k and column k equal to zero.

DEFINITION: A good k is an *assignable* good if it only appears in one of the utility functions U_m, U_f, U_a, and U_b.

Men's and women's clothing expenditures are examples of private assignable goods. These goods are central to identification in DLP and they are here as well. What makes private assignable goods unique and especially useful for identification is that by definition, the quantities that the household purchases are equivalent to what individuals in the household consume. In other words, there are no economies of scale or sharing for these goods making household-level consumption in some sense equivalent to individual-level consumption. However, because I lack a private assignable good for foster and non-foster children, I must make use of partially assignable goods.

DEFINITION: A good k is a *partially assignable* good if it only appears in two of the utility functions U_m, U_f, U_a, and U_b.

An example of a partially assignable good is children's clothing expenditures, which are partially assignable to foster and non-foster children. Specifically, children's clothing only appears in the utility functions for foster and non-foster children, U_a and U_b. In other contexts, children's clothing expenditures can be classified as partially assignable to boys and girls, or potentially to young and old children. Other examples of partially assignable goods commonly found in household survey data include alcohol and tobacco, which are assignable to adults, but only partially assignable to adult men and women.

The distinction between assignable and partially assignable goods is in some ways determined by the question the researcher is interested in answering. For example, DLP are interested in estimating intrahousehold inequality between men, women, and children within the household, and are therefore less interested in understanding inequality *among* children within the household, as I am in this context. They assume all children have the same utility function, U_c, or that $U_a = U_b$.[51] As a result, children's clothing expenditures are assignable, as they only appear in U_c. In my context, where I allow foster and non-foster children to have different utility functions and ultimately different resource shares, children's clothing expenditures now

[51] All utility functions are allowed to vary by observable household characteristics, such as age, education, and gender.

appear in both U_a and U_b and are therefore no longer assignable.

ASSUMPTION A2: Assume that the demand functions include a private assignable good for men and women, denoted as goods m and f. Assume that the demand functions include a private partially assignable good for foster and non-foster children, denoted as good c.

The household demand functions for the private assignable goods for men and women can be written as follows:

$$z^k_{s_{ab}} = H^k_{s_{ab}} = h^k(A'_{s_{ab}} p, \eta^k_{s_{ab}}(p) y) \text{ for } k \epsilon \{m, f\} \tag{A20}$$

For the foster and non-foster children, household demand functions for the private partially assignable good can be written as follows:

$$z^c_{s_{ab}} = H^c_{s_{ab}} = \sigma_a h^a(A'_{s_{ab}} p, \eta^a_{s_{ab}}(p) y) + \sigma_b h^b(A'_{s_{ab}} p, \eta^b_{s_{ab}}(p) y) \tag{A21}$$

In practice, I take the household demand functions for foster child clothing, and non-foster child clothing, and sum them together. Taking this action is possible since the goods are private. In the empirical application, this means that I assume clothing is not shared across child types.

Define p_m and p_f to be the prices of the private assignable goods and define p_c to be the price of the private partially assignable good. Define $\bar{p}$ to be the vector of prices for all private goods excluding p_m, p_f, and p_c. Assume $\bar{p}$ is nonempty.

ASSUMPTION A3: Each person $t \epsilon \{m, f, a, b\}$ has the following indirect utility function:[52]

$$V_t(p, y) = \psi_t \Big[u_t \Big(\frac{y}{G^t(\tilde{p})}, \frac{\bar{p}}{p_t} \Big), \tilde{p} \Big] \tag{A22}$$

where G^t is some function that is nonzero, differentiable, and homogeneous of degree one, ψ_t and u_t are strictly positive, differentiable, and strictly monotonically increasing in their first arguments, and differentiable and homogenous of degree zero in their remaining elements.[53]

By Roy's identity, the demand functions for the private assignable goods $k \epsilon \{m, f, a, b\}$ can

[52] As discussed in DLP, the indirect utility function only has to take this form for low levels of expenditure. For simplicity, I assume the indirect utility function is the same across all expenditure levels.
[53] Asssumption A3 is a modified version of Assumption B3 in DLP.

be written as follows:

$$h^k(y,p) = \frac{\partial u_k\Big(\frac{y}{G^k(\tilde{p})}, \frac{\bar{p}}{p_k}\Big)'}{\partial(\bar{p}/p_k)} \frac{\bar{p}}{p_k^2} \frac{G^k(\tilde{p})}{u_k'\Big(\frac{y}{G^k(\tilde{p})}, \frac{\bar{p}}{p_k}\Big)} = \tilde{f}_k\Big(\frac{y}{G^k(\tilde{p})}, p_k, \bar{p}\Big)y$$

Since p_k and $\bar{p}$ do not change when replaced by $A'_{s_{ab}}p$, substituting the above equation into Equation (A20) gives the household demand functions for the assignable goods:

$$H^k_{s_{ab}}(y,p) = \tilde{f}_k\Big(\frac{\eta^k_{s_{ab}}(p)y}{G^k(\tilde{A}'_{s_{ab}}\tilde{p})}, p_k, \bar{p}\Big)\eta^k_{s_{ab}}(p)y$$

The Engel curve by definition holds price constant, and can then be written as:

$$H^k_{s_{ab}}(y) = \tilde{f}_k\Big(\frac{\eta^k_{s_{ab}}y}{G^k_{s_{ab}}}\Big)\eta^k_{s_{ab}}y \tag{A23}$$

