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

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**Abstract**

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

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

**JEL Codes**: D1, I32, J12, J13

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# 1 Introduction

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

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

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

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

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

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

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

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

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

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

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

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

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

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

In the empirical application, I study foster children in Sub-Saharan Africa (SSA). Foster children have become a population of increasing interest as economists have come to recognize the diversity of household structures that exist in certain parts of the world. Child fostering is most common in SSA where it varies from 8 percent in Burkina Faso to as high as 25 percent in Zimbabwe.[5] In Malawi, 13 percent of children are fostered and 17 percent of households have a foster child. While some of these children are orphans, the majority are children who are voluntarily sent away by their parents to live with close relatives.[6] Children are fostered for many reasons, including child labour, 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.[7] I contribute to this literature by quantifying the extent of consumption inequality between foster and non-foster children.

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

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

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

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

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

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

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

## 2 Collective Model of the Household

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

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

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

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

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

## 2.1 Model

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

Households consume $K$ types of goods at market prices $p = (p^1, ..., p^K)'$. Let $z_s = (z_s^1, ..., z_s^K)$ be the $K$ - vector of observed quantities purchased by the household. The vector of unobserved quantities consumed by individuals within the household is denoted by $x_t = (x_t^1, ..., x_t^K)$. 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,[11] and $\sigma_t$ 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. Non-zero off diagonal elements occur when the amount a good is shared depends on the consumption of other goods.

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

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

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

[12] As in Dunbar et al. (2013), children are modelled as having their own utility function. This differs from other work which treats children as a public good that is consumed by altruistic parents (Browning et al., 2014).

[13] This assumption is data driven. In the estimation, I allow preferences and resource allocations to vary with certain characteristics, such as child age and gender, so that households with older foster children may allocate more to foster children.

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

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

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

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

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

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* $\eta_s^t$, which is defined as the fraction of total household resources that are allocated to each individual of type $t$.[14] By definition, resource shares for men, women, foster, and non-foster children sum to one. In Section 4, I compare resource shares of foster and non-foster children to test for intrahousehold inequality.

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

How should resource shares be interpreted? Resource shares are the share of the shadow budget allocated to each person type within the household. The shadow budget includes spending on public, private, and partially shared goods. Resource shares are not necessarily a measure of individual welfare though, as they do not account for differences in leisure, health, or altruism. Nonetheless, higher resource shares indicate higher consumption, and therefore greater material well-being. This result holds only if the shadow price of public goods does not vary across individuals within the household (Chiappori and Meghir, 2014, 2015). However, with a linear consumption technology function (i.e., $z_s = A_s(x_a + x_b + x_m + x_f)$), Lindahl prices will be the same across people and resource shares can be used as a measure of intrahousehold

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

inequality (Browning et al., 2013).

## 2.2 Demand for Private Assignable Goods

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

Let $W_s^t(y,p)$ 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:[15]

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

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).[16]

# 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. In particular, I use children's clothing, which is partially assignable to both foster and non-foster children.

[15] See Section A.8 for details of the derivation.

[16] 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.

I demonstrate two different sets of assumptions to identify resource shares in this context. I begin in Section 3.1 by summarizing how DLP use private assignable goods to identify resource shares. I then present a new approach to identify resource shares using expenditure on private partially assignable goods in Sections 3.2. A second method is provided in Section 3.3. I comment on the relative merits of each approach at the end of Section 3.

## 3.1 Identification with Private Assignable Goods

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

Assume individuals have preferences given by a Piglog indirect utility function (Deaton and Muellbauer, 1980): $V_t(p,y) = b_t(p)(\ln y - a_t(p))$.[17] Using Roy's identity, the budget share functions are given by $w_t(p,y) = \delta_t(p) + \beta_t(p)\ln y$ 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 the budget share functions into Equation (3) results in the system of clothing Engel curves given below:

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

where $W_s^t$ are budget shares for the private assignable good for person type $t$ in household $s$. I drop prices from Equation (4) as Engel curves describe the relationship between budget shares and total expenditure holding prices fixed. The number of foster and non-foster children in the household is given by $\sigma_a$ and $\sigma_b$, 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]

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

[18] Menon et al. (2012) show that this is a reasonable assumption. 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. Importantly, resource shares can depend on variables highly correlated with expenditure, such as individual wages, remittances, or wealth. Lastly, resource shares need to be independent of household expenditure only at low levels of household expenditure.

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

The SAT restriction, first used in Lewbel and Pendakur (2008), restricts how the prices of shared goods enter each person's utility function. In effect, it restricts changes in the prices of shared goods to have a pure income effect on each person's demand for clothing.[19] Under this restriction, identification is achieved by comparing Engel curves across households of different sizes for a given individual type. To better understand what this restriction entails, consider the demand for a purely public good such as housing. As the household size increases, the shadow price of rent decreases. This change in the price of rent may have an effect on each person's demand for clothing. However, under SAT, this price change can only affect the demand for clothing in way that's independent of total expenditure. That is, changes in household size can shift the Engel curve for clothing up and down, but not change the shape of it. The identification method developed in Section 3.2 builds upon this similarity assumption.[20]

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

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

The key complication for my purposes is the absence of a separate private assignable good for foster and non-foster children in the data; I do not observe the budget shares for foster and non-foster child clothing, $W_s^a$ and $W_s^b$, but rather their sum $W_s^c = W_s^a + W_s^b$, where $W_s^c$ is the budget share for *child* clothing. This is a widespread data problem that is present in a variety of settings where inequality among children is of interest; consumption surveys rarely contain data on goods that are assignable to specific types of children. To work around the lack of sufficient data, I now develop a new methodology to identify resource shares in the absence of private assignable good.

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

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

## 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 (4) as a single Engel curve for children's clothing, and I begin by imposing the SAT restriction (i.e., $\beta_s^t = \beta^t$):

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

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

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

Suppose there are four one-child-type households $s \in \{s_{10}, s_{20}, s_{01}, s_{02}\}$ where, for example, $s_{10}$ denotes a household with one foster child and no foster children.[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 $\eta_s^t$ that needs to be identified (twelve total) and there are four shape parameters $\beta^t$ 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 one-child-type households is provided in the Appendix.

[21] In the empirical application the sample includes households with as many as four 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 $\beta^t$, but not the intercept preference parameter $\delta_s^t$.

I next move to the composite households which is where the main contribution of this paper lies. With SAT, preferences for clothing are similar across household sizes. I modify this restriction by assuming that preferences are both similar across households sizes *and across household compositions*; that is, preferences for clothing are similar across one-child-type and composite households. In words, the foster child's marginal propensity to consume clothing is independent of the number of non-foster children present in the household, and vice versa. I take $\beta^t$ 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.11. I discuss potential violations to this identification approach in Sections A.2, A.3, and A.4 of the Appendix.

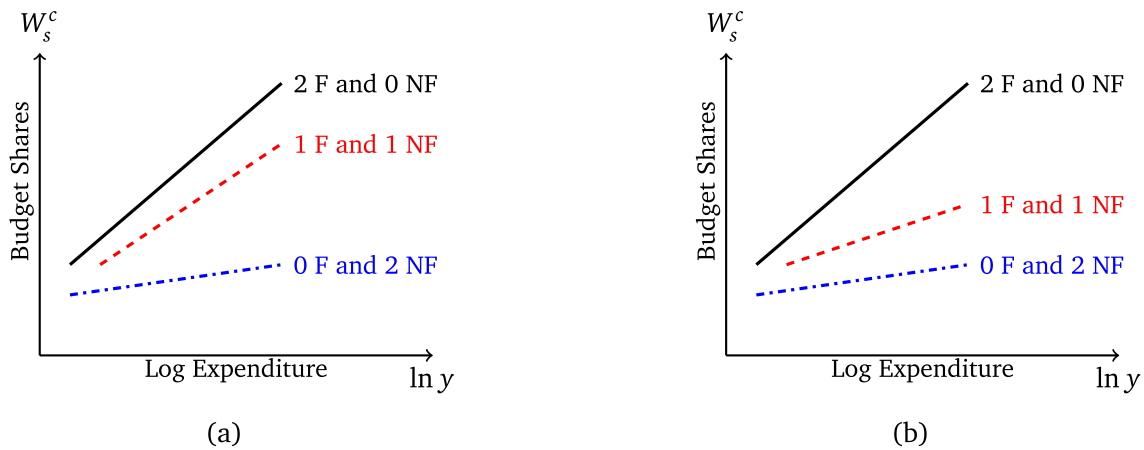
A graphical representation of the intuition is provided in Figure 1. Each graph plots the children's clothing Engel curve for three different household compositions. If the *slope* of the children's clothing Engel curve in the composite household (1 F and 1 NF) is more similar to the slope of the Engel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

## 3.3 Identification with Partially Assignable Goods Using SAP

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

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

**Figure 1:** Graphical Intuition for Identification




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

This system of equations is identical to System (5) except now the shape parameter $\beta$ 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 ($\eta_s^m$, $\eta_s^f$, and either $\eta_s^a$ or $\eta_s^b$) and a single preference parameter $\beta_s$ that need to be identified. Moreover, there are four equations: three Engel curves slopes, and the restriction that resource shares sum to one. With four equations and four unknowns, resource shares are identified for each one-child-type household.

Moving to the composite households, it is easy to see how identification fails. For each household type, there are five unknowns; four resource shares (both $\eta_s^a$ and $\eta_s^b$ are now non-zero) and again a single preference parameter $\beta_s$. 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 $\beta^t$ does not change. However, with the SAP restriction, there is a different $\beta_s$ for each household type, and therefore as the number of household types increases, so too does the number of preference parameters that need to be identified.

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

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

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

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

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

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

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

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

# 4 Application: Child Fostering in Malawi

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

## 4.1 Background

Child fostering, or kinship care, is the practice of sending one's biological children to live with close relatives. I use a broader definition of foster children to include all individuals age 14 and under who are living in households away from both of their biological parents. This definition includes children in kinship care, but also orphans and adopted children. Child fostering rates vary by country and are highest in West African societies (Grant and Yeatman, 2012). In Malawi, fostering is also quite common with 17 percent of households having a foster child.[23] Figure 2a presents the percentage of children fostered by age in Malawi (the green solid line). Overall, 13.1 percent of children are fostered (Malawi Integrated Household Survey 2016), 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 commonly divides foster children into two categories: those who are fostered for voluntary reasons, and those who are not (Serra, 2009). Non-voluntary, or crisis fostering occurs when the child is orphaned, or has parents who are ill and unable to care for their child. Non-voluntary fostering has become substantially more common as a result of the AIDS epidemic. Voluntary, or purposive child fostering occurs when the child's parents voluntarily send 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, agricultural shocks, or to facilitate adult labour (by reducing parenting responsibilities).[25] Finally, children are also often fostered as a

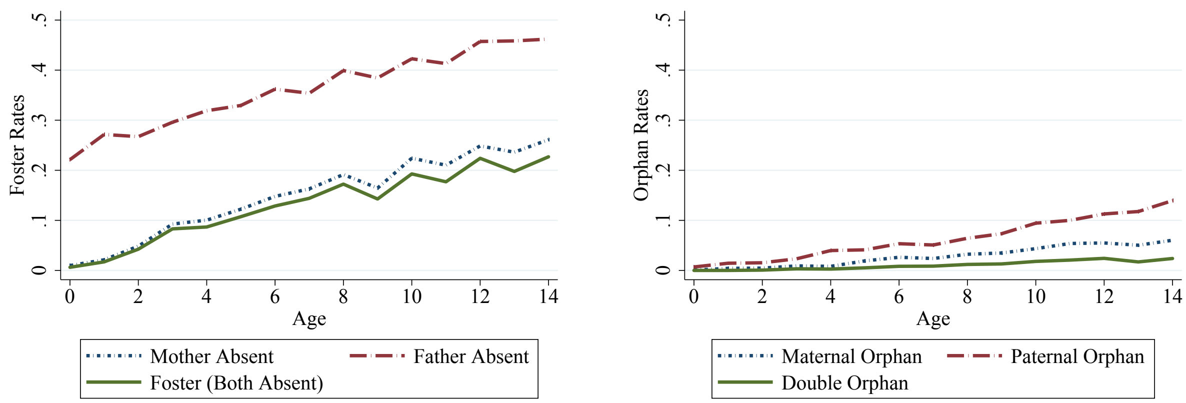
[23] Grant and Yeatman (2012) use DHS data to examine the prevalence of fostering and orphanhood across sub-Saharan African countries.

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

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

result of their parents divorce and subsequent remarriage (Grant and Yeatman, 2014). This cause is especially prevalent in Malawi as almost half of all marriages end in divorce, with remarriage rates being equally high (Reniers, 2003; Cherchye et al., 2018).

**Figure 2:** Foster and Orphan Status by Age




**(a)** **(b)**

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

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

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

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

## 4.2 Data

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

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

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

From the data, I select a sample of 17,203 households. For ease of estimation, I exclude households that have less than one or more than four men and women, or less than one or more than four 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 A16.

**Table 1:** Descriptive Statistics

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

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

Table 1 reports descriptive statistics for the estimation sample. Households have on average 5 individuals. The average age of foster children (9.36) is significantly higher than that of non-foster children (5.90). This is consistent with child labour and education being reasons households foster children. Roughly 33 percent of foster children have lost at least one parent.

