Child Fostering and Intrahousehold Inequality

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February 17, 2017

Abstract

How are foster children treated relative to non-foster children? Do they consume less than other members of the household? Child fostering is ubiquitous in Africa and the wellbeing of these children, who may be particularly vulnerable to impoverishment, is not well known. But assessing poverty for individual children can be a daunting task, since consumption is typically measured at the household level and many goods in the household are shared. To address this problem, I extend Dunbar et al. (2013) and estimate a collective model of household behavior designed to capture *resource shares*, that is, the share of total household expenditure allocated to each household member. Resource shares are identified by observing how expenditure on assignable clothing varies with income and household size. I show that the data requirements for estimating individual poverty incidence are less demanding than previously thought under reasonable restrictions to how resource shares vary across household structure. I find that standard poverty indices substantially understate foster child poverty, and that foster children consume a slightly smaller share of household resources than non-foster children. This difference is driven by orphaned foster children, suggesting kinship networks play an important role in foster child treatment.

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1 Introduction

In parts of Africa, a significant portion of children live away from both of their biological parents.[1] Some of these children are orphans, but the majority are children who are voluntarily sent away by their parents to live with other families. Despite the size of this population, little is known about how foster children are treated within the household. These children live in some of the poorest countries in the world, and being away from both parents, are particularly vulnerable to impoverishment. In this paper, I analyze foster child welfare along several different dimensions, focusing primarily on individual-level consumption. I quantify the share of household resources allocated to foster children in order to calculate individual-level poverty rates. Moreover, I determine what factors influence this allocation; Are orphaned foster children differently than foster children whose parents simply live in a different household? Does gender matter in foster child treatment? Do aunts and uncles or grandparents make for better foster caretakers?

To answer these questions, I model households using the collective framework following Chiappori (1988, 1992), where households are thought of as a collection of individuals, each with their own utility function. The goal of the model is to identify *resource shares*, that is, the share of total household resources consumed by each person in the household. However, identifying resource shares is far from straightforward for two reasons. First, consumption data is typically collected at the household level, and second, goods are shared. Dunbar, Lewbel and Pendakur (2013) (DLP henceforth) demonstrate that resource shares can be identified by observing how expenditure on assignable clothing varies with household expenditure and household size. Because I do not observe assignable clothing (or any other assignable good) for foster or non-foster children, I'm forced to extend DLP, and develop a method to identify resource shares in the absence of assignable goods. In particular, I use Engel curves for *partially* assignable goods to identify foster and non-foster child resource shares.[2] The cost of the relaxed data requirements are two additional model assumptions that restrict the way in which foster child resource shares vary across household sizes to be independent of the number of non-foster children present, and vice versa. I explain these restrictions in more detail in section 4.

I estimate the model using detailed consumption and expenditure data from Malawian households. I then use the predicted resource shares to analyze consumption differences between foster and non-foster children using the fact that conditional on household con-

[1] Fostering rates vary considerably by country and can be as high as 37 percent in Namibia, for example (Akresh (2005)).

[2] In my context child clothing is partially assignable to foster and non-foster children.

sumption, higher resource shares translate into higher individual consumption. The results demonstrate that foster children consume a slightly smaller share of household resources relative to non-foster children, with the extent of this difference depending on the household composition. I then divide foster children by the reason they were fostered by classifying them as either an orphaned foster child, or a non-orphaned foster child. I find that orphaned foster children appear to be particularly disadvantaged, with orphaned foster child consumption being 72.9 percent of that of non-orphaned foster children. Gender does not appear to be a key determinant of child treatment.

I next estimate individual-level poverty rates using the predicted resource shares. Traditional measures of poverty 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 and find that foster child poverty is being substantially understated. This is important for several reasons. First, coverage for government programs is rarely universal and policymakers must find ways to identify the poor. Different methods that are used to identify the poor, such as proxy-means testing, use household-level measures. This project adds to recent evidence (Brown et al. (2016a,b)) that relying on household-level measures will result in a substantial number of individuals, especially children, being classified as non-poor, and thus non-beneficiaries of different programs. My results suggest intrahousehold inequality must be accounted for when targeting poverty programs.

I conclude my analyses by providing context for the above consumption results by comparing school attendance levels and child labor rates for foster and non-foster children. The results suggest that foster children attend school and work at roughly the same rates as non-foster children. However, once I decompose foster children by orphan status, I find that orphaned foster children have lower school enrollment than non-foster children.[3]

Foster children have become a population of increasing interest as economists have come to recognize the variety of household structures that exist in Sub-Saharan Africa. Seminal work by Ainsworth (1995) and Akresh (2005) provide important contributions to understanding the underlying economic reasons children are fostered. Akresh (2005) in particular is able to clearly identify why households both take in foster children, and send their own children away by using a personally constructed data set. By surveying both the sending and receiving households in the same foster network, Akresh (2005) demonstrates the importance of risk sharing and child labor in child fostering decisions. Serra (2009) provides a theoretical framework for understanding child fostering and reaches similar conclusions.

[3] 38 percent of foster children in the sample are orphaned.