However, because there are no private assignable goods for foster and non-foster children, I write the Engel curve for the private partially assignable good for children in place of $H^a_{s_{ab}}$ and $H^b_{s_{ab}}$ as follows:

$$H^c_{s_{ab}}(y) = \tilde{f}_a\Big(\frac{\eta^a_{s_{ab}}y}{G^a_{s_{ab}}}\Big)\sigma_a\eta^a_{s_{ab}}y + \tilde{f}_b\Big(\frac{\eta^b_{s_{ab}}y}{G^b_{s_{ab}}}\Big)\sigma_b\eta^b_{s_{ab}}y \tag{A24}$$

Define the matrix Ω' by

$$\Omega' = \begin{bmatrix} \frac{\eta^m_{10}}{\eta^m_{20}} & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\eta^f_{10}}{\eta^f_{20}} & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\eta^m_{01}}{\eta^m_{02}} & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{\eta^f_{01}}{\eta^f_{02}} & -1 \\ 0 & -1 & 0 & 0 & 0 & \frac{\eta^m_{10}}{\eta^m_{01}} & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & \frac{\eta^f_{10}}{\eta^f_{01}} \\ \frac{\eta^m_{10}}{\eta^m_{20}} - \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & \frac{\eta^f_{10}}{\eta^f_{20}} - \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\eta^m_{01}}{\eta^m_{02}} - \frac{\eta^b_{01}}{\eta^b_{02}} & 0 & \frac{\eta^f_{01}}{\eta^f_{02}} - \frac{\eta^b_{01}}{\eta^b_{02}} & 0 \end{bmatrix}$$

ASSUMPTION A4: The matrix Ω' is finite and nonsingular. $f^k(0) \neq 0$ for $k \in \{m, f, a, b\}$.

Finiteness of Ω' requires that resource shares are never zero. The matrix is nonsingular provided resource shares are not equal across household sizes. An example of a potential violation would be if parents in households with one fostered child have the exact same resource shares as parents in households with two fostered children, which is unlikely.

The condition that $f^k(0) \neq 0$ requires that the Engel curves for the private assignable and partially assignable goods are continuous and bounded away from zero.

DEFINITION: A *composite* household is a household that contains at least one foster and one non-foster child, or more concisely ($\sigma_a > 0$ and $\sigma_b > 0$).

DEFINITION: A *one-child-type* household is a household that has children, but is not a composite household, or more concisely ($\sigma_a > 0$ and $\sigma_b = 0$) or ($\sigma_a = 0$ and $\sigma_b > 0$) .

ASSUMPTION A5: Assume households with either only foster children, or only non-foster children are observed. With four different person types, there must be at least four different one-child-type households in the data.

For Assumption A5 to hold in this context, it is necessary to observe both one-child-type households with one or two foster children (s_{10} and s_{20}), and also one-child-type households with one or two non-foster children (s_{01} and s_{02}). This requirement is easily met but may be more difficult in other contexts. For example, if one was interested in analyzing intrahousehold inequality between widows and non-widow adult women, it is rare to have multiple widows in the same household. In this case, identification could be achieved by observing a one-child-type household with only a widow present, and three different household types with only non-widowed adult women present.

Using one-child-type and composite households in some sense mirrors the central identification assumption of Browning et al. (2013). They use households with single men or single women ("one-person-type households") to identify preferences in households with married couples ("composite households"). Similarly, I use the one-child-type households to impose structure on the composite households. I would however argue that my use of one-child-type households is much weaker than their use of single person households as married men and women likely have different preferences than single men and women, while it is not obvious why foster and non-foster child preferences should differ significantly across one-child-type and composite households.

ASSUMPTION A6: Preferences for clothing for foster and non-foster children are not identical. That is, $f^a(0) \neq f^b(0)$.

Resource shares will be identified by determining whether preferences for children's clothing in the composite households look more like the foster only households, or the non-foster only households. If those preferences are identical, then this method will not work.

Theorem 1. *Let Assumptions A1, A2, A3, A4, A5 and A6 hold for all household sizes s_{ab} in some set S, with one-child-type households $s_{ab} \in \{s_{01}, s_{10}, s_{02}, s_{20}\}$, and composite households s_{ab}.*[54] *Assume the household's Engel curves for the private, assignable good $H^t_{s_{ab}}(y)$ for $t \in \{m, f\}$ and $s_{ab} \in S$ are identified. Assume the household's Engel curve for the private, partially assignable good $H^c_{s_{ab}}$ for $s_{ab} \in S$ is identified. Then resource shares $\eta^t_{s_{ab}}$ for all household members $t \in \{m, f, a, b\}$ in household sizes $s_{ab} \in S$ are identified.*

The above theorem is a generalization of the DLP identification strategy using the SAT restriction. I next show how resource shares can be recovered using the SAP restriction. This theorem is an extension of Theorem 1 in DLP.

Define p_m and p_f to be the prices of the private assignable goods. Define p_c to be the price of the private partially assignable goods. The price of all other goods is given by $\tilde{p}$. As in DLP, define the square matrix $\tilde{A}_{s_{ab}}$ such that the set of prices given by $A'_{s_{ab}}$ includes the private and partially assignable good prices, p_m, p_f, and p_c, as well as all other prices, given by $A'_{s_{ab}}$.