Households in Malawi are very poor, with the average real annual per capita household expenditure equal to 920,000 MWK (approximately US$ 1,200 in 2016).[26] Lastly, households spend a large fraction of their income on food (62.5 percent), which consistent with the high level of poverty in Malawi.

## 4.3 Estimation

To estimate the model, I add an error term to the clothing Engel curves for men, women, and children. Since the error terms of the Engel curves are likely to be correlated across equations, the system is estimated using Non-linear Seemingly Unrelated Regression.[27] To match the data used in the empirical analysis, I now account for households with multiple men and women with $\sigma_m$ denoting the number of men, and $\sigma_f$ denoting the number of women.

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

The objects of interest are the resource shares for foster and non-foster children, given by $\eta_s^a$ and $\eta_s^b$, respectively. The estimation allows for considerable heterogeneity as $\eta_s^t$ and $\delta_s^t$, and 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. 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.[28]

For the main estimation result, I restrict the slope preference parameter to be the same across household sizes, and across composite and one-child type households.[29] This is the

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

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

[28] 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.

[29] Tommasi and Wolf (2016) demonstrate that "flat" Engel curves result in unstable resource share estimates

key assumption discussed in Section 3.2. Moreover, I impose the ratio restrictions provided in Equations (7) and (8). This restriction is not necessary for identification, but it improves the estimation as fewer parameters need to be identified. As a robustness check, I estimate the model with different combinations of identification assumptions (see Table 3 in Section 4.4)).

## 4.4 Results

I begin by presenting average predicted resource shares for men, women, non-foster, and foster children in Table 2. These are the average *per-person* resource shares across all household compositions. The results suggest that the average non-foster child consumes 11.1 percent of the household budget, while the average foster child consumes only 14.3 percent. This, however, does not imply unequal treatment because foster children are on average nearly four years older than non-foster children, and it's reasonable to assume that older children consume more goods (especially when food is such a large component of expenditures). Moreover, foster children tend to live in smaller households where resource shares will be mechanically larger. This motivates comparing foster and non-foster child resource shares for a given household size and household characteristics.

**Table 2:** Predicted Resource Shares

| | Observations | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Men | 17,203 | 0.356 | 0.389 | 0.115 |
| Women | 17,203 | 0.295 | 0.326 | 0.090 |
| Non-Foster Children | 15,654 | 0.111 | 0.103 | 0.032 |
| Foster Children | 2,990 | 0.147 | 0.141 | 0.044 |

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

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

when estimating DLP. This is fortunately not the case in the data. Table A17 in the Appendix presents parameter estimates for the slope preference parameter $\beta$ for each of the main specifications.

are given by household composition, which is determined by the number foster and non-foster children present, where for example, “1 NF 0 F" indicates a household with 1 non-foster child and 0 foster children. The motivation for this grouping of the results is that, if all children are treated equally, then foster and non-foster child resource shares should not vary for a given household size. The predictions are made for a reference household, which I define as a household with one man, one woman, and all other covariates (except for age) set to their median value.[30] Instead of using the median value for foster and non-foster child age, I set both to seven to make the predicted resource shares more comparable. The brackets are the 95 percent confidence intervals of the predicted values.

Panel A of Figure 3 provides the predicted resource shares for reference households with one or two children. For households with one non-foster child, and zero foster children (“1 NF 0 F"), the non-foster child consumes 19.8 percent of the household budget. Similarly, for households with one foster child, and zero non-foster children (“0 NF 1 F"), the foster child is allocated roughly 20.5 percent of the household budget. This provides little evidence of discrimination. Panels B, C, and D present the results for households with two, three, and four total children respectively, and again, the results do not demonstrate a systematic pattern of unequal treatment towards foster children.

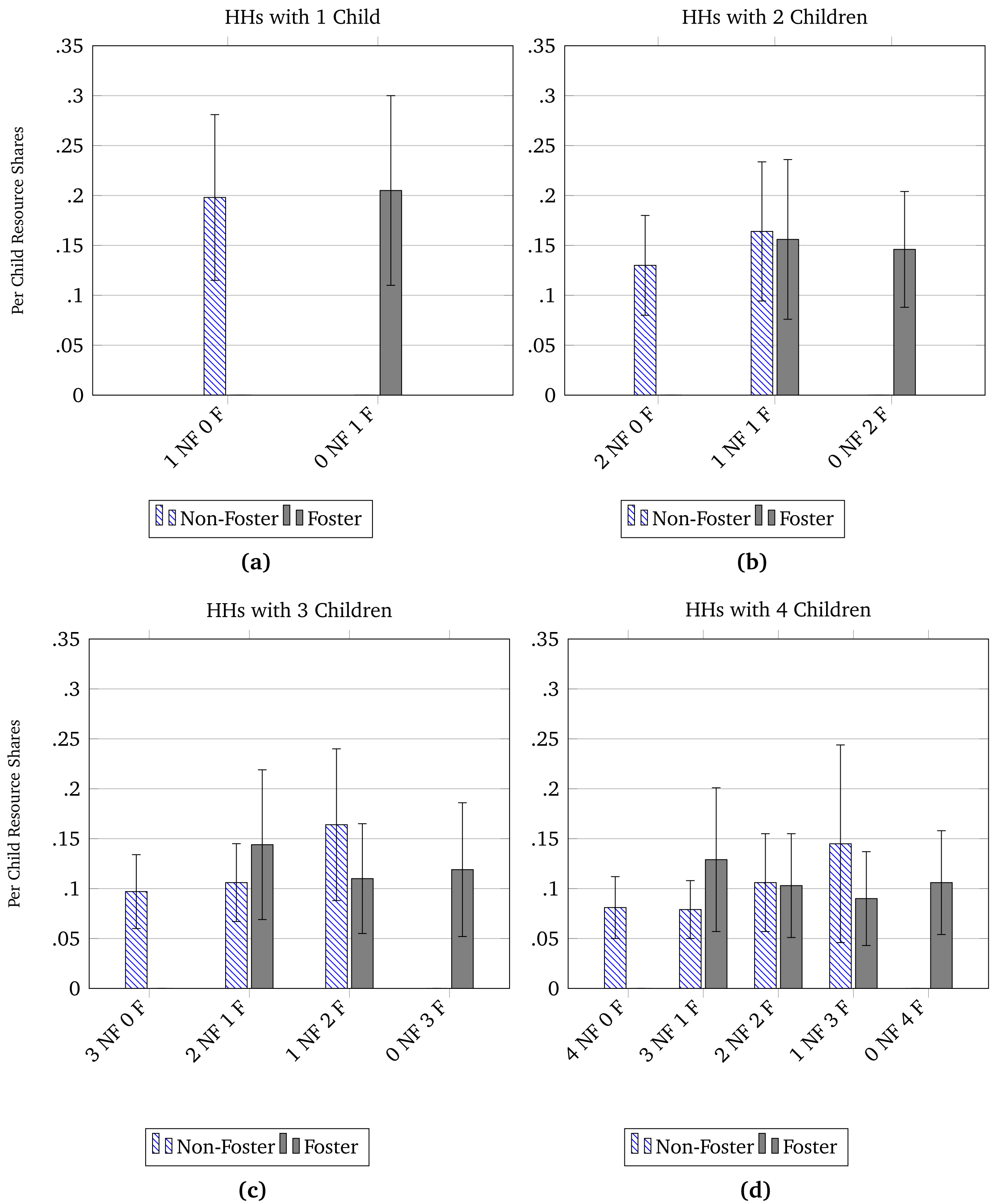
Tables A18 and A19 in the Appendix present the parameter estimates of the resource share functions for foster and non-foster children. The parameter estimates in these tables are used to construct Figure 3. Table A18 focuses on the preference factors (i.e., the demographic characteristics of the household) whereas Table A19 displays the household type indicators.[31] Notably, child age is an important factor in resource shares for both foster and non-foster children, which highlights the importance of accounting for child age when comparing the well-being of different types of children. Most other preference factors are insignificant suggesting that household composition is the main factor in determining how resources are allocated within the household.[32]

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

I next exclude several alternative types of households where the assumptions of the collective model may be less likely to hold. Specifically, households with multiple adult men or women, or households where the household head has multiple wives may not necessarily bargain in a cooperative way. As I result, I first exclude any non-nuclear household from the sample, where a nuclear household is defined as having one man and one woman who are married.[33] Columns (2a) and (2b) of Table A20 display these results. While several parameter estimates differ in magnitude, none are statistically different. I next exclude polygamous households. In the main estimation sample, only 8 percent of household heads are part of a polygamous marriage. The results are presented in columns (3a) and (3b) of Table A20, and are again similar in magnitude to the main estimation results.

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

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

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

**Table 3:** Resource Share Estimates by Identification Assumptions

| | Foster Children | | | | Non-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 | | | | | 0.202*** | 0.197*** | 0.254*** | 0.237*** |
| | | | | | (0.0584) | (0.054) | (0.050) | (0.049) |
| 1 Non-Foster 1 Foster | 0.193*** | 0.149*** | 0.146*** | 0.151*** | 0.0688 | 0.101*** | 0.119*** | 0.106*** |
| | (0.0745) | (0.0567) | (0.0502) | (0.0510) | (0.0552) | (0.039) | (0.041) | (0.040) |
| 0 Non-Foster 2 Foster | 0.279*** | 0.286*** | 0.299*** | 0.312*** | | | | |
| | (0.0826) | (0.079) | (0.065) | (0.064) | | | | |
| 3 Non-Foster 0 Foster | | | | | 0.239*** | 0.231*** | 0.301*** | 0.281*** |
| | | | | | (0.0649) | (0.060) | (0.051) | (0.051) |
| 2 Non-Foster 1 Foster | 0.169** | 0.137** | 0.142*** | 0.147*** | 0.124* | 0.148* | 0.171*** | 0.156*** |
| | (0.0771) | (0.055) | (0.048) | (0.049) | (0.0702) | (0.0459) | (0.0461) | (0.0450) |
| 1 Non-Foster 2 Foster | 0.276*** | 0.215*** | 0.201*** | 0.206*** | 0.0407 | 0.102** | 0.132*** | 0.115*** |
| | (0.0828) | (0.0704) | (0.0587) | (0.0590) | (0.0631) | (0.043) | (0.044) | (0.042) |
| 0 Non-Foster 3 Foster | 0.339*** | 0.350*** | 0.358*** | 0.368*** | | | | |
| | (0.100) | (0.096) | (0.074) | (0.071) | | | | |
| **Covariates** | | | | | | | | |
| Average Age non-Foster | -0.357 | -0.237 | -0.283 | -0.269 | 1.172* | 1.487** | 2.302*** | 2.463*** |
| | (0.752) | (0.776) | (0.754) | (0.775) | (0.598) | (0.586) | (0.646) | (0.644) |
| Average Age non-Foster$^2$ | 0.0288 | 0.019 | 0.021 | 0.019 | -0.0654 | -0.084** | -0.123** | -0.136*** |
| | (0.0539) | (0.055) | (0.054) | (0.055) | (0.0427) | (0.042) | (0.049) | (0.048) |
| Average Age Foster | 1.808 | 2.416* | 2.836** | 2.645 | -0.182 | -0.608 | -0.868 | -0.890 |
| | (1.697) | (1.306) | (1.217) | (1.850) | (2.209) | (1.858) | (1.867) | (1.881) |
| Average Age Foster$^2$ | -0.0878 | -0.120 | -0.146* | -0.135 | 0.0228 | 0.047 | 0.062 | 0.061 |
| | (0.105) | (0.090) | (0.083) | (0.111) | (0.124) | (0.106) | (0.108) | (0.107) |
| Matrilineal Village | 0.0175 | 0.018 | 0.019 | 0.018 | 0.00812 | 0.008 | 0.003 | 0.006 |
| | (0.0119) | (0.012) | (0.013) | (0.013) | (0.00956) | (0.009) | (0.012) | (0.011) |
| Proportion of | -0.0237 | -0.017 | -0.009 | -0.008 | 0.0296 | 0.025 | 0.024 | 0.024 |
| Fostered Orphaned | (0.0298) | (0.026) | (0.026) | (0.030) | (0.0234) | (0.025) | (0.030) | (0.029) |
| Sample Size | 17,203 | 17,203 | 17,203 | 17,203 | 17,203 | 17,203 | 17,203 | 17,203 |
| Log Likelihood | 150,455 | 150,470 | 151,395 | 150,484 | 150,455 | 150,470 | 151,395 | 150,484 |

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

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

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

The results being similar across specifications is not by itself suggestive that the results are robust; the results could, in theory, be incorrect in a similar way across specifications. How concerning is this? While the data used in this paper is not suitable to fully test every aspect of the model, recent work by Bargain et al. (2018), Brown et al. (2018), and Lechene et al. (2019) have provided support for the collective approach in other contexts. These studies use unique data sets containing either individual-level consumption data, assignable food consumption, or individual-level health data to test the validity of Dunbar et al. (2013) and recent extensions.