I deviate from this strand of the literature by focusing on the welfare impacts of child fostering as opposed to why it occurs in the first place. Specifically, I add to the literature on child fostering by focusing on how foster children are treated within the household by quantifying intrahousehold inequality between foster and non-foster children. Existing studies in this field focus primarily on orphans, who are sometimes referred to as "crisis" foster children (Serra (2009)). Intrahousehold inequality in relationship to orphanhood has been subject to extensive research due to the enormity of the AIDS epidemic in Sub-Saharan Africa. My study expands upon previous work by focusing on differences in individual-level consumption, whereas the majority of studies in this literature have so far focused on differences in school enrollment between orphaned and non-orphaned children (e.g. Case et al. (2004), Ainsworth and Filmer (2006), Evans and Miguel (2007)).[4] Previous research focusing on education has done so at least partly due to its observability in the data. On the contrary, the share of household consumption allocated to individual household members is not directly observable. Focusing on consumption has several benefits over focusing on education. Most importantly, individual consumption serves as a good proxy for child health, which is typically not measured for children above age five in household surveys.[5] Secondly, it will allow for the calculation of poverty rates by foster status, which is of great importance to policymakers interested in targeting government programs more effectively.

Lastly, I add to the vast literature on intrahousehold resource allocation and the collective model. This strand of research, beginning with work by Chiappori (1988, 1992), Apps and Rees (1988), and Browning et al. (1994) emphasizes that households are a collection of individuals, each with their own distinct preferences. The primary assumption of the collective model is that the way in which households allocate resources is Pareto efficient. While there are many branches of research in this field, my paper borrows heavily from, and builds off of recent work on the estimation of the level of resource shares. Key studies in this literature include Browning et al. (2013) (BCL), Lise and Seitz (2011), Lewbel and Pendakur (2008), and DLP.

BCL introduce a consumption technology function using Barten (1964) scales to the collective model, and (among other contributions) demonstrate how the level of resource shares can be identified. Lewbel and Pendakur (2008) add to BCL, by showing how the BCL

[4] A notable exception is Case et al. (2000) who study how *household* food consumption spending varies by the fostering status of the household's children. I build upon Case et al. (2000) by using a structural model to estimate resource shares, which is what allows for the estimation of individual-level consumption, as opposed to household-level measures in a unitary framework which may obscure potential intrahousehold inequality.

[5] Household-level measures of consumption and wealth inadequately predict poor health in women and children in Sub-Saharan Africa (Brown et al. (2016b)).

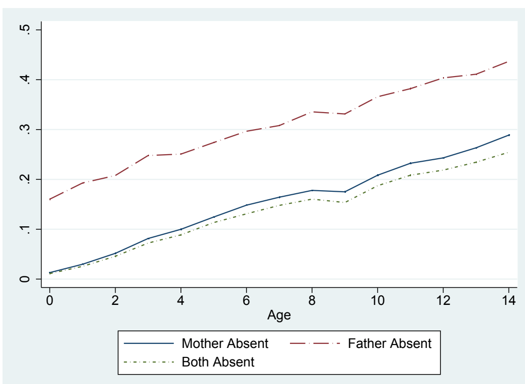
model can be identified by comparing Engel curves for single men, single women, and men and women in childless couples. This modification greatly simplifies the estimation of the level of resource shares. A weakness of Lewbel and Pendakur (2008) and BCL is that neither of these papers are able to identify child resource shares. DLP solve this issue, and simplify the estimation further, by identifying resource shares off of Engel curves for a single private assignable good. I extend DLP to allow for identification of resource shares when private goods are only partially assignable by adding additional restrictions to the model. Given that assignable goods are difficult to find in the data, my contribution provides a framework for expanding research on intrahousehold allocation into areas previously difficult to examine. In particular, the methodological contribution of this paper is applicable to other settings, including analyses of differences in treatment between boys and girls, widows and married women, or any other context where intrahousehold inequality is of interest.

A related area of study that deserves mention is research on intrahousehold inequality among children using expenditures on adult goods to derive child costs, or the Rothbarth method (Rothbarth (1943)). The general idea behind the Rothbarth method is that one can compare spending on adult goods for childless couples with spending on adult goods in childless couples and infer expenditure on children from that comparison. This method ignores economies of scale in consumption, and moreover, it requires the strong assumption that parent's preferences do not change once they have children. Deaton (1989) uses an identification strategy similar to the Rothbarth method to test for intrahousehold inequality between boys and girls in Côte d'Ivoire and Thailand. In particular, Deaton examines how expenditure on adult goods varies with the number of boys and girls in the household; if spending on adult goods is lower when boys are present relative to when girls are, all else equal, then that provides suggestive evidence parents are favoring boys. Deaton's method can therefore identify the existence of discrimination, but not its extent, as I am able to do in this study.