ASSUMPTION B3: Assume each person $t \in \{m, f, a, b\}$ faces the budget constraint defined by (y, p) and has preferences over the private assignable and partially assignable goods, $k \in \{m, f, c\}$ given by the following indirect utility function:

$$V_t(p, y) = \psi_t\Big[\nu(\frac{y}{G^t(p)}) + F^t(p), \tilde{p}\Big] \tag{A25}$$

for some some functions ψ_t, F, and G^t where G^t is nonzero, differentiable, and homogenous of degree one, ν is differentiable and strictly monotonically increasing, $F^t(p)$ is differentiable, homogenous of degree zero, and is such that $\partial F^t(p)/\partial p_t = \phi(p) \neq 0$. Lastly, ψ_t is differentiable and strictly monotonically increasing in its arguments, and differentiable and homogenous of degree zero in the remaining arguments.

ASSUMPTION B4: For foster and non-foster children, the person-specific expenditure deflators are equal. That is, $G^a = G^b = G^c$, where G^c denotes the expenditure deflator for children.

[54] Resource shares are identified for any composite household provided there is a sufficient number of one-child-type households. In the empirical application, there are ten such households.

By Roy's identity the demand functions for private assignable goods are as follows:

$$
\begin{aligned}
h^k(y,p) =& \frac{v'\left(\frac{y}{G^k(p)}\right)\frac{y}{G^{k2}(p)}\frac{\partial G^k(p)}{\partial p_k} + \frac{\partial F^k(p)}{\partial p_k}}{v'\left(\frac{y}{G^k(p)}\right)\frac{1}{G^k(p)}} \\
=& \frac{y}{G^k(p)}\frac{\partial G^k(p)}{\partial p_k} + \frac{\phi(p)}{v'\left(\frac{y}{G^k(p)}\right)}\frac{y}{y/G^k(p)} = \delta^k(p)y + g\Big(\frac{y}{G^k(p)}, p\Big)y
\end{aligned}
$$

Adding the demand functions for foster and non-foster child assignable goods results in the following equation:

$$
h^a(y,p) + h^b(y,p) = \Big(\delta^a(p) + \delta^b(p)\Big)y + g\Big(\frac{y}{G^c(p)}, p\Big)y
$$

For the private assignable goods for adults, I derive the following household-level demand function.

$$
H^k(y,p) = \delta^k(A'_{s_{ab}}p)\eta^k_{s_{ab}}(p)y + g\Big(\frac{\eta^k_{s_{ab}}(p)y}{G^k(A'_{s_{ab}}p)}, p\Big)\eta^k_{s_{ab}}(p)y
$$

Let $\eta^c = \sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}}$. Then the household-level demand functions for children's clothing is given by:

$$
H^c(y,p) = \Big(\delta^a(A'_{s_{ab}}p) + \delta^b(A'_{s_{ab}}p)\Big)\eta^c_{s_{ab}}(p)y + g\Big(\frac{\eta^c_{s_{ab}}(p)y/(\sigma_a + \sigma_b)}{G^c(A'_{s_{ab}}p)}\Big)\eta^c_{s_{ab}}(p)y
$$

The Engel curves for adults ($k \in \{m, f\}$) and children are then as follows:

$$
H^k_{s_{ab}}(y) = \delta^k_{s_{ab}}\eta^k_{s_{ab}}y + g_{s_{ab}}\Big(\frac{\eta^k_{s_{ab}}y}{G^k_{s_{ab}}}\Big)\eta^k_{s_{ab}}y \tag{A26}
$$

and

$$
H^c_{s_{ab}}(y) = \Big(\delta^a_{s_{ab}} + \delta^b_{s_{ab}}\Big)\eta^c_{s_{ab}}y + g\Big(\frac{\eta^c_{s_{ab}}y/(\sigma_a + \sigma_b)}{G^c_{s_{ab}}}\Big)\eta^c_{s_{ab}}y \tag{A27}
$$

ASSUMPTION B5:[55] The function $g_{s_{ab}}$ is twice differentiable. Let $g'_{s_{ab}}(y)$ and $g''_{s_{ab}}(y)$ be the first and second derivatives of $g_{s_{ab}}$. Assume either that $\lambda_{s_{ab}} = \lim_{y\to 0}[y^{\zeta} g''_{s_{ab}}(y)/g'_{s_{ab}}]^{\frac{1}{1-\zeta}}$ is finite and nonzero for some constant $\zeta \neq 1$ or that $g_{s_{ab}}$ is a polynomial in $\ln y$.

Assumption B5 requires that there be some nonlinearity in the demand function so that g'' is not zero.

[55] This is Assumption A4 from DLP.

ASSUMPTION B6: The ratio of foster and non-foster child resource shares in households with σ_a and $\sigma_{a'}$, and σ_b and $\sigma_{b'}$ foster and non-foster children is constant across household sizes.

$$\frac{\eta^a_{s_{a0}}}{\eta^a_{s_{a+1,0}}} = \frac{\eta^a_{s_{ab}}}{\eta^a_{s_{a+1,b}}} \text{ and } \frac{\eta^b_{s_{0b}}}{\eta^b_{s_{0,b+1}}} = \frac{\eta^b_{s_{ab}}}{\eta^b_{s_{a,b+1}}} \tag{A28}$$

for σ_a and $\sigma_b \epsilon \{1,2\}$.