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

I analyse the importance of child labour in two ways. First, I allow foster child resource shares to vary with whether any foster children worked outside the household in the previous week. The parameter does not have a causal interpretation, but it allows me to determine if working more is associated with greater foster child consumption. These results are presented in column (1) of Table 4 and show no difference. I test this a different way by splitting the sample by whether foster children are working. In column (2), I exclude households with

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

| | Child Labour | | | Remittances | | |
|---|---|---|---|---|---|---|
| | Work in Resource Share Function | Foster Child Working | No Foster Child Working | Remittances in Resource Share Function | Foster HH Received Remittances | Foster HH No Remittances |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Household Type Indicators** | | | | | | |
| 1 Non-Foster 1 Foster | 0.155*** | 0.182 | 0.142** | 0.149*** | 0.165** | 0.150* |
| | (0.057) | (0.106) | (0.063) | (0.057) | (0.079) | (0.080) |
| 0 Non-Foster 2 Foster | 0.278*** | 0.354*** | 0.273*** | 0.283*** | 0.311*** | 0.266** |
| | (0.078) | (0.132) | (0.089) | (0.079) | (0.093) | (0.119) |
| 2 Non-Foster 1 Foster | 0.137** | 0.160 | 0.135** | 0.136** | 0.149** | 0.145* |
| | (0.054) | (0.101) | (0.062) | (0.055) | (0.069) | (0.075) |
| 1 Non-Foster 2 Foster | 0.218*** | 0.256** | 0.208*** | 0.216*** | 0.248*** | 0.195** |
| | (0.070) | (0.122) | (0.080) | (0.070) | (0.088) | (0.099) |
| 0 Non-Foster 3 Foster | 0.337*** | 0.411*** | 0.332*** | 0.345*** | 0.387*** | 0.300** |
| | (0.094) | (0.151) | (0.108) | (0.096) | (0.112) | (0.143) |
| **Covariates** | | | | | | |
| Foster Child Working | 0.038 | | | | | |
| | (0.040) | | | | | |
| Remittances/Expenditure | | | | 0.030 | | |
| | | | | (0.053) | | |
| Average Age non-Foster | -0.247 | -1.292 | -0.086 | -0.207 | 0.247 | -0.695 |
| | (0.757) | (1.474) | (0.879) | (0.789) | (0.949) | (1.066) |
| Average Age non-Foster$^2$ | 0.021 | 0.080 | 0.013 | 0.017 | -0.017 | 0.051 |
| | (0.054) | (0.107) | (0.061) | (0.056) | (0.067) | (0.074) |
| Average Age Foster | 2.386* | 2.165 | 2.078 | 2.347 | 1.341 | 2.498* |
| | (1.448) | (8.523) | (1.923) | (4.139) | (1.894) | (1.395) |
| Average Age Foster$^2$ | -0.123 | -0.160 | -0.093 | -0.116 | -0.042 | -0.122 |
| | (0.097) | (0.405) | (0.123) | (0.233) | (0.134) | (0.095) |
| Proportion Non-Foster Female | -0.004 | -0.035 | -0.003 | -0.005 | -0.009 | 0.002 |
| | (0.017) | (0.040) | (0.020) | (0.019) | (0.021) | (0.025) |
| Proportion Foster Female | -0.027 | -0.037 | -0.022 | -0.029 | -0.042 | -0.003 |
| | (0.033) | (0.062) | (0.036) | (0.038) | (0.050) | (0.034) |
| Rural | -0.002 | -0.009 | -0.003 | -0.000 | 0.000 | -0.002 |
| | (0.012) | (0.033) | (0.014) | (0.014) | (0.016) | (0.016) |
| Matrilineal Village | 0.017 | 0.040 | 0.013 | 0.018 | 0.014 | 0.019 |
| | (0.012) | (0.027) | (0.014) | (0.013) | (0.014) | (0.018) |
| Proportion of Fostered Orphaned | -0.021 | -0.029 | -0.019 | -0.018 | -0.029 | -0.017 |
| | (0.029) | (0.049) | (0.034) | (0.029) | (0.036) | (0.038) |
| Sample Size | 17,203 | 14,777 | 16,639 | 17,203 | 15,891 | 15,525 |
| Log Likelihood | 150,467 | 128,613 | 145,433 | 150,465 | 138,463 | 135,569 |

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

foster children that do not work from the sample, while column (3) restricts the sample to foster households where none of these children worked. Here, the results suggest that labour may matter in a limited way.

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

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

# 5 Poverty Analysis

Resource shares are a desirable object to identify in part because they allow for the estimation of individual-level consumption. I can therefore use the predicted resource shares to estimate foster and non-foster child poverty rates that account for the unequal distribution of goods within the household. Importantly, everyone in the household may not be poor; it is possible for the adults to be living above the poverty line, but the children below it. Moreover, not all children need to be poor; non-foster children may be above the poverty line with the foster children below it, and vice versa. This analysis therefore differs from the more traditional approach to estimating poverty which relies on household-level measures that ignore intrahousehold inequality.

I classify adults as poor using a 76.89 MWK a day poverty line. This is the poverty line the World Bank uses for the 2016 Malawi Integrated Household Survey. For children, I use several different poverty lines based on the average age of foster or non-foster children in the household. Setting a single poverty line for children abstracts from potential inequality, as older children require more resources than younger children to maintain the same standard of living, and foster children tend to be significantly older than non-foster children. To determine these age-specific poverty lines, I assume that the child poverty line is proportional to the calorie requirements for children of that age relative to adults.[34] So if a six-year-old child requires half as many calories as an adult, then their poverty line would be half of the adult poverty line, or 38.44 MWK a day.

As a point of comparison, I calculate household-level poverty rates where I assume an equal distribution of resources within the household. The household-level poverty rates use the OECD adult equivalent scale, where the number of adult equivalents in the household is given by $1+0.5\times N_c+0.7\times(N_a-1)$, where $N_c$ is the number of children and $N_a$ is the number of adults. A household is poor if per adult equivalent consumption is less than 76.89 MWK a day. Since the OECD equivalence scale is somewhat arbitrary, the main focus of the poverty analysis is to examine relative levels of poverty across person types, rather than levels of poverty.[35]

**Table 5:** Estimated Poverty Rates by Household Size

| Number of Children | Sample Size: # Households | Individual Poverty Rates | | | | Assuming Equal Distribution |
|---|---|---|---|---|---|---|
| | | Foster | Non-Foster | Men | Women | |
| | | (1) | (2) | (3) | (4) | (5) |
| 1 | 4,820 | 0.301 | 0.140 | 0.329 | 0.339 | 0.144 |
| 2 | 5,106 | 0.427 | 0.292 | 0.364 | 0.404 | 0.191 |
| 3 | 4,470 | 0.444 | 0.475 | 0.396 | 0.420 | 0.241 |
| 4 | 2,807 | 0.543 | 0.635 | 0.502 | 0.458 | 0.330 |
| All Households | 17,203 | 0.425 | 0.433 | 0.382 | 0.397 | 0.209 |

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

Table 5 presents poverty rates for individuals by household size, defined by the number of children in the household. Columns (1) - (4) provide individual poverty rates computed us-

[34] 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.

[35] 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.

ing the predicted resource shares. Since resource shares are divided equally within a person type, poverty does not vary across e.g., two foster children in the same household. Column (5) presents the household-level poverty rates. Comparing column (5) to the individual-level poverty rates clearly illustrates that traditional household-level measures fail to identify individuals who are poor, particularly women and children. This result is consistent with Dunbar et al. (2013) and recent work on using health measures to analyse the ability of household-level measures to capture individual-level poverty (Brown et al., 2016).

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

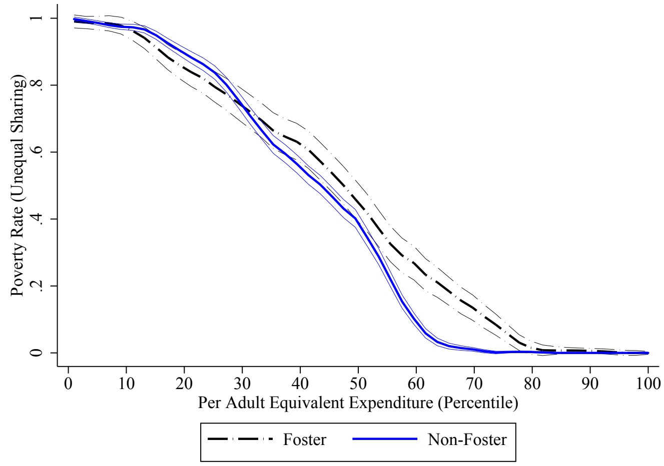
Motivated by existence of inequality both across and within households, I present the results in a different way. I plot individual poverty rates for foster and non-foster children by percentiles of the per-adult equivalent household expenditure distribution. These results are displayed in Figure A1. As expected, individual poverty rates decline as household expenditure increases. For certain levels of household expenditure, foster child poverty (the black dashed line) is higher than non-foster child poverty (the blue solid line), and vice-versa. Again, there is no clear evidence of unequal treatment between foster and non-foster children. Household-level measures of poverty are similarly likely to misclassify foster and non-foster children as non-poor. Specifically, 30.1 percent of foster children living in non-poor households are themselves poor. For non-foster children, the rate of misclassification is 26.2 percent. Nonetheless, these results demonstrate the importance of accounting for intrahousehold inequality when designing policy as there are poor individuals living in non-poor households. To efficiently target anti-poverty programs, it is essential to accurately identify poor individuals, not just poor households.[36]

# 6 Conclusion

The household is in many ways a black box to economists. Understanding the inner workings of the household is difficult and measuring the treatment of children within the household is far

[36] 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 4:** Individual Poverty Rates by Household Expenditure Percentile




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

from straightforward. I build upon recent work by Dunbar et al. (2013) to demonstrate how resource shares can be identified using expenditure on partially assignable clothing. Like Dunbar et al. (2013), I rely on observing how clothing budget shares vary with household expenditure to identify resource shares. I differ in that I weaken the data requirements necessary for identification. Future work can use this methodology in other contexts where intrahousehold inequality is of interest, but assignable goods are not present in the data.

I use this new approach to measure inequality among children. While the unequal treatment of children is present in a variety of contexts, I focus on foster children in Malawi who live in situations that may leave them particularly susceptible to impoverishment. The findings of this paper demonstrate that for the most part, foster children are treated the same as other children and that extended family members are capable caretakers. Nonetheless, I find that child poverty is being understated by poverty measures that rely on household-level measures of consumption. This result emphasizes the importance of designing government programs that target not just poor households, but specifically poor individuals. Household-level poverty rates may underestimate poverty rates for certain individual who have less power within the household, such as children. Future work should investigate heterogeneity in foster child treatment, which would benefit from connecting the findings of this paper with past research on *why* children are fostered (Ainsworth, 1995; Akresh, 2009; Beck et al., 2015). Bridging these two areas of study will help determine the underlying mechanisms that influence foster children treatment, and ultimately allow for better policy design.

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# A Appendix

The Appendix is organised as follows: I first build upon the consumption results by analysing education and child labour differences across foster and non-foster children in Section A.1. In Section A.2, I examine the extent to which clothing is shared across foster and non-foster children. I also conduct several tests to determine how durable clothing is. In Section A.3, I examine whether in-kind transfers are biasing the results. Next, in Section A.4, I provide several tests of the identification assumptions. In Section A.5, I discuss how the selection of foster children into certain types of households may affect the results. I test Pareto efficiency in Section A.6. Section A.7 gives numerical examples of the ratio restrictions. I specify the full model in Section A.8. Sections A.9 and A.10 provides additional figures and tables. Finally, I present the identification theorems in Section A.11.

## A.1 School Enrolment 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. Alternatively, if a household has a stronger than normal harvest, they may foster in children to help with farm work. This suggests child labour may be higher among foster children.

**Empirical Strategy:** Unlike consumption, both school enrolment and work hours are observable at the individual level using standard household-level survey data. This facilitates a direct comparison of enrolment rates and child labour between foster and non-foster children. I begin by assigning children to two mutually exclusive groups: both biological parents absent (i.e., foster children), or at least one parent present.

I estimate the following regression for child $i$ living in household $h$ in region $s$ in year $t$:

$$Y_{ihst} = \alpha + \gamma F_i + \pi_h + \psi_{st} + X_i\delta + \epsilon_{ihst} \tag{A1}$$

where $Y_{ihst}$ is an indicator for school enrolment 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. $X_i$ is a vector of individual characteristics, such as child age and gender. The parameter of interest is $\gamma$, which captures the effect of the absence of a child's parents on the various outcomes of interest. 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.

Existing work has found orphaned-foster children have lower school enrolment (Case et al., 2004; Ainsworth and Filmer, 2006). I therefore 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: non-orphaned non-foster; orphaned non-foster; non-orphaned foster; orphaned foster. I estimate the following specification:

$$Y_{ihst} = \alpha + \gamma_1 O_i + \gamma_2 F_i + \gamma_3 (O_i \times F_i) + \pi_h + \psi_{st} + X_i \delta + \epsilon_{ihst} \tag{A2}$$

where $F_i$ and $O_i$ are indicators for foster and orphan status respectively. The parameters of interest are now $\gamma_1, \gamma_2$ and $\gamma_3$, which capture the differential effects of the child's foster and orphan status on school enrolment 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 and IHS4) and the Malawi Integrated Panel Survey. Descriptive statistics are presented in Table A22 in the Appendix.