This assumption restricts the way in which resource shares vary across household types. In effect, it imposes that resource shares for foster and non-foster children in one-child-type and composite households behave in a similar fashion. Stated differently, this is an independence assumption: the ratio of foster child resource shares in a households with σ_a and σ_{a+1} foster children is independent of the number of *non-foster* children present in those households, and vice versa.

Other studies using the DLP identification strategy have imposed similar restrictions to improve precision in the estimation, but not for identification reasons. For example, Calvi (2016) parametrizes resource shares in such a way that per person resource shares decrease linearly in the number of household members. In the notation of this study, that would mean assuming $\eta^a_{s_{a,0}} - \eta^a_{s_{a+1,0}} = \eta^a_{s_{ab}} - \eta^a_{s_{a+1,b}}$. On the contrary, I impose that the percent decline is constant, as opposed to the absolute decline. In several specifications, DLP make a similar restriction that per child resource shares decrease linearly in the number of children.

ASSUMPTION B7: 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.

$$\frac{\eta^a_{s_{10}}}{\eta^b_{s_{01}}} = \frac{\eta^a_{s_{11}}}{\eta^b_{s_{11}}} \tag{A29}$$

Similar to Assumption B6, this restriction assumes households with only foster on non-foster children are similar to households with both types of children. To better understand this restriction, consider the following example given below:

Household	σ_a	σ_b	$\eta^a_{s_{ab}}$	$\eta^b_{s_{ab}}$	Assumption B6
A	1	0	24	0	
B	0	1	0	21	
C	1	1	16	14	$\frac{24}{21} = \frac{\eta^a_{10}}{\eta^b_{01}} = \frac{\eta^a_{11}}{\eta^b_{11}} = \frac{16}{14}$

Here, Household's A and B are one-child-type, whereas Household C is a composite household. Assumption B6 requires that foster and non-foster child resource shares in Household C, $\eta^a_{11}$and η^b_{11}, are proportional to foster and non-foster child resource shares in Household's A and B. In particular, if $\eta^a_{10} = 24$, and $\eta^b_{01} = 21$, then $\frac{\eta^a_{11}}{\eta^b_{11}} = \frac{24}{21}$. Importantly, this restriction directly applies to only a single composite household type.

Define the matrix Ω'' by

$$\Omega'''' = \begin{bmatrix} \frac{\eta^m_{11}}{\eta^a_{11}} + \frac{\eta^f_{11}}{\eta^a_{11}} + 1 & \frac{\eta^m_{11}}{\eta^b_{11}} + \frac{\eta^f_{11}}{\eta^b_{11}} + 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2(\frac{\eta^m_{21}}{\eta^a_{21}} + \frac{\eta^f_{21}}{\eta^a_{21}} + 1) & \frac{\eta^m_{21}}{\eta^b_{21}} + \frac{\eta^f_{21}}{\eta^b_{21}} + 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\eta^m_{12}}{\eta^a_{12}} + \frac{\eta^f_{12}}{\eta^a_{12}} + 1 & 2(\frac{\eta^m_{12}}{\eta^b_{12}} + \frac{\eta^f_{12}}{\eta^b_{12}} + 1) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{\eta^m_{22}}{\eta^a_{22}} + \frac{\eta^f_{22}}{\eta^a_{22}} + 1 & \frac{\eta^m_{22}}{\eta^b_{22}} + \frac{\eta^f_{22}}{\eta^b_{22}} + 1 \\ -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 \\ 0 & -1 & 0 & 0 & 0 & \frac{\eta^b_{01}}{\eta^b_{02}} & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & \frac{\eta^b_{01}}{\eta^b_{02}} \\ \frac{1}{\eta^a_{10}} & \frac{-1}{\eta^b_{01}} & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

ASSUMPTION B8: The matrix Ω'' is finite and nonsinuglar.

This is true as long as resource shares are nonzero.

Theorem 2. *Let Assumptions A1, A2, A5, B3, B4, B5, B6, B7, and B8 hold for all household sizes s_{ab} in some set S, with $s_{ab} \in \{s_{01}, s_{10}, s_{02}, s_{20}, s_{11}, s_{12}, s_{21}, s_{22}\}$. Assume the household's Engel curves for the private, assignable good $H^k_{s_{ab}}(y)$ for $k \in \{m, f\}$ for $s_{ab} \in S$ are identified. Assume the household's Engel curve for the private, partially assignable good $H^c_{s_{ab}}$ for $s_{ab} \in S$ is identified. Then resource shares $\eta^t_{s_{ab}}$ for all household members $t \in \{m, f, a, b\}$ in household sizes $s_{ab} \in S$ are identified.*

A.6 Identification Proofs

A.6.1 Proof of Theorem 1

This proof follows the proof of Theorem 2 in DLP, and extends it to identify resource shares in the absence of assignable goods for each person type. The proof proceeds in two steps. In the first step, I demonstrate resource shares are identified in the one-child-type households; this follows directly from DLP. In the second step, I extend DLP to demonstrate how resource shares are identified in the absence of private assignable goods.

By Assumption A3, the Engel curve functions for the assignable and partially assignable goods are given by Equations (A23) and (A24). Let $s_{ab} \in \{s_{10}, s_{20}, s_{01}, s_{02}\}$ be the different one-child-type households. Then since the functions H^k and H^c are identified for $k \in \{m, f\}$, ζ^k_{20}, ζ^k_{02}, and ζ^k_{01} defined as $\zeta^k_{20} = \lim_{y\to 0} H^k_{10}(y)/H^k_{20}(y)$, $\zeta^k_{02} = \lim_{y\to 0} H^k_{10}(y)/H^k_{02}(y)$, and $\zeta^k_{01} = \lim_{y\to 0} H^k_{10}(y)/H^k_{01}(y)$ are all identified. Moreover, $\zeta^a_{20} = \lim_{y\to 0} H^a_{10}(y)/H^a_{20}(y)$ and $\zeta^b_{02} = \lim_{y\to 0} H^b_{01}(y)/H^b_{02}(y)$ can be identified for foster and non-foster children, respectively.

Then for $k \in \{m, f\}$:

$$\zeta^k_{20} = \frac{f^k(0)\eta^k_{10}}{f^k(0)\eta^k_{20}} = \frac{\eta^k_{10}}{\eta^k_{20}} \quad \text{and} \quad \zeta^k_{02} = \frac{f^k(0)\eta^k_{01}}{f^k(0)\eta^k_{02}} = \frac{\eta^k_{01}}{\eta^k_{02}} \quad \text{and} \quad \zeta^k_{01} = \frac{f^k(0)\eta^k_{10}}{f^k(0)\eta^k_{01}} = \frac{\eta^k_{10}}{\eta^k_{01}}$$

The same ratio for foster and non-foster children in households with only one child type can be identified:

$$\zeta^a_{20} = \frac{(f^a(0)\eta^a_{10} + 0\times f^b(0)\eta^b_{10})}{(2f^a(0)\eta^a_{20} + 0\times f^b(0)\eta^b_{20})} = \frac{\eta^a_{10}}{2\eta^a_{20}} \quad \text{and} \quad \zeta^b_{02} = \frac{(0\times f^a(0)\eta^a_{01} + f^b(0)\eta^b_{01})}{(0\times f^a(0)\eta^a_{02} + 2f^b(0)\eta^b_{02})} = \frac{\eta^b_{01}}{2\eta^b_{02}}$$

Using that resource shares must sum to one, the following equations can be written, first for households with only non-foster children:

$$\begin{aligned}
&\zeta^m_{s_{20}}\eta^m_{s_{20}} + \zeta^f_{s_{20}}\eta^f_{s_{20}} + \zeta^a_{s_{20}}\sigma_a\eta^a_{s_{20}} = \eta^m_{10} + \eta^f_{10} + \eta^a_{10} = 1\\
&\zeta^m_{s_{20}}\eta^m_{s_{20}} + \zeta^f_{s_{20}}\eta^f_{s_{20}} + \zeta^a_{s_{20}}(1 - \eta^m_{s_{20}} - \eta^f_{s_{20}}) = 1\\
&(\zeta^m_{s_{20}} - \zeta^a_{s_{20}})\eta^m_{s_{20}} + (\zeta^f_{s_{20}} - \zeta^a_{s_{20}})\eta^f_{s_{20}} = 1 - \zeta^a_{s_{20}}
\end{aligned}$$

and then for households with only foster children:

$$\begin{aligned}
&\zeta^m_{s_{02}}\eta^m_{s_{02}} + \zeta^f_{s_{02}}\eta^f_{s_{02}} + \zeta^b_{s_{02}}\sigma_b\eta^b_{s_{02}} = \eta^m_{01} + \eta^f_{01} + \eta^b_{01} = 1\\
&\zeta^m_{s_{02}}\eta^m_{s_{02}} + \zeta^f_{s_{02}}\eta^f_{s_{02}} + \zeta^b_{s_{02}}(1 - \eta^m_{s_{02}} - \eta^f_{s_{02}}) = 1\\
&(\zeta^m_{s_{02}} - \zeta^b_{s_{02}})\eta^m_{s_{02}} + (\zeta^f_{s_{02}} - \zeta^b_{s_{02}})\eta^f_{s_{02}} = 1 - \zeta^b_{s_{02}}
\end{aligned}$$

These above equations for $t \epsilon \{m,f\}$, give the matrix equation

$$\begin{bmatrix} \zeta_{20}^m & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \zeta_{20}^f & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \zeta_{02}^m & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \zeta_{02}^f & -1 \\ 0 & -1 & 0 & 0 & 0 & \zeta_{01}^m & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & \zeta_{01}^f \\ \zeta_{20}^m - \zeta_{20}^a & 0 & \zeta_{20}^f - \zeta_{20}^a & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \zeta_{02}^m - \zeta_{02}^b & 0 & \zeta_{02}^f - \zeta_{02}^b & 0 \end{bmatrix} \times \begin{bmatrix} \eta_{20}^m \\ \eta_{10}^m \\ \eta_{20}^f \\ \eta_{10}^f \\ \eta_{02}^m \\ \eta_{01}^m \\ \eta_{02}^f \\ \eta_{01}^f \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1-\zeta_{20}^a \\ 1-\zeta_{02}^b \end{bmatrix}$$

The 8×8 matrix in this equation equals the previously defined matrix Ω' which was assumed to be nonsingular. Therefore the system can be solved for $\eta_{s_{a0}}^m$, $\eta_{s_{0b}}^m$, $\eta_{s_{a0}}^f$, and $\eta_{s_{0b}}^f$. Non-foster child resource shares and foster child resource shares can then be identified for one-child-type only households by $\eta_{s_{a0}}^a = (1-\eta_{s_{a0}}^m - \eta_{s_{a0}}^f)/\sigma_a$ and $\eta_{s_{0b}}^b = (1-\eta_{s_{0b}}^m - \eta_{s_{0b}}^f)/\sigma_b$.