**Results:** I begin by analysing the difference in school enrolment rates between foster and non-foster children. I estimate Equation (A1) and present the results in Table A1. The coefficient of interest $\gamma$ 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 enrolment 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

**Table A1:** School Enrollment by Foster Status

| | LPM | | | Probit |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Foster Child | -0.022*** | -0.011 | -0.047*** | -0.077* |
| | (0.006) | (0.007) | (0.014) | (0.041) |
| Sample Size | 35,198 | 35,198 | 35,198 | 35,198 |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Controls | Yes | Yes | Yes | Yes |
| Household Controls | | Yes | Yes | Yes |
| Household Fixed Effects | | | Yes | |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all children age 6 to 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

evidence that foster children are enrolled in school at lower rates than non-foster children.

I next examine whether this pattern is driven by orphaned-foster children. I estimate Equation (A2) with four foster categories that account for orphanhood. The results are presented in Table A2. Columns (1) to (3) present results from a linear probability model with increasing controls moving left to right. The findings largely show that orphaned foster children are driving the results, as these 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 15.2 percentage points less likely to be enrolled in school than non-orphaned non-foster children.

Table A3 provides the child labour results. In columns (1) and (2), I examine the relationship between foster status and hours worked doing chores,[37] 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.[38] I add controls moving from left to right. The results provide little evidence that work around the house differs substantially between foster and non-foster children, which is contrary to what the theoretical literature suggests (Serra, 2009), but consistent

[37] Chores include fetching wood and fetching water.

[38] 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.

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

| | LPM | | | Probit |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Fostering Categories** | | | | |
| Non-Orphaned Foster | -0.016** | -0.004 | -0.049*** | -0.038 |
| | (0.008) | (0.008) | (0.018) | (0.050) |
| Orphaned Foster | -0.038*** | -0.025** | -0.041** | -0.152*** |
| | (0.010) | (0.010) | (0.018) | (0.056) |
| Orphaned Non-Foster | -0.021** | -0.010 | 0.009 | -0.052 |
| | (0.010) | (0.010) | (0.024) | (0.056) |
| Sample Size | 35,198 | 35,198 | 35,198 | 35,198 |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Controls | Yes | Yes | Yes | Yes |
| Household Controls | | Yes | Yes | Yes |
| Household Fixed Effects | | | Yes | |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all children age 6 to 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

with recent empirical work by Beck et al. (2015). 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. Table A4 accounts for orphanhood when examining the effect of foster status on child labour. The results provide some evidence that orphaned-foster children work more than non-orphaned non-foster children. The results in column (2), which account for differences in household characteristics, suggest that orphaned-foster children spend 0.66 more hours per week. The results for work outside the household counterintuitively suggest non-orphaned foster children work less than non-orphaned non-foster children.

**Table A3:** Weekly Hours Worked by Fostering Status

| | Chores | | Work Outside HH | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Foster Child | 0.601*** | 0.224 | 0.193 | -0.693 |
| | (0.202) | (0.226) | (0.412) | (0.451) |
| Sample Size | 35,198 | 35,198 | 35,198 | 35,198 |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Controls | Yes | Yes | Yes | Yes |
| Household Controls | | Yes | Yes | |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all children age 6 to 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 | 0.560* | 0.486 | 0.490 | 0.058 |
| | (0.309) | (0.322) | (0.600) | (0.622) |
| Non-Orphaned Foster | 0.530** | 0.070 | -0.092 | -1.141** |
| | (0.245) | (0.271) | (0.499) | (0.535) |
| Orphaned Foster | 0.874*** | 0.656** | 0.815 | 0.046 |
| | (0.315) | (0.323) | (0.646) | (0.665) |
| Sample Size | 35,198 | 35,198 | 35,198 | 35,198 |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Controls | Yes | Yes | Yes | Yes |
| Household Controls | | Yes | | Yes |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all children age 6 to 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.2 Is Clothing a Private Good?

**Sharing of Purchased Clothing** 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.[39] Hand-me-down clothing is a separate issue that is discussed later. 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 A5 presents the results. In the age-restricted sample, resource shares for foster children are not statistically different from the unrestricted results, and are quite similar. There is also not any consistent increase in non-foster child resource shares with the age restrictions.

To examine this in a different way, I estimate children's clothing Engel curves. Specifically, I allow the Engel curve to vary with the presence of multiple types of children in the same age group. If sharing of clothes between foster and non-foster children were present, we would expect the coefficients on these variables to be negative. The results are presented in Table A6. In column (1), I include indicators for four different age groups. In column (2) I include an indicator for having both a foster and non-foster child in any age group. Sharing of clothing does not appear to matter for children age 4 and above. However, households that have both a foster and non-foster child age 0 to 3 do spend less on clothing. While this is not ideal, only 33 out of 17,203 households fit this description. Overall, the results do not suggest that sharing is having a large effect on the model estimates.

**Hand-Me-Down Clothing** Given the age difference of foster and non-foster children, one might further be concerned about hand-me-down clothing. Specifically, clothing may be better characterized as a semi-durable good rather than non-durable. In the model and estimation, I define children's clothing expenditures to be the amount the household spends on children's

[39] 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.

**Table A5:** Determinants of Resource Shares: Age-Restricted Sample

| | Non-Foster Children | | Foster Children | |
|---|---|---|---|---|
| | Main Results | Age-Restricted Sample | Main Results | Age-Restricted Sample |
| | (1a) | (2a) | (1b) | (2b) |
| **Household Type Indicators** | | | | |
| 2 Non-Foster 0 Foster | 0.197*** | 0.206*** | | |
| | (0.054) | (0.055) | | |
| 1 Non-Foster 1 Foster | 0.101*** | 0.105*** | 0.149*** | 0.125** |
| | (0.039) | (0.039) | (0.0567) | (0.0483) |
| 0 Non-Foster 2 Foster | | | 0.286*** | 0.264*** |
| | | | (0.079) | (0.072) |
| 3 Non-Foster 0 Foster | 0.231*** | 0.240*** | | |
| | (0.060) | (0.060) | | |
| 2 Non-Foster 1 Foster | 0.148*** | 0.151*** | 0.137** | 0.100** |
| | (0.0459) | (0.0460) | (0.055) | (0.045) |
| 1 Non-Foster 2 Foster | 0.102** | 0.081* | 0.215*** | 0.193*** |
| | (0.043) | (0.046) | (0.0704) | (0.0615) |
| 0 Non-Foster 3 Foster | | | 0.350*** | 0.326*** |
| | | | (0.096) | (0.090) |
| **Covariates** | | | | |
| Average Age non-Foster | 1.487** | 1.718*** | -0.237 | 0.222 |
| | (0.586) | (0.588) | (0.776) | (0.636) |
| Average Age non-Foster$^2$ | -0.084** | -0.098** | 0.019 | -0.023 |
| | (0.042) | (0.042) | (0.055) | (0.046) |
| Average Age Foster | -0.608 | -0.379 | 2.416* | 2.448* |
| | (1.858) | (2.421) | (1.306) | (1.290) |
| Average Age Foster$^2$ | 0.047 | 0.038 | -0.120 | -0.118 |
| | (0.106) | (0.131) | (0.090) | (0.083) |
| Proportion Non-Foster Female | -0.015 | -0.013 | -0.006 | -0.010 |
| | (0.011) | (0.011) | (0.018) | (0.016) |
| Proportion Foster Female | 0.008 | 0.015 | -0.030 | -0.026 |
| | (0.027) | (0.026) | (0.032) | (0.024) |
| Rural | 0.003 | 0.008 | -0.001 | 0.002 |
| | (0.011) | (0.011) | (0.012) | (0.010) |
| Matrilineal Village | 0.008 | 0.008 | 0.018 | 0.018* |
| | (0.009) | (0.009) | (0.012) | (0.010) |
| Proportion of Fostered Orphaned | 0.025 | 0.024 | -0.017 | -0.010 |
| | (0.025) | (0.023) | (0.026) | (0.024) |
| Sample Size | 17,203 | 16,766 | 17,203 | 16,766 |
| Log Likelihood | 150,470 | 146,417 | 150,470 | 146,417 |

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

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

**Table A6:** Child Clothing Expenditures by Child Age Composition

| Dependent Varaible: Child Clothing Budget Shares | (1) | (2) |
|---|---|---|
| Foster and Non-Foster Age 0-3 | -0.005** | |
| | (0.002) | |
| Foster and Non-Foster Age 4-7 | 0.000 | |
| | (0.002) | |
| Foster and Non-Foster Age 8-11 | -0.000 | |
| | (0.002) | |
| Foster and Non-Foster Age 12-14 | 0.002 | |
| | (0.002) | |
| Foster and Non-Foster in Same Age Group | | 0.000 |
| | | (0.001) |
| Sample Size | 17,203 | 17,203 |
| Region Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. Column (1) includes indicators for whether at least one foster or non-foster child in a given age group. Column (2) includes a single indicator equal to one if any age group has both a foster and non-foster child. Additional controls include log household expenditure and the number of each person-type within the household. * p<0.1, ** p<0.05, *** p<0.01

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 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 $\delta_s^t$, but not the slope parameter $\beta^t$ of Equation (5). As a result, if foster or non-foster children consume a large amount of hand-me-down clothing, then they would have a lower $\delta_s^t$ 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., $\beta^t$).

To examine this empirically, I estimate household-level children's clothing Engel curves. The test will rely on the following two assumptions; first, hand-me-down clothing only exists within gender. That is, younger boys can consume clothing that was once worn by older boys, but younger boys cannot consume clothing that was once worn by older girls. Moreover, I make the strong assumption that boys and girls have identical preferences for clothing. Then, conditional on household size, we would expect clothing expenditure to be less in households with same-gender children if hand-me-down clothing were present.

Let $Boys\_HH = 1$ if the household has more male than female children, and 0 otherwise. Let $Girls\_HH = 1$ if the household has more female than male children, and 0 otherwise. The omitted category will be households with an equal number of male and female children, where hand-me-down clothing is potentially less common. To test this hypothesis, I estimate the following regression:

$$W_s^{clothing} = \beta_0 + \beta_1 Boys\_HH + \beta_2 Girls\_HH + \beta_3 \ln y + \gamma X_s + \epsilon_s \tag{A3}$$

where $W_s^{clothing}$ is purchased children's clothing in a household of type $s$, $X_s$ is a vector of household characteristics that includes year and region fixed effects, as well as the number of men, women, and children in the household. Log household expenditure is given by $\ln y$. If hand-me-down clothing were present, we would expect $\beta_1 < 0$ and $\beta_2 < 0$, as (unobserved) hand-me-down clothing would substitute for (observed) purchased clothing.

However, as discussed above, this is permissible as long as the extent of hand-me-done clothing consumption is independent of household expenditure. I therefore interact the gender composition of the household's children with log household expenditure.

$$\begin{aligned} W_s^{clothing} =& \beta_0 + \beta_1 Boys\_HH + \beta_2 Girls\_HH + \beta_3 \ln y \\ &+ \beta_4 (Boys\_HH * \ln y) + \beta_5 (Girls\_HH * \ln y) + \gamma X_s + \epsilon_s \end{aligned} \tag{A4}$$

If hand-me-down clothing were changing the marginal propensity of child clothing consumption, we would expect $\beta_4 \neq 0$ and $\beta_5 \neq 0$.

The results are provided in Table A7. Column (1) presents the results from Equation (A3). The results suggest that households with more girls than boys spend more on clothing than those with an equal number of boys and girls, all else equal. No difference is seen between households with a majority boys and those with an equal share. This suggests that either hand-me-down clothing is present, at least for girls, or that boys and girls have different preferences for clothing. I am unable to distinguish between these explanations with the given data.

In column (2), I present results from Equation (A4). Here I interact the gender composition of the household with log expenditure. The purpose of this exercise is to determine if hand-me-down clothing enters the model in such a way that may bias the results. Encouragingly, the results suggest that the extent of hand-me-down clothing consumption does not vary by household expenditure.

Overall, hand-me-down clothing is not conclusively absent. A natural question then is to what extent this may bias the results. This question relates more generally to the validity of using clothing as a private assignable good. In response, I would cite two recent papers that take different approaches to validate the use of clothing as a means to identify resource shares.

**Table A7:** Child Clothing Expenditures by Gender Composition

| Dependent Varaible: Child Clothing Budget Shares | (1) | (2) |
|---|---|---|
| Boys_HH | -0.001 | -0.001 |
| | (0.001) | (0.007) |
| Girls_HH | -0.001** | 0.008 |
| | (0.001) | (0.009) |
| Log Household Expenditure | 0.004*** | 0.004*** |
| | (0.000) | (0.000) |
| Boys_HH × Log Household Expenditure | | 0.000 |
| | | (0.001) |
| Girls_HH × Log Household Expenditure | | -0.001 |
| | | (0.001) |
| Sample Size | 17,203 | 17,203 |
| Covariates | Yes | Yes |
| Child Number Fixed Effects | Yes | Yes |
| Region Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. Boys_HH is an indicator equal to one if the majority of children in the household are boys. Girls_HH is the equivalent for girls. Additional covariates include the number of men and women in the household, the share of children who are fostered, and whether the household lives in an urban or rural area. * p<0.1, ** p<0.05, *** p<0.01

Recent work by Bargain et al. (2018) and Lechene et al. (2019) provide evidence that hand-me-down clothing is not likely to significantly bias the results. Bargain et al. (2018) use a data set containing observable individual consumption to show that clothing works extremely well as an assignable good to identify resource shares in the framework of a collective household model. Lechene et al. (2019) demonstrate that using clothing and food result in similar resource share estimates, and food clearly has no durable elements.