I now show resource shares are identified in any given composite household. Recall that the functions H^k are identified for $k \epsilon \{m,f\}$. It follows that for any household type s_{ab}, $\zeta_{s_{ab}}^k$ defined as $\zeta_{s_{ab}}^k = \lim_{y\to 0} H_{10}^k(y)/H_{s_{ab}}^k(y)$ can be identified.

Then for $k \epsilon \{m,f\}$:

$$\zeta_{s_{ab}}^k = \frac{f^k(0)\eta_{10}^k}{f^k(0)\eta_{s_{ab}}^k} = \frac{\eta_{10}^k}{\eta_{s_{ab}}^k}$$

With η_{10}^k already identified, resource shares for men and women in the composite household types can be recovered. This is a simple extension of DLP where there are more household types than individual types.

I now aim to separately identify non-foster and foster child resource shares in households with both types of children. Define $\zeta_{s_{ab}}^a$ as follows: $\zeta_{s_{ab}}^a = \lim_{y\to 0} H_{s_{ab}}^c(y)/H_{10}^c(y)$. Moreover, define $\zeta_{01}^b = \lim_{y\to 0} H_{01}^c(y)/H_{10}^c(y)$. Then we can write:

$$\zeta_{s_{ab}}^a = \frac{f^a(0)\eta_{s_{ab}}^a + f^b(0)\eta_{s_{ab}}^b}{f^a(0)\eta_{10}^a} = \frac{\eta_{s_{ab}}^a}{\eta_{10}^a} + \frac{f^b(0)\eta_{s_{ab}}^b}{f^a(0)\eta_{10}^a} \tag{A30}$$

Furthermore,

$$\zeta_{01}^b = \frac{f^b(0)\eta_{01}^b}{f^a(0)\eta_{10}^a} \to \frac{f^b(0)}{f^a(0)} = \frac{\zeta_{01}^b\eta_{10}^a}{\eta_{01}^b} = \kappa$$

where η_{10}^a and η_{01}^b have already been identified. Thus, the ratio $f^b(0)/f^a(0) = \kappa$ is identified. Substituting κ into equation (A30) results in the following expression:

$$\zeta_{s_{ab}}^a = \frac{\eta_{s_{ab}}^a}{\eta_{10}^a} + \kappa\frac{\eta_{s_{ab}}^b}{\eta_{10}^a} \tag{A31}$$

where only $\eta_{s_{ab}}^a$ and $\eta_{s_{ab}}^b$ are unknown. Then since resource shares for men and women have already been identified for households of type s_{ab}, and because resource shares sum to one, we can solve for $\eta^a_{s_{ab}}$ and $\eta^b_{s_{ab}}$. This has a unique solution following Assumption A6.

A.6.2 Proof of Theorem 2

The proof proceeds in two steps. In the first step, I demonstrate resource shares are identified in the one-child-type households; this follows directly from DLP. In the second step, I extend DLP to demonstrate how resource shares can be identified in the absence of private assignable goods.

By Assumption B3, Engel curves for the private assignable goods for men and women are given by Equation (A26) and by Assumptions B3 and B4, the Engel curve for the private partially assignable good is given by Equation (A27). Define $\tilde{h}^k_{s_{ab}}(y) = \partial[H^k_{s_{ab}}(y)/y]\partial y$ and $\lambda_{s_{ab}} = \lim_{y\to 0}[y^\zeta g^{''}_{s_{ab}}(y)/g^{'}_{s_{ab}}]^{\frac{1}{1-\zeta}}$, where $\zeta \neq 1$ (the log polynomial case, where $\zeta = 1$ is considered in the second case).

Case 1: $g_{s_{ab}}$ is not a polynomial in logarithms.

Let $\sigma_c = \sigma_a + \sigma_b$ be the total number of children. Then since $H^k_{s_{ab}}(y)$ are identified for $k \in \{m, f, c\}$, we can identify $\kappa^k_{s_{ab}}$ for men and women defined as follows:

$$
\begin{aligned}
\kappa^k_{s_{ab}} &= \left(y^\zeta \frac{\partial \tilde{h}^k_{s_{ab}}(y)/\partial y}{\tilde{h}^k_{s_{ab}}(y)} \right)^{\frac{1}{1-\zeta}} \\
&= \left(\left(\frac{\eta^k_{s_{ab}}}{G^k_{s_{ab}}}\right)^{-\zeta} \left(\frac{\eta^k_{s_{ab}} y}{G^k_{s_{ab}}}\right)^{\zeta} \left[g^{''}_{s_{ab}}\left(\frac{\eta^k_{s_{ab}} y}{G^k_{s_{ab}}}\right) \frac{\eta^{k^3}_{s_{ab}}}{G^{k^2}_{s_{ab}}} \right] / \left[g^{'}_{s_{ab}}\left(\frac{\eta^k_{s_{ab}} y}{G^k_{s_{ab}}}\right) \frac{\eta^{k^2}_{s_{ab}}}{G^k_{s_{ab}}} \right] \right)^{\frac{1}{1-\zeta}} \\
&= \frac{\eta^k_{s_{ab}}}{G^k_{s_{ab}}} \left(y^\zeta_{k,s_{ab}} \frac{g^{''}_{s_{ab}}(y_{k,s_{ab}})}{g^{'}_{s_{ab}}(y_{k,s_{ab}})} \right)^{\frac{1}{1-\zeta}}
\end{aligned}
$$