## A.3 In-Kind Transfers

One potential concern is that foster children are receiving clothing and other goods from their biological parents. This may lead to downwardly biased resource share estimates for foster children. I examine the degree to which both in-kind transfers and remittances may be affecting foster child demand for clothing. I use self-reported measures of in-kind transfers (i.e., non-monetary transfers received from other households) and remittances.[40]

[40] Unfortunately I do not observe the types of goods received, only their estimated value.

To determine if these transfers affect clothing consumption, I regress child clothing budget shares on log in-kind transfers and remittances. Moreover, I allow the relationship between transfers and child clothing budget shares to vary with the presence of foster children. I control for several household characteristics, such as log household expenditure. If foster children were receiving clothing from other households, we would expect their demand for clothing to be decreasing in the value of in-kind transfers. This proves not to be the case for both in-kind transfers and remittances. The results, presented in Table A8, show that in-kind transfers have no effect on clothing demand, nor does this relationship vary by the presence of a foster child in the household. The same finding holds for remittances.

**Table A8:** Child Clothing Expenditures by Transfers

| Dependent Varaible: Child Clothing Budget Shares | In-Kind Transfers | | Remittances | |
|---|---|---|---|---|
| | (1) | (2) | (3) | ( 4) |
| Log In-Kind Transfers | 0.00002 | 0.00001 | | |
| | (0.00004) | (0.00005) | | |
| Foster Household | | -0.00140*** | | -0.00176*** |
| | | (0.00049) | | (0.00040) |
| Foster Household × Log In-Kind Transfers | | 0.00005 | | |
| | | (0.00009) | | |
| Log Remittances | | | 0.00002 | 0.00003 |
| | | | (0.00002) | (0.00003) |
| Foster Household × Log Remittances | | | | 0.00004 |
| | | | | (0.00006) |
| Sample Size | 17,203 | 17,203 | 17,203 | 17,203 |
| Region Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. Remittances are monetary transfers from non-residents to the household. In-kind transfers are non-monetary remittances. Columns (2) and (4) allow the effect of in-kind transfers and remittances to vary with the presence of a foster child within the household. Additional controls include log household expenditure and child age. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

I next include in-kind transfers as a covariate in the resource share functions. If this covariate is negatively associated with foster child resource shares, that may suggest measurement error in the foster child resource share estimates. These results are presented in Table A9 in column (2). In a different specification, I restrict the sample to households that received any in-kind transfers. These results are presented in column (3). In both specifications, in-kind transfers do not seem to be affecting the results.

**Table A9:** Determinants of Foster Child Treatment: In-Kind Transfers

| | Main Results<br><br><br>(1) | In-Kind Transfers in Resource Share Function<br>(2) | HH Received In-Kind Transfers<br><br>(3) |
|---|---|---|---|
| **Household Type Indicators** | | | |
| 1 Non-Foster 1 Foster | 0.149*** | 0.154*** | 0.156** |
| | (0.0567) | (0.058) | (0.062) |
| 0 Non-Foster 2 Foster | 0.286*** | 0.281*** | 0.275*** |
| | (0.079) | (0.081) | (0.086) |
| 2 Non-Foster 1 Foster | 0.137** | 0.141** | 0.140** |
| | (0.055) | (0.056) | (0.060) |
| 1 Non-Foster 2 Foster | 0.215*** | 0.220*** | 0.219*** |
| | (0.0704) | (0.071) | (0.076) |
| 0 Non-Foster 3 Foster | 0.350*** | 0.340*** | 0.329*** |
| | (0.096) | (0.098) | (0.104) |
| **Covariates** | | | |
| In-Kind/Expenditure | | -0.105 | |
| | | (0.583) | |
| Average Age non-Foster | -0.237 | -0.236 | -0.170 |
| | (0.776) | (0.762) | (0.842) |
| Average Age non-Foster$^2$ | 0.019 | 0.019 | 0.013 |
| | (0.055) | (0.054) | (0.059) |
| Average Age Foster | 2.416* | 2.383* | 2.101 |
| | (1.306) | (1.242) | (1.695) |
| Average Age Foster$^2$ | -0.120 | -0.125 | -0.102 |
| | (0.090) | (0.085) | (0.110) |
| Proportion Non-Foster Female | -0.006 | -0.002 | 0.003 |
| | (0.018) | (0.017) | (0.019) |
| Proportion Foster Female | -0.030 | -0.027 | -0.029 |
| | (0.032) | (0.032) | (0.038) |
| Rural | -0.001 | -0.001 | -0.002 |
| | (0.012) | (0.012) | (0.013) |
| Matrilineal Village | 0.018 | 0.016 | 0.015 |
| | (0.012) | (0.011) | (0.013) |
| Proportion of Fostered Orphaned | -0.017<br>(0.026) | -0.019<br>(0.028) | -0.016<br>(0.034) |
| Sample Size | 17,203 | 17,203 | 16,927 |
| Log Likelihood | 150,470 | 150,465 | 148,083 |

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

## A.4 Are the Restrictions Valid?

**Are One-Child-Type and Composite Households Similar?** 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. I analyse the validity of this assumption indirectly. 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 A10 presents sample means for several household characteristics by the different household compositions.

**Table A10:** Sample Means by Household Composition

| | One-Child-Type | | Composite |
|---|---|---|---|
| | Only Non-Foster (1) | Only Foster (2) | (3) |
| Men | 1.332 | 1.485 | 1.551 |
| Women | 1.296 | 1.413 | 1.531 |
| Non-Foster | 2.314 | | 1.712 |
| Foster | | 1.655 | 1.215 |
| Log Real Total Expenditures | 11.941 | 12.015 | 12.029 |
| Year=2010 | 0.429 | 0.408 | 0.407 |
| Year=2013 | 0.143 | 0.158 | 0.185 |
| Foster Child Age | | 9.275 | 9.444 |
| Non-Foster Child Age | 5.846 | | 6.476 |
| Proportion Orphaned of Foster Children | | 0.300 | 0.369 |
| Proportion Female of non-Foster | 0.502 | | 0.493 |
| Proportion Female of Foster | | 0.552 | 0.557 |
| Average Age Women | 29.903 | 49.342 | 32.511 |
| Average Age Men | 32.668 | 42.860 | 33.330 |
| Average Education Women | 1.042 | 0.774 | 32.511 |
| Average Education Men | 1.252 | 1.129 | 33.330 |
| Share Women Age 15-18 | 0.071 | 0.096 | 0.096 |
| Share Men Age 15-18 | 0.102 | 0.200 | 0.150 |
| Rural | 0.811 | 0.828 | 0.722 |
| Matrilineal Village | 0.543 | 0.526 | 0.514 |
| Sample Size | 14,213 | 1,549 | 1,441 |

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

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 A11 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.

**Table A11:** 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 | 23.45 | 30.78 | 19.05 |
| Uncle/Aunt Only | 10.76 | 18.67 | 6.01 |
| Grandparent(s) Only | 43.02 | 10.51 | 62.56 |
| Adopted | 12.85 | 20.94 | 7.98 |
| Other* | 9.91 | 19.09 | 4.39 |
| Sample Size | 3,168 | 1,189 | 1,979 |

Notes: Malawi Integrated Household Panel Survey 2016. The sample includes all foster children. *Other includes children living with an older sibling, other relatives, or other non-relatives.

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.[41] The results are presented in Table A12. Columns (1) and (2) compare 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.

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

**Table A12:** Sample Means by Household Composition

| | Matched Sample | | Matched Sample | |
|---|---|---|---|---|
| | Non-Foster Only (1) | Composite (2) | Foster Only (3) | Composite (4) |
| Men | 1.557 | 1.551 | 1.615 | 1.613 |
| Women | 1.476 | 1.531 | 1.641 | 1.654 |
| Non-Foster | 1.691 | 1.712 | | 1.608 |
| Foster | | 1.215 | 1.361 | 1.359 |
| Log Real Total Expenditures | 12.059 | 12.029 | 12.067 | 12.098 |
| Year=2010 | 0.399 | 0.407 | 0.396 | 0.396 |
| Year=2013 | 0.144 | 0.185 | 0.182 | 0.184 |
| Foster Child Age | | 9.444 | 8.952 | 8.190 |
| Non-Foster Child Age | 6.483 | 6.476 | | 8.856 |
| Proportion Orphaned of Foster Children | | 0.369 | 0.307 | 0.285 |
| Proportion Female of non-Foster | 0.490 | 0.493 | | 0.503 |
| Proportion Female of Foster | | 0.557 | 0.537 | 0.542 |
| Average Age Women | 32.388 | 32.511 | 38.391 | 39.070 |
| Average Age Men | 33.111 | 33.330 | 36.163 | 37.303 |
| Average Education Women | 1.205 | 1.173 | 1.033 | 1.030 |
| Average Education Men | 1.426 | 1.405 | 1.302 | 1.290 |
| Share Women Age 15-18 | 0.091 | 0.096 | 0.136 | 0.138 |
| Share Men Age 15-18 | 0.145 | 0.150 | 0.201 | 0.195 |
| Rural | 0.701 | 0.722 | 0.755 | 0.753 |
| Matrilineal Village | 0.514 | 0.514 | 0.527 | 0.495 |
| Sample Size | 1,411 | 1,411 | 732 | 732 |

Notes: Malawi 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 1,411 composite households that are matched with a corresponding one-child-type non-foster household. There are 1549 households with only foster children, and out of those households I select 732 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.

**Are Ratio Restrictions 1 and 2 Valid?** To test the validity of the ratio restrictions, I estimate the model following the identification approach developed in Section 3.2. Using this method, I do not need to assume any relationship in resource shares across household types. I can then test whether or not the estimated resource shares are consistent with Ratio Restriction's 1 and 2. Specifically, I test the following null hypotheses which are assumed to hold by Restriction 1: $\eta^a_{s_{a0}} = \frac{\eta^a_{s_{a+1,0}}\eta^a_{s_{ab}}}{\eta^a_{s_{a+1,b}}}$ and $\eta^b_{s_{0b}} = \frac{\eta^b_{s_{0,b+1}}\eta^b_{s_{ab}}}{\eta^b_{s_{a,b+1}}}$ for households with one to four foster and non-foster children; and Restriction 2: $\eta^b_{11} = \frac{\eta^a_{11}\eta^b_{01}}{\eta^a_{10}}$. 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 parameter estimates used for these tests are presented in Table

A13.[42]

**Table A13:** Determinants of Resource Shares: Estimation with SAT Restriction

| | Non-Foster Children | Foster Children |
|---|---|---|
| | (1) | (2) |
| | NLSUR | NLSUR |
| 1 non-Foster 0 Foster | 0.137*** | |
| | (0.0507) | |
| 2 non-Foster 0 Foster | 0.202*** | |
| | (0.0584) | |
| 3 non-Foster 0 Foster | 0.239*** | |
| | (0.0649) | |
| 4 non-Foster 0 Foster | 0.273*** | |
| | (0.0728) | |
| 0 non-Foster 1 Foster | | 0.200*** |
| | | (0.0689) |
| 1 non-Foster 1 Foster | 0.0688 | 0.193*** |
| | (0.0552) | (0.0745) |
| 2 non-Foster 1 Foster | 0.124* | 0.169** |
| | (0.0702) | (0.0771) |
| 3 non-Foster 1 Foster | 0.181** | 0.148* |
| | (0.0739) | (0.0756) |
| 0 non-Foster 2 Foster | | 0.279*** |
| | | (0.0826) |
| 1 non-Foster 2 Foster | 0.0407 | 0.253*** |
| | (0.0631) | (0.0864) |
| 2 non-Foster 2 Foster | 0.120 | 0.243*** |
| | (0.0760) | (0.0787) |
| 0 non-Foster 3 Foster | | 0.339*** |
| | | (0.100) |
| 1 non-Foster 3 Foster | 0.0396 | 0.330*** |
| | (0.0577) | (0.0983) |
| 0 non-Foster 4 Foster | | 0.403*** |
| | | (0.120) |
| Sample Size | 17,203 | |
| Log Likelihood | 150,455 | |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-4 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. 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

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.

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

## A.5 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 the material well-being of children 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 well-being 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 using covariates included in the model 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.[43] The motivation behind this procedure is to improve the common support of the different types of households. 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 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 a concern.[44]

[43] See Table A12 columns (1) and (2).

[44] I lack a sufficient number of households to proceed with a similar analysis of one-child-type foster households.

**Table A14:** Predicted Resource Shares: Households with Only Non-Foster Children

| Household Type | Main Results (1) | Restricted Sample (2) |
|---|---|---|
| 1 non-Foster 0 Foster | 0.198*** | 0.245** |
| | (0.0425) | (0.106) |
| 2 non-Foster 0 Foster | 0.131*** | 0.170*** |
| | (0.025) | (0.064) |
| 3 non-Foster 0 Foster | 0.097*** | 0.129*** |
| | (0.019) | (0.045) |
| 4 non-Foster 0 Foster | 0.081*** | 0.103*** |
| | (0.016) | (0.038) |
| Sample Size | 17,203 | 1,441 |
| Log Likelihood | 150,470 | 12,650 |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The full sample includes all households with 1-4 men and women, and 1-4 children. The restricted sample is selected using nearest neighbor propensity score matching. In total, there are 1,441 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

## A.6 Testing Pareto Efficiency

One of the central assumptions of the collective model is that the ultimate allocation of resources is Pareto efficient. That is, there is no way of reallocating goods in such a way that makes one person better off, without making someone else worse off. Pareto efficiency is a testable assumption. Past work has tested it in the context of Malawi (Dunbar et al., 2013) and has failed to reject the assumption. But the test was conducted on a sample of households from 2004, and only on nuclear households. Encouragingly, recent work by Rangel and Thomas (2019) tests Pareto efficiency in complex households in Burkina Faso and fails to reject the assumption.

I use the Malawian data to conduct several tests of Pareto efficiency as well. To do so, I rely on distribution factors. Distribution factors are variables that affect the relative standing of each person in the household, but not each person's preferences. Stated differently, these are variables that enter the Pareto weights, but not each person's individual utility function. Examples include divorce laws or the share of assets owned by a particular person in the household. In this context, I rely on the kinship system in the village the household resides (patrilineal vs. matrilineal), and education differences across adult men and women.

I follow the literature (Browning and Chiappori (1998), Browning et al. (2014), Bourguignon et al. (2009)) and rely on the distribution proportionality property. This property re-

**Table A15:** Testing Pareto Efficiency

| | Sample | | |
|---|---|---|---|
| | All Households | Nuclear Only | Extended Only |
| | (1) | (2) | (3) |
| *Test of equality of ratios between:* | | | |
| *1) Men's Clothing and Food Shares* | | | |
| Wald statistic | 0.059 | 0.004 | 0.286 |
| p-value | 0.809 | 0.947 | 0.593 |
| *2) Men's Clothing, Women's Clothing, and Food Budget Shares* | | | |
| Wald statistic | 0.771 | 0.044 | 0.558 |
| p-value | 0.680 | 0.978 | 0.757 |
| *3) Men's Clothing , Women's Clothing, Children's Clothing, and Food Budget Shares* | | | |
| Wald statistic | 0.785 | 1.620 | 1.119 |
| p-value | 0.853 | 0.655 | 0.773 |

Malawi Integrated Household Survey and Integrated Household Panel Survey. Tests for proportionality restriction of the effects of distribution factors (matrilineal village and average education differences across adult men and women) across outcomes (Browning and Chiappori, 1998). The underlying regression models include the same household level controls used in the main estimation results. Only households with one married woman and one married man are included in Column 2. Only households with more than one woman or more than one man are included in Column 3.

quires the ratio of the impact of two distribution factors on demand to be proportional across goods.

I estimate the following Engel curves:

$$W_s^k = \alpha_0^k + \beta_1^k d_s^1 + \beta_2^k d_s^2 + X_s' \gamma_s^k + \epsilon_s^k \tag{A5}$$

where $W_s^k$ is either the household's food budget share ($k$ = food), or clothing budget shares for men, women, and children ($k$ = men's, women's, or children's clothing) in a household of type $s$. The distribution factors are given by $d_s^1$ and $d_s^2$. I include a vector of household characteristics (the same presented in Table 1).

Pareto efficiency holds when $\frac{\beta_1^k}{\beta_2^k} = \frac{\beta_1^j}{\beta_2^j}$ for $j \neq k$. I follow Brown et al. (2018) and conduct the tests separately for all households, nuclear households, and extended family households. I use a non-linear Wald test for the equality of the ratios, and consistently fail to reject them. The results are presented in Table A15. The obvious caveat to these tests is that they are dependant on the validity of the distribution factors.

## A.7 Ratio Restriction Examples

The following tables illustrate examples of the ratio restrictions for households with two or fewer children. The same logic extends to all household sizes.

| Household | # Non-Foster | # Foster | $\eta^a_{s_{ab}}$ | Ratio Restriction 1 |
|---|---|---|---|---|
| A | 1 | 0 | 20 | |
| B | 2 | 0 | 15 | |
| C | 1 | 1 | 16 | |
| D | 2 | 1 | $\eta^a_{21} = 12$ | $\frac{16}{\eta^a_{21}} = \frac{20}{15} \rightarrow \frac{16}{12} = \frac{20}{15}$ |

Household A has one non-foster child and zero foster children. That child consumes 20 percent of the budget. Household B has two non-foster children and *each* non-foster child consumes 15 percent of the budget. So adding a non-foster children decreased the non-foster child resource shares by 25 percent, when there are no foster children present. According to Ratio Restriction 1, this 25 percent decline must be independent of the number of foster children present in the household. That is, when their is one foster child present, we still see the 25 percent decline (non-foster child resource shares decrease from 16 to 12.)

To better understand Ratio Restriction 2, consider the following example:

| Household | # Non-Foster | # Foster | $\eta^a_{s_{ab}}$ | $\eta^b_{s_{ab}}$ | Ratio Restriction 2 |
|---|---|---|---|---|---|
| A | 1 | 0 | 20 | 0 | |
| B | 0 | 1 | 0 | 20 | |
| C | 1 | 1 | 16 | $\eta^b_{11} = 16$ | $\frac{20}{20} = \frac{\eta^a_{10}}{\eta^b_{01}} = \frac{\eta^a_{11}}{\eta^b_{11}} = \frac{16}{16}$ |

Here, Households A and B are one-child-type, whereas Household C is a composite household. Ratio Restriction 2 requires that foster and non-foster child resource shares in Household C, $\eta^a_{11}$and $\eta^b_{11}$, are proportional to foster and non-foster child resource shares in Households A and B. In particular, if $\eta^a_{10} = 20$, and $\eta^b_{01} = 20$, then $\frac{\eta^a_{11}}{\eta^b_{11}} = \frac{20}{20}$. Importantly, this restriction applies to only a single composite household type.

## A.8 Fully Specified Model

In this section, I follow Dunbar et al. (2013) and write a fully specified household model that is consistent with the restrictions contained in Section 3.

Let $y$ be household expenditure, and $\tilde{p}$ be the price vector of all goods aside from the private assignable goods given by $p_t$. While more general formulations are possible, I start with assuming individuals have sub-utility over goods 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 non-zero, 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 can be relaxed 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. 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 are 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 be rewritten:

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

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 are derived using Roy's Identify on the indirect utility functions given in Equation (A23), where individual income is used $\eta_s^t y$ and individuals face the Lindahl price vector $A_s p$.

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

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

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

Budget shares $h_t^k(\eta_s^t y, A_s' p)/y$ are required to be between zero and one. Furthermore, the adding up constraint requires that budget shares sum to one:[45]

$$\sum_{k} \frac{h_t^k(\eta_s^t y, A_s' p)}{y} = 1 \tag{A14}$$

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

$$z_s^k = A_s \sum_{t \epsilon \{m,f,a,b\}} h_t^k(A_s' p, \eta_s^t(p) y) \tag{A15}$$

Dividing the individual demand functions by household expenditure produces the budget share equations:

$$\frac{h_t^k(\eta_s^t y, A_s' p)}{y} = \tilde{\delta}_t^k(A_s' p)\eta_s^t - \psi_t^k(A_s' p)\eta_s^t \ln(\eta_s^t y) \tag{A16}$$

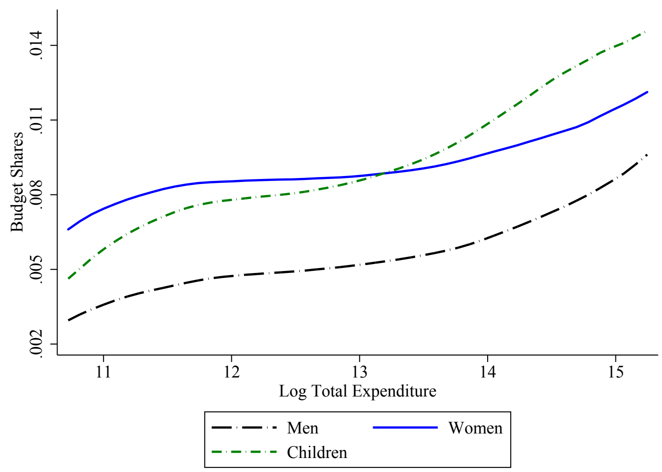
The analysis in this paper uses Engel curves for private goods, which simplifies the above equations even further. First, Engel curves demonstrate how budget shares vary with income holding prices constant. Thus prices can be dropped from the above equation. Secondly, the consumption technology drops 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:

$$W_s^t(y) = \frac{h_s^t(y)}{y} = \eta_s^t \delta_s^t + \eta_s^t \beta_s^t (\ln y + \ln \eta_s^t) \tag{A17}$$

[45] In the estimation of the model, the adding up constraint is ignored as I am not estimating a full demand system.

## A.9 Additional Figures

**Figure A1:** Clothing Engel Curves




Notes: The Figure displays non-parametric clothing Engel curves for men, women, and children.

## A.10 Additional Tables

**Table A16:** Household Structure

| | | # Foster | | | | |
|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | 4 |
| # Non-Foster | 0 | 0 | 872 | 417 | 182 | 78 |
| | 1 | 3,948 | 501 | 135 | 40 | 0 |
| | 2 | 4,188 | 409 | 95 | 0 | 0 |
| | 3 | 3,744 | 261 | 0 | 0 | 0 |
| | 4 | 2,333 | 0 | 0 | 0 | 0 |

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

**Table A17:** Slope Preference Parameters

| Slope Preference Parameter | SAT No Restrictions (1) | SAT Restrictions (2) | SAP (3) | SAT+SAP (4) |
|---|---|---|---|---|
| **SAT** | | | | |
| $\beta^a$ | 0.017*** | 0.017*** | | |
| | (0.004) | (0.003) | | |
| $\beta^b$ | 0.008*** | 0.007** | | |
| | (0.003) | (0.003) | | |
| $\beta^f = \beta^m$ | 0.009*** | 0.009*** | | |
| | (0.002) | (0.001) | | |
| **SAP** | | | | |
| $\beta_{one}$ | | | 0.012*** | |
| | | | (0.001) | |
| $\beta_{s_{nonfoster}}$ | | | 0.000* | |
| | | | (0.000) | |
| $\beta_{s_{foster}}$ | | | -0.000 | |
| | | | (0.000) | |
| $\beta_{s_{men}}$ | | | -0.001 | |
| | | | (0.000) | |
| $\beta_{s_{women}}$ | | | -0.001* | |
| | | | (0.000) | |
| **SAT + SAP** | | | | |
| $\beta$ | | | | 0.011*** |
| | | | | (0.001) |
| Sample Size | 17,203 | 17,203 | 17,203 | 17,203 |
| Log Likelihood | 150,455 | 150,470 | 151,395 | 150,484 |

Notes: Malawi Integrated Household Survey, and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-4 children. The table presents parameter estimates for the slope preference parameter $\beta_s^t$ for the four sets of identification assumptions. "SAT? is the similar across household types assumption. "SAP? is the similar across person types assumption. In columns (1) and (2), I allow slope preferences to differ across foster children, non-foster children, and adults, but they are assumed to be identical across household sizes. In column (3), $\beta_s$ can differ across household sizes (i.e., the number of each person type), but not person types. In column (4), the slope preference parameter is assumed to be identical across household sizes and person types. * p<0.1, ** p<0.05, *** p<0.01