and for children:

$$\kappa^c_{s_{ab}} = \Big(y^{\zeta} \frac{\partial \tilde{h}^c_{s_{ab}}(y)/\partial y}{\tilde{h}^c_{s_{ab}}(y)} \Big)^{\frac{1}{1-\zeta}} =$$

$$\Big(\big(\frac{\eta^c_{s_{ab}}}{G^c_{s_{ab}} s_c} \big)^{-\zeta} \big(\frac{\eta^c_{s_{ab}} y}{G^c_{s_{ab}} s_c} \big)^{\zeta} \big[g^{''}_{s_{ab}} \big(\frac{\eta^c_{s_{ab}} y}{G^c_{s_{ab}} s_c} \big) \frac{\eta^{c^3}_{s_{ab}}}{G^{c2}_{s_{ab}} s^2_c} \big] / \big[g^{'}_{s_{ab}} \big(\frac{\eta^c_{s_{ab}} y}{G^c_{s_{ab}} s_c} \big) \frac{\eta^{c^2}_{s_{ab}}}{G^c_{s_{ab}} s_c} \big] \Big)^{\frac{1}{1-\zeta}}$$

$$= \frac{\eta^c_{s_{ab}}}{G^c_{s_{ab}} s_c} \Big(y^{\zeta}_{c,s_{ab}} \frac{g^{''}_{s_{ab}}(y_{c,s_{ab}})}{g^{'}_{s_{ab}}(y_{c,s_{ab}})} \Big)^{\frac{1}{1-\zeta}}$$

Then for $k \epsilon \{m, f\}$, $\kappa^k_{s_{ab}}(0) = \frac{\eta^k_{s_{ab}}}{G^k_{s_{ab}}} \lambda_{s_{ab}}$, and we can identify $\rho^k_{s_{ab}}(y)$ defined as:

$$\rho^k_{s_{ab}}(y) = \frac{\tilde{h}^k_{s_{ab}}(y/\kappa^k_{s_{ab}}(0))}{\kappa^k_{s_{ab}}(0)} = g^{'}_{s_{ab}} \big(\frac{y}{\lambda_{s_{ab}}} \big) \frac{\eta^k_{s_{ab}}}{\lambda_{s_{ab}}}$$

and for $k = c$, $\kappa^c_{s_{ab}}(0) = \frac{\eta^c_{s_{ab}}}{G^c_{s_{ab}} s_c} \lambda_{s_{ab}}$, and we can identify $\rho^c_{s_{ab}}(y)$ defined as:

$$\rho^c_{s_{ab}}(y) = \frac{\tilde{h}^c_{s_{ab}}\Big(y/\kappa^c_{s_{ab}}(0)\Big)}{\kappa^c_{s_{ab}}(0)} = g^{'}_{s_{ab}} \big(\frac{y}{\lambda_{s_{ab}}} \big) \frac{\eta^c_{s_{ab}}}{\lambda_{s_{ab}}}$$

and we can write $\gamma^k_{s_{ab}}$ for $k \epsilon \{m, f\}$:

$$\gamma^k_{s_{ab}} = \frac{\tilde{\rho}^k_{s_{ab}}}{\tilde{\rho}^c_{s_{ab}}} = \Big(g^{'}_{s_{ab}} \big(\frac{y}{\lambda_{s_{ab}}} \big) \frac{\eta^k_{s_{ab}}}{\lambda_{s_{ab}}} \Big) / \Big(g^{'}_{s_{ab}} \big(\frac{y}{\lambda_{s_{ab}}} \big) \frac{\eta^c_{s_{ab}}}{\lambda_{s_{ab}}} \Big) = \frac{\eta^k_{s_{ab}}}{(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})} \tag{A32}$$

Case 2: Before proceeding with the proof, I examine the case where $g_{s_{ab}}$ is a polynomial in logarithms (the end result will be Equation (A32) and I will proceed with both cases simultaneously afterwards). Suppose $g_{s_{ab}}$ is a polynomial of degree λ in logarithms. Then

$$g_{s_{ab}} \big(\frac{\eta^k_{s_{ab}} y}{G^k} \big) = \sum_{l=0}^{\lambda} \Big(\ln \big(\frac{\eta^k_{s_{ab}}}{G^k_{s_{ab}}} \big) + \ln(y) \Big)^l c_{s_{ab},l}$$

Then for $k \epsilon \{m, f\}$:

$$\gamma^k_{s_{ab}} = \big(\frac{\partial^{\lambda}[H^k_{s_{ab}}(y)/y]}{\partial(\ln y)^{\lambda}} \big) / \big(\frac{\partial^{\lambda}[H^c_{s_{ab}}(y)/y]}{\partial(\ln y)^{\lambda}} \big) =$$

$$\frac{c_{s_{ab},\lambda} \eta^k_{s_{ab}}}{c_{s_{ab},\lambda}(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})} = \frac{\eta^k_{s_{ab}}}{(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})} \tag{A33}$$

which is the same as Equation (A32). Then since resource shares must sum to one:

$$
\begin{aligned}
&\gamma^m_{s_{ab}}(\sigma_a\eta^a_{s_{ab}}+\sigma_b\eta^b_{s_{ab}})+\gamma^f_{s_{ab}}(\sigma_a\eta^a_{s_{ab}}+\sigma_b\eta^b_{s_{ab}})+\sigma_a\eta^a_{s_{ab}}+\sigma_b\eta^b_{s_{ab}}=\\
&\eta^m_{s_{ab}}+\eta^f_{s_{ab}}+\sigma_a\eta^a_{s_{ab}}+\sigma_b\eta^b_{s_{ab}}=1\\
&\sigma_a\eta^a_{s_{ab}}(\gamma^m_{s_{ab}}+\gamma^f_{s_{ab}}+1)+\sigma_b\eta^b_{s_{ab}}(\gamma^m_{s_{ab}}+\gamma^f_{s_{ab}}+1)=1
\end{aligned}
\tag{A34}
$$

For one-child-type households, σ_a or σ_b equals zero, and Equation (A34) simplifies significantly. For households that only have foster children, Equation (A34) can be written as follows:

$$\sigma_a\eta^a_{s_{ab}}(\gamma^m_{s_{ab}}+\gamma^f_{s_{ab}}+1)=1$$

which can be solved for $\eta^a_{s_{ab}}=\frac{1}{\sigma_a(\gamma^m_{s_{ab}}+\gamma^f_{s_{ab}}+1)}$. Similarly, $\eta^b_{s_{ab}}=\frac{1}{\sigma_b(\gamma^m_{s_{ab}}+\gamma^f_{s_{ab}}+1)}$.

With resource shares for foster and non-foster children identified, resource shares for men and women in the one-child-type households can then be solved for since $\eta^t_{s_{ab}}=\gamma^t_{s_{ab}}(\sigma_a\eta^a_{s_{ab}}+\sigma_b\eta^b_{s_{ab}})$ for $t\in\{m,f\}$.

I next move to the composite households $s_{ab}\in\{s_{11},s_{21},s_{12},s_{22}\}$. Note that now, for each household type, resource shares for both foster and non-foster children need to be identified (η^a and η^b). For the one-child-type households, one of those two parameters was zero. From Equation (A34) I can write the following four equations:

$$
\begin{bmatrix}
1+\gamma^m_{11}+\gamma^f_{11} & 1+\gamma^m_{11}+\gamma^f_{11} & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 2(1+\gamma^m_{21}+\gamma^f_{21}) & 1+\gamma^m_{21}+\gamma^f_{21} & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 1+\gamma^m_{12}+\gamma^f_{12} & 2(1+\gamma^m_{12}+\gamma^f_{12}) & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 1+\gamma^m_{22}+\gamma^f_{22} & 1+\gamma^m_{22}+\gamma^f_{22}
\end{bmatrix}
\times
\begin{bmatrix}\eta^a_{11}\\ \eta^b_{11}\\ \eta^a_{21}\\ \eta^b_{21}\\ \eta^a_{12}\\ \eta^b_{12}\\ \eta^a_{22}\\ \eta^b_{22}\end{bmatrix}
=
\begin{bmatrix}1\\1\\1\\ \frac{1}{2}\end{bmatrix}
$$

Clearly the above system is underidentified as there are eight unknowns and only four equations. I now impose Assumptions B6 and B7, which add an additional five equations to the system. Note that the resource shares for the one-child-type households have already been identified (i.e. η^a_{10} is known at this point). This results in the following system of nine equations

$$
\begin{bmatrix}
1+\gamma^m_{11}+\gamma^f_{11} & 1+\gamma^m_{11}+\gamma^f_{11} & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 2(1+\gamma^m_{21}+\gamma^f_{21}) & 1+\gamma^m_{21}+\gamma^f_{21} & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 1+\gamma^m_{12}+\gamma^f_{12} & 2(1+\gamma^m_{12}+\gamma^f_{12}) & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 1+\gamma^m_{22}+\gamma^f_{22} & 1+\gamma^m_{22}+\gamma^f_{22}\\
-1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0\\
0 & -1 & 0 & 0 & 0 & \frac{\eta^b_{01}}{\eta^b_{02}} & 0 & 0\\
0 & 0 & 0 & -1 & 0 & 0 & 0 & \frac{\eta^b_{01}}{\eta^b_{02}}\\
\frac{1}{\eta^a_{10}} & \frac{-1}{\eta^b_{01}} & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\times
\begin{bmatrix}\eta^a_{11}\\ \eta^b_{11}\\ \eta^a_{21}\\ \eta^b_{21}\\ \eta^a_{12}\\ \eta^b_{12}\\ \eta^a_{22}\\ \eta^b_{22}\end{bmatrix}
=
\begin{bmatrix}1\\1\\1\\ \frac{1}{2}\\0\\0\\0\\0\\0\end{bmatrix}
$$

This eight by nine matrix is equal to the matrix Ω'' defined earlier with $\gamma^t_{s_{ab}} = \frac{\eta^m_{s_{ab}}}{\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}}}$, which is nonsingular by Assumption B8. The system can therefore be solved for $\eta^a_{s_{ab}}$ and $\eta^b_{s_{ab}}$. Resource shares for men and women can then be solved for since $\eta^t_{s_{ab}} = \gamma^t_{s_{ab}}(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})$ for $t \in \{m, f\}$.