**Table A18:** Determinants of Resource Shares: Preference Factors

| | Non-Foster Children<br>(1)<br>NLSUR | Foster Children<br>(2)<br>NLSUR |
|---|---|---|
| North | -0.003 | 0.010 |
| | (0.013) | (0.015) |
| Central | -0.002 | -0.002 |
| | (0.009) | (0.012) |
| Year=2010 | -0.025** | -0.017 |
| | (0.010) | (0.011) |
| Year=2013 | -0.020 | 0.003 |
| | (0.014) | (0.015) |
| Average Age non-Foster | 1.487** | -0.237 |
| | (0.586) | (0.776) |
| Average Age non-Foster$^2$ | -0.084** | 0.019 |
| | (0.042) | (0.055) |
| Average Age Foster | -0.608 | 2.416* |
| | (1.858) | (1.306) |
| Average Age Foster$^2$ | 0.047 | -0.120 |
| | (0.106) | (0.090) |
| Proportion of Fostered Orphaned | 0.025 | -0.017 |
| | (0.025) | (0.026) |
| Fraction Female non-Foster | -0.015 | -0.006 |
| | (0.011) | (0.018) |
| Fraction Female Foster | 0.008 | -0.030 |
| | (0.027) | (0.032) |
| Average Age Women | 0.454* | 0.075 |
| | (0.261) | (0.280) |
| Average Age Women$^2$ | -0.008** | -0.001 |
| | (0.004) | (0.004) |
| (Average Age Men - Average Age Women) | -0.084 | -0.029 |
| | (0.058) | (0.056) |
| (Average Age Men - Average Age Women)$^2$ | 0.003 | 0.002 |
| | (0.002) | (0.002) |
| Average Education Men | -0.005 | 0.002 |
| | (0.008) | (0.011) |
| Average Education Women | -0.005 | -0.007 |
| | (0.008) | (0.010) |
| Rural | 0.003 | -0.001 |
| | (0.011) | (0.012) |
| Share of Adult Women Age 15-18 | 0.033 | 0.017 |
| | (0.033) | (0.034) |
| Share of Adult Men Age 15-18 | 0.001 | 0.019 |
| | (0.024) | (0.026) |
| Matrilineal Village | 0.008 | 0.018 |
| | (0.009) | (0.012) |
| Sample Size | 17,203 | |
| Log Likelihood | 150,470 | |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-4 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. 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 A19:** Determinants of Resource Shares: Household Type Indicators

| | Non-Foster Children<br>(1)<br>NLSUR | Foster Children<br>(2)<br>NLSUR |
|---|---|---|
| 1 non-Foster 0 Foster | 0.134*** | |
| | (0.047) | |
| 2 non-Foster 0 Foster | 0.197*** | |
| | (0.054) | |
| 3 non-Foster 0 Foster | 0.231*** | |
| | (0.060) | |
| 4 non-Foster 0 Foster | 0.262*** | |
| | (0.067) | |
| 0 non-Foster 1 Foster | | 0.198*** |
| | | (0.067) |
| 1 non-Foster 1 Foster | 0.149*** | 0.117*** |
| | (0.0567) | (0.0349) |
| 2 non-Foster 1 Foster | 0.148*** | 0.137** |
| | (0.0459) | (0.055) |
| 3 non-Foster 1 Foster | 0.174*** | 0.122** |
| | (0.0513) | (0.055) |
| 0 non-Foster 2 Foster | | 0.286*** |
| | | (0.079) |
| 1 non-Foster 2 Foster | 0.102** | 0.216*** |
| | (0.043) | (0.0704) |
| 2 non-Foster 2 Foster | 0.149*** | 0.199*** |
| | (0.0529) | (0.0677) |
| 0 non-Foster 3 Foster | | 0.350*** |
| | | (0.096) |
| 1 non-Foster 3 Foster | 0.082 | 0.264*** |
| | (0.055) | (0.085) |
| 2 non-Foster 3 Foster | 0.214*** | 0.183*** |
| | (0.0538) | (0.0520) |
| 0 non-Foster 4 Foster | | 0.416*** |
| | | (0.114) |
| No. Men | -0.003 | -0.003 |
| | (0.007) | (0.007) |
| No. Women | -0.004 | -0.002 |
| | (0.010) | (0.009) |
| Sample Size | 17,203 | |
| Log Likelihood | 150,470 | |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all households with 1-4 men and women, and 1-4 children. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. 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 A20:** Determinants of Resource Shares: Alternative Household Types

| | Non-Foster Children | | | Foster Children | | |
|---|---|---|---|---|---|---|
| | Main Results (1a) | Nuclear Households (2a) | No Polygamous Households (3a) | Main Results (1b) | Nuclear Households (2b) | No Polygamous Households (3b) |
| **Household Type Indicators** | | | | | | |
| 2 Non-Foster 0 Foster | 0.197*** | 0.200*** | 0.197*** | | | |
| | (0.054) | (0.058) | (0.053) | | | |
| 1 Non-Foster 1 Foster | 0.101*** | 0.116** | 0.100*** | 0.149*** | 0.132 | 0.155*** |
| | (0.039) | (0.046) | (0.038) | (0.0567) | (0.086) | (0.055) |
| 0 Non-Foster 2 Foster | | | | 0.286*** | 0.317*** | 0.306*** |
| | | | | (0.079) | (0.120) | (0.077) |
| 3 Non-Foster 0 Foster | 0.231*** | 0.239*** | 0.229*** | | | |
| | (0.060) | (0.066) | (0.058) | | | |
| 2 Non-Foster 1 Foster | 0.148*** | 0.178*** | 0.144*** | 0.137** | 0.119 | 0.141*** |
| | (0.0459) | (0.055) | (0.044) | (0.055) | (0.085) | (0.052) |
| 1 Non-Foster 2 Foster | 0.102** | 0.073 | 0.102** | 0.215*** | 0.282*** | 0.223*** |
| | (0.043) | (0.046) | (0.042) | (0.0704) | (0.109) | (0.068) |
| 0 Non-Foster 3 Foster | | | | 0.350*** | 0.391*** | 0.374*** |
| | | | | (0.096) | (0.146) | (0.093) |
| **Covariates** | | | | | | |
| Average Age non-Foster | 1.487** | 1.970*** | 1.915*** | -0.237 | -0.373 | -0.365 |
| | (0.586) | (0.710) | (0.612) | (0.776) | (1.187) | (0.752) |
| Average Age non-Foster$^2$ | -0.084** | -0.136** | -0.112*** | 0.019 | 0.046 | 0.025 |
| | (0.042) | (0.053) | (0.043) | (0.055) | (0.085) | (0.054) |
| Average Age Foster | -0.608 | -1.326 | -0.933 | 2.416* | 0.925 | 2.077 |
| | (1.858) | (2.017) | (2.023) | (1.306) | (2.194) | (1.611) |
| Average Age Foster$^2$ | 0.047 | 0.073 | 0.065 | -0.120 | -0.012 | -0.105 |
| | (0.106) | (0.114) | (0.112) | (0.090) | (0.144) | (0.099) |
| Proportion Non-Foster Female | -0.015 | -0.015 | -0.013 | -0.006 | -0.032 | -0.011 |
| | (0.011) | (0.013) | (0.011) | (0.018) | (0.031) | (0.017) |
| Proportion Foster Female | 0.008 | -0.016 | 0.013 | -0.030 | 0.002 | -0.048 |
| | (0.027) | (0.033) | (0.026) | (0.032) | (0.043) | (0.034) |
| Rural | 0.003 | -0.012 | 0.004 | -0.001 | 0.005 | -0.002 |
| | (0.011) | (0.014) | (0.011) | (0.012) | (0.022) | (0.012) |
| Matrilineal Village | 0.008 | -0.000 | 0.009 | 0.018 | 0.004 | 0.019 |
| | (0.009) | (0.011) | (0.009) | (0.012) | (0.023) | (0.011) |
| Proportion of | 0.025 | 0.020 | 0.022 | -0.017 | -0.020 | -0.011 |
| Fostered Orphaned | (0.025) | (0.032) | (0.025) | (0.026) | (0.045) | (0.029) |
| Sample Size | 17,203 | 9,609 | 15,816 | 17,203 | 9,609 | 15,816 |
| Log Likelihood | 150,470 | 83,284 | 138,106 | 150,470 | 83,284 | 138,106 |

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

**Table A21:** Determinants of Resource Shares: Accounting for Wealth

| | Non-Foster Children | | Foster Children | |
|---|---|---|---|---|
| | Main Results | Wealth in Resource Function | Main Results | Wealth in Resource Function |
| | (1a) | (2a) | (1b) | (2b) |
| **Household Type Indicators** | | | | |
| 2 Non-Foster 0 Foster | 0.197*** | 0.198*** | | |
| | (0.054) | (0.052) | | |
| 1 Non-Foster 1 Foster | 0.101*** | 0.100*** | 0.149*** | 0.146*** |
| | (0.039) | (0.038) | (0.0567) | (0.060) |
| 0 Non-Foster 2 Foster | | | 0.286*** | 0.300*** |
| | | | (0.079) | (0.082) |
| 3 Non-Foster 0 Foster | 0.231*** | 0.229*** | | |
| | (0.060) | (0.057) | | |
| 2 Non-Foster 1 Foster | 0.148*** | 0.141*** | 0.137** | 0.141** |
| | (0.0459) | (0.0430) | (0.055) | (0.058) |
| 1 Non-Foster 2 Foster | 0.102** | 0.107*** | 0.215*** | 0.214*** |
| | (0.043) | (0.041) | (0.0704) | (0.0740) |
| 0 Non-Foster 3 Foster | | | 0.350*** | 0.377*** |
| | | | (0.096) | (0.097) |
| **Covariates** | | | | |
| Log Value of Household Assets | | -0.000 | | 0.001 |
| | | (0.001) | | (0.002) |
| Average Age non-Foster | 1.487** | 1.918*** | -0.237 | -0.320 |
| | (0.586) | (0.603) | (0.776) | (0.799) |
| Average Age non-Foster$^2$ | -0.084** | -0.110*** | 0.019 | 0.023 |
| | (0.042) | (0.042) | (0.055) | (0.057) |
| Average Age Foster | -0.608 | -0.569 | 2.416* | 2.789* |
| | (1.858) | (1.969) | (1.306) | (1.613) |
| Average Age Foster$^2$ | 0.047 | 0.046 | -0.120 | -0.139 |
| | (0.106) | (0.110) | (0.090) | (0.102) |
| Proportion Non-Foster Female | -0.015 | -0.014 | -0.006 | -0.010 |
| | (0.011) | (0.010) | (0.018) | (0.019) |
| Proportion Foster Female | 0.008 | 0.009 | -0.030 | -0.036 |
| | (0.027) | (0.026) | (0.032) | (0.035) |
| Rural | 0.003 | 0.002 | -0.001 | -0.000 |
| | (0.011) | (0.011) | (0.012) | (0.014) |
| Matrilineal Village | 0.008 | 0.007 | 0.018 | 0.020 |
| | (0.009) | (0.009) | (0.012) | (0.013) |
| Proportion of Fostered Orphaned | 0.025 | 0.020 | -0.017 | -0.015 |
| | (0.025) | (0.026) | (0.026) | (0.030) |
| Sample Size | 17,203 | 17,203 | 17,203 | 17,203 |
| Log Likelihood | 150,470 | 150,202 | 150,470 | 150,202 |

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

**Table A22:** Descriptive Statistics: Education and Child Labour

| | Mean | Std. Dev. | Min | Max | Sample Size |
|---|---|---|---|---|---|
| **Foster Status** | | | | | |
| Both Parents Present | 0.598 | 0.490 | 0 | 1 | 35,198 |
| Father Present Mother Absent and Alive | 0.016 | 0.125 | 0 | 1 | 35,198 |
| Father Present Maternal Orphan | 0.008 | 0.089 | 0 | 1 | 35,198 |
| Mother Present Father Absent and Alive | 0.143 | 0.350 | 0 | 1 | 35,198 |
| Mother Present Paternal Orphan | 0.056 | 0.230 | 0 | 1 | 35,198 |
| Both Absent and Alive | 0.114 | 0.317 | 0 | 1 | 35,198 |
| Double Orphan | 0.023 | 0.149 | 0 | 1 | 35,198 |
| Both Absent Paternal Orphan | 0.023 | 0.149 | 0 | 1 | 35,198 |
| Both Absent Maternal Orphan | 0.020 | 0.140 | 0 | 1 | 35,198 |
| **Individual and Household Characteristics** | | | | | |
| Enrolled in School | 0.886 | 0.317 | 0 | 1 | 35,198 |
| Hours Worked in Chores Past Week | 1.604 | 5.115 | 0 | 96 | 35,198 |
| Hours Worked (Excluding Chores) Past Week | 2.369 | 4.457 | 0 | 49 | 35,198 |
| Log Expenditure per Capita | 11.795 | 0.663 | 9.308 | 15.376 | 35,198 |
| Log Remmitances Per Capita | 0.781 | 6.131 | -4.554 | 14.846 | 35,198 |
| North | 0.206 | 0.404 | 0 | 1 | 35,198 |
| Central | 0.355 | 0.478 | 0 | 1 | 35,198 |
| South | 0.440 | 0.496 | 0 | 1 | 35,198 |
| Year = 2010 | 0.428 | 0.495 | 0 | 1 | 35,198 |
| Year = 2013 | 0.151 | 0.358 | 0 | 1 | 35,198 |
| Year = 2016 | 0.421 | 0.494 | 0 | 1 | 35,198 |
| Male Sibling Age 0-6 | 0.558 | 0.724 | 0 | 5 | 35,198 |
| Female Siblings Age 0-6 | 0.568 | 0.725 | 0 | 5 | 35,198 |
| Male Siblings Age 7-14 | 0.636 | 0.763 | 0 | 6 | 35,198 |
| Female Siblings Age 7-14 | 0.644 | 0.768 | 0 | 6 | 35,198 |
| Men | 1.302 | 0.928 | 0 | 9 | 35,198 |
| Women | 1.449 | 0.773 | 0 | 7 | 35,198 |
| Age | 9.767 | 2.580 | 6 | 14 | 35,198 |
| Female | 0.507 | 0.500 | 0 | 1 | 35,198 |
| Urban | 0.831 | 0.374 | 0 | 1 | 35,198 |
| Age Household Head | 44.359 | 12.994 | 13 | 104 | 35,198 |
| Female Household Head | 0.264 | 0.441 | 0 | 1 | 35,198 |
| Education of Household Head | 5.768 | 4.084 | 0 | 14 | 35,198 |

Notes: Malawi Integrated Household Survey and Integrated Household Panel Survey. The sample includes all children age 6 to 14.

## A.11 Identification Theorems

What follows are extended versions of the identification theorems in Dunbar et al. (2013). 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 Dunbar et al. (2013). I discuss where and why I differ throughout the Theorems.

Let $h_t^k(p,y)$ be the Marshallian demand function for good $k$ and let the consumption 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:[46]

$$\begin{aligned} \max_{x_m,x_f,x_a,x_b} \tilde{U}_{s_{ab}}[U_m(x_m),U_f(x_f),U_a(x_a),U_b(x_b),p/y] \text{ such that} \\ z_{s_{ab}} = A_{s_{ab}}[x_m + x_f + \sigma_a x_a + \sigma_b x_b] \text{ and} \\ y = z'p \end{aligned} \tag{A18}$$

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:

$$z^k_{s_{ab}} = H^k_{s_{ab}}(p,y) = A^k_{s_{ab}}\Big[\sum_{t\epsilon\{m,f,a,b\}} \sigma_t h_t(A'_{s_{ab}}p, \eta^t_{s_{ab}}y)\Big] \tag{A19}$$

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

$$\eta^m_{s_{ab}} + \eta^f_{s_{ab}} + \sigma_a\eta^a_{s_{ab}} + \sigma_b\eta^b_{s_{ab}} = 1 \tag{A20}$$

ASSUMPTION A1: Equations (A18), (A19), and (A20) 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 assump-

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

tion. Resource shares can still depend on other variables correlated with household expenditure such as the individual wages for men and women.

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 Dunbar et al. (2013) 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, 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, Dunbar et al. (2013) 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 $U_a = U_b$. 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 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:

$$z^k_{s_{ab}} = H^k_{s_{ab}} = h^k(A'_{s_{ab}}p, \eta^k_{s_{ab}}(p)y) \text{ for } k \epsilon \{m, f\} \tag{A21}$$

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

$$z^c_{s_{ab}} = H^c_{s_{ab}} = \sigma_a h^a(A'_{s_{ab}}p, \eta^a_{s_{ab}}(p)y) + \sigma_b h^b(A'_{s_{ab}}p, \eta^b_{s_{ab}}(p)y) \tag{A22}$$

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:[47]

$$V_t(p, y) = \psi_t\Big[u_t\Big(\frac{y}{G^t(\tilde{p})}, \frac{\bar{p}}{p_t}\Big), \tilde{p}\Big] \tag{A23}$$

where $G^t$ is some function that is nonzero, differentiable, and homogeneous of degree one, $\psi_t$ 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.[48]

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

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

[47] 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.

[48] Assumption A3 is a modified version of Assumption B3 in Dunbar et al. (2013).

Since $p_k$ and $\bar{p}$ do not change when replaced by $A'_{s_{ab}}p$, substituting the above equation into Equation (A21) 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:

$$H^k_{s_{ab}}(y) = \tilde{f}_k\Big(\frac{\eta^k_{s_{ab}}y}{G^k_{s_{ab}}}\Big)\eta^k_{s_{ab}}y \tag{A24}$$

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:

$$H^c_{s_{ab}}(y) = \tilde{f}_a\Big(\frac{\eta^a_{s_{ab}}y}{G^a_{s_{ab}}}\Big)\sigma_a\eta^a_{s_{ab}}y + \tilde{f}_b\Big(\frac{\eta^b_{s_{ab}}y}{G^b_{s_{ab}}}\Big)\sigma_b\eta^b_{s_{ab}}y \tag{A25}$$

Define the matrix $\Omega'$ 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 $\Omega'$ is finite and nonsingular. $f^k(0) \neq 0$ for $k \in \{m, f, a, b\}$.

Finiteness of $\Omega'$ 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 analysing 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 $s_{ab}$.*[49] *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 Dunbar et al. (2013) 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 Dunbar et al. (2013).

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:

$$V_t(p, y) = \psi_t\Big[\nu(\frac{y}{G^t(p)}) + F^t(p), \tilde{p}\Big] \tag{A26}$$

for some some functions $\psi_t$, $F$, and $G^t$ where $G^t$ is nonzero, differentiable, and homogenous of degree one, $\nu$ 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, $\psi_t$ 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.

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

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

[49] 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.

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:

$$H^k_{s_{ab}}(y)=\delta^k_{s_{ab}}\eta^k_{s_{ab}}y+g_{s_{ab}}\Big(\frac{\eta^k_{s_{ab}}y}{G^k_{s_{ab}}}\Big)\eta^k_{s_{ab}}y \tag{A27}$$

and

$$H^c_{s_{ab}}(y)=\Big(\delta^a_{s_{ab}}+\delta^b_{s_{ab}}\Big)\eta^c_{s_{ab}}y+g\Big(\frac{\eta^c_{s_{ab}}y/(\sigma_a+\sigma_b)}{G^c_{s_{ab}}}\Big)\eta^c_{s_{ab}}y \tag{A28}$$

ASSUMPTION B5:[50] 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.

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

$$\frac{\eta^a_{s_{a0}}}{\eta^a_{s_{a+1,0}}}=\frac{\eta^a_{s_{ab}}}{\eta^a_{s_{a+1,b}}}\quad\text{and}\quad\frac{\eta^b_{s_{0b}}}{\eta^b_{s_{0,b+1}}}=\frac{\eta^b_{s_{ab}}}{\eta^b_{s_{a,b+1}}} \tag{A29}$$

[50] This is Assumption A4 from DLP.

for $\sigma_a$ 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 $\sigma_a$ and $\sigma_{a+1}$ foster children is independent of the number of *non-foster* children present in those households, and vice versa.

Other studies using the Dunbar et al. (2013) identification strategy have imposed similar restrictions to improve precision in the estimation, but not for identification reasons. For example, Calvi (Forthcoming) 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, Dunbar et al. (2013) 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.

$$\frac{\eta^a_{s_{10}}}{\eta^b_{s_{01}}} = \frac{\eta^a_{s_{11}}}{\eta^b_{s_{11}}} \tag{A30}$$

Similar to Assumption B6, this restriction assumes households with only foster on non-foster children are similar to households with both types of children.

Define the matrix $\Omega''$ 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 $\Omega''$ is finite and nonsingular.

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.12 Identification Proofs

### A.12.1 Proof of Theorem 1

This proof follows the proof of Theorem 2 in Dunbar et al. (2013), 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 Dunbar et al. (2013). In the second step, I extend Dunbar et al. (2013) 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 (A24) and (A25). 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 $k \in \{m, f\}$, $\zeta^k_{20}$, $\zeta^k_{02}$, and $\zeta^k_{01}$ 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 $t \in \{m, f\}$, give the matrix equation

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

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

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

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

$$
\zeta^k_{s_{ab}} = \frac{f^k(0)\eta^k_{10}}{f^k(0)\eta^k_{s_{ab}}} = \frac{\eta^k_{10}}{\eta^k_{s_{ab}}}
$$

With $\eta^k_{10}$ already identified, resource shares for men and women in the composite household types can be recovered. This is a simple extension of Dunbar et al. (2013) 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 $\zeta^a_{s_{ab}}$ as follows: $\zeta^a_{s_{ab}} = \lim_{y \to 0} H^c_{s_{ab}}(y)/H^c_{10}(y)$. Moreover, define $\zeta^b_{01} = \lim_{y \to 0} H^c_{01}(y)/H^c_{10}(y)$. Then we can write:

$$\zeta^a_{s_{ab}} = \frac{f^a(0)\eta^a_{s_{ab}} + f^b(0)\eta^b_{s_{ab}}}{f^a(0)\eta^a_{10}} = \frac{\eta^a_{s_{ab}}}{\eta^a_{10}} + \frac{f^b(0)\eta^b_{s_{ab}}}{f^a(0)\eta^a_{10}} \tag{A31}$$

Furthermore,

$$\zeta^b_{01} = \frac{f^b(0)\eta^b_{01}}{f^a(0)\eta^a_{10}} \rightarrow \frac{f^b(0)}{f^a(0)} = \frac{\zeta^b_{01}\eta^a_{10}}{\eta^b_{01}} = \kappa$$

where $\eta^a_{10}$ and $\eta^b_{01}$ have already been identified. Thus, the ratio $f^b(0)/f^a(0) = \kappa$ is identified. Substituting $\kappa$ into equation (A31) results in the following expression:

$$\zeta^a_{s_{ab}} = \frac{\eta^a_{s_{ab}}}{\eta^a_{10}} + \kappa\frac{\eta^b_{s_{ab}}}{\eta^a_{10}} \tag{A32}$$

where only $\eta^a_{s_{ab}}$ and $\eta^b_{s_{ab}}$ 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.12.2 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 Dunbar et al. (2013). In the second step, I extend Dunbar et al. (2013) 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 (A27) and by Assumptions B3 and B4, the Engel curve for the private partially assignable good is given by Equation (A28). 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:

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

and for children:

$$\kappa^c_{s_{ab}} = \left( y^{\zeta} \frac{\partial \tilde{h}^c_{s_{ab}}(y)/\partial y}{\tilde{h}^c_{s_{ab}}(y)} \right)^{\frac{1}{1-\zeta}} =$$
$$\left( \Big(\frac{\eta^c_{s_{ab}}}{G^c_{s_{ab}} s_c}\Big)^{-\zeta} \Big(\frac{\eta^c_{s_{ab}} y}{G^c_{s_{ab}} s_c}\Big)^{\zeta} \Big[ g^{''}_{s_{ab}} \Big(\frac{\eta^c_{s_{ab}} y}{G^c_{s_{ab}} s_c}\Big) \frac{\eta^{c^3}_{s_{ab}}}{G^{c^2}_{s_{ab}} s_c^2} \Big] / \Big[ g^{'}_{s_{ab}} \Big(\frac{\eta^c_{s_{ab}} y}{G^c_{s_{ab}} s_c}\Big) \frac{\eta^{c^2}_{s_{ab}}}{G^c_{s_{ab}} s_c} \Big] \right)^{\frac{1}{1-\zeta}}$$
$$= \frac{\eta^c_{s_{ab}}}{G^c_{s_{ab}} s_c} \left( y^{\zeta}_{c,s_{ab}} \frac{g^{''}_{s_{ab}}(y_{c,s_{ab}})}{g^{'}_{s_{ab}}(y_{c,s_{ab}})} \right)^{\frac{1}{1-\zeta}}$$

Then for $k \in \{m, f\}$, $\kappa^k_{s_{ab}}(0) = \frac{\eta^k_{s_{ab}}}{G^k_{s_{ab}}} \lambda_{s_{ab}}$, 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:

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

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

$$\gamma^k_{s_{ab}} = \frac{\tilde{\rho}^k_{s_{ab}}}{\tilde{\rho}^c_{s_{ab}}} = \left( g^{'}_{s_{ab}}\Big(\frac{y}{\lambda_{s_{ab}}}\Big) \frac{\eta^k_{s_{ab}}}{\lambda_{s_{ab}}} \right) / \left( g^{'}_{s_{ab}}\Big(\frac{y}{\lambda_{s_{ab}}}\Big) \frac{\eta^c_{s_{ab}}}{\lambda_{s_{ab}}} \right) = \frac{\eta^k_{s_{ab}}}{(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})} \tag{A33}$$

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 (A33) and I will proceed with both cases simultaneously afterwards). Suppose $g_{s_{ab}}$ is a polynomial of degree $\lambda$ 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 $k \in \{m, f\}$:

$$\begin{aligned} \gamma^k_{s_{ab}} =& \Big(\frac{\partial^\lambda [H^k_{s_{ab}}(y)/y]}{\partial(\ln y)^\lambda}\Big) / \Big(\frac{\partial^\lambda [H^c_{s_{ab}}(y)/y]}{\partial(\ln y)^\lambda}\Big) = \\ & \frac{c_{s_{ab},\lambda}\eta^k_{s_{ab}}}{c_{s_{ab},\lambda}(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})} = \frac{\eta^k_{s_{ab}}}{(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}})} \end{aligned} \tag{A34}$$

which is the same as Equation (A33). Then since resource shares must sum to one:

$$\begin{aligned} & \gamma^m_{s_{ab}}(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}}) + \gamma^f_{s_{ab}}(\sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}}) + \sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}} = \\ & \eta^m_{s_{ab}} + \eta^f_{s_{ab}} + \sigma_a \eta^a_{s_{ab}} + \sigma_b \eta^b_{s_{ab}} = 1 \\ & \sigma_a \eta^a_{s_{ab}}(\gamma^m_{s_{ab}} + \gamma^f_{s_{ab}} + 1) + \sigma_b \eta^b_{s_{ab}}(\gamma^m_{s_{ab}} + \gamma^f_{s_{ab}} + 1) = 1 \end{aligned} \tag{A35}$$

For one-child-type households, $\sigma_a$ or $\sigma_b$ equals zero, and Equation (A35) simplifies significantly. For households that only have foster children, Equation (A35) 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 ($\eta^a$ and $\eta^b$). For the one-child-type households, one of those two parameters was zero. From Equation (A35) 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 under-identified 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. $\eta^a_{10}$ 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 $\Omega''$ 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 $t \in \{m, f\}$.