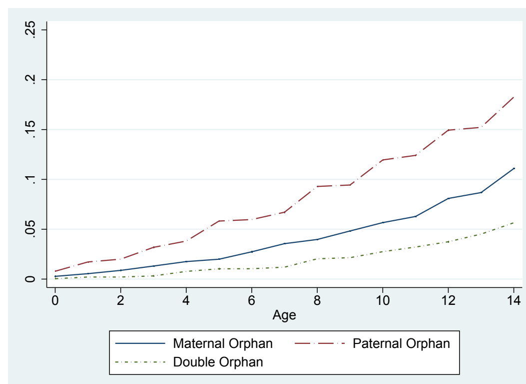
The rest of the paper is organized as follows. Section 2 gives a brief description of child fostering as a cultural institution in East Africa. In Section 3, I present the DLP model of household decision making. Section 4 provides a brief summary of my identification results. I discuss the data and estimation strategy in Sections 5 and 6 respectively. In Section 7, I then present my main results which establish that foster children receive a smaller share of household resources than non-foster children. I use those results to conduct a poverty analysis in Section 8. Section 9 examines the robustness of my results. Lastly, Section 10 analyzes school enrollment and child labor rates among foster children to provide context for the consumption results.

2 Child Fostering in East Africa

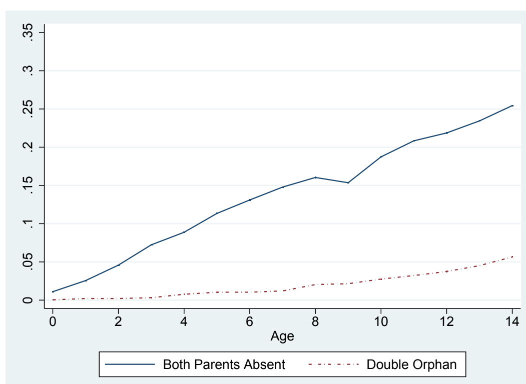
Child fostering can be thought of as a cultural institution where biological parents transfer the parental rights of their children to some other household. Fostering rates vary by country and are highest in West African societies, but are quite common in East Africa as well. Figure 1a provides descriptive evidence of the amount of fostered children in Malawi, where a foster child is classified as a child who is living away from *both* parents. Out of all children age 14 and under, 13.1 percent are fostered. Figure 1a also demonstrates fostering rates are increasing with age. This is consistent with education and child labor being the primary motivation to foster children. Figure 1b displays orphan rates by age, and finally, figure 1c demonstrates that the majority of fostered children are not double orphans; parents are in fact sending their children to live in other households.



(a)



(b)



(c)

Figure 1: Foster and Orphan Status by Age

Child fostering can be either voluntary or non-voluntary. Non-voluntary or crisis fostering occurs when the child is orphaned, or has parents who are ill and have no choice but to foster out their child. This situation has become substantially more common as a result of the AIDS epidemic. Voluntary or purposive child fostering, on the other hand, 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; It could be to provide educational access for the child, to strengthen kinship networks, to increase fertility, to reallocate child labor across households, or due to agricultural shocks.[6] Children are also often fostered as a result of their parents divorce and subsequent remarriage (Grant and Yeatman (2014)). This is especially prevalent in Malawi as almost half of all marriages end in divorce, with remarriage rates being equally high (Reniers (2003)). Data limitations prevent me from examining in detail the reasons households foster children, as I only observe the receiving household. I am therefore unable to determine whether, for example, children fostered due to negative agricultural shocks are treated differently than children fostered for child labor related reasons. I can however differentiate between children who are involuntarily fostered due to orphanhood and those who are not, and I ultimately find this distinction matters for foster child treatment.

There are several reasons why foster children may be treated worse than non-foster children. First, parents are likely to be more altruistic towards their own biological children. This theory, known as Hamilton's Rule (Hamilton (1964)), hypothesizes that altruism is increasing in relatedness; Parents care more for their children relative to their nephews and nieces, and they care more about their nephews and nieces than their neighbor'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; children who are more closely related to their caregivers should experience better access to education, lower levels of child labor, and a higher share of household consumption. I test the implications of Hamilton's Rule in this study.

3 Collective Model of the Household

I now present a structural model of Malawian households using the collective framework. Households are thought of as a collection of individuals, where each person has their own preferences, and faces their own personal budget constraint. Each person's budget constraint will be in part determined by their resource share, which is defined as the share of the total household budget allocated to each individual in the household. Resource shares are a desirable object to identify as it will allow for both a test of inequality within the household, and act as a tool to estimate individual-level poverty rates.

[6] See Ainsworth (1995), Akresh (2005), and Serra (2009) for a detailed analysis of why households foster children.

The household consists of four types of individuals, each with their own type-specific utility function: men (m), women (w), foster (a), and non-foster (b) children.[7] I index household types s_{ab} by the number of foster and non-foster children in the household, given by s_a and s_b respectively. Consistent with the standard characterization of collective households, I make no assumptions about the bargaining process which determines how resources are allocated across household members, only that the ultimate allocation is Pareto efficient.[8] I account for economies of scale in consumption using a Gorman (1976) linear technology function.[9] Individuals have caring preferences, in the sense that they are allowed to get utility from the utility of other household members, though not the consumption of specific goods.

Households consume K types of goods at market prices $p = (p^1, ..., p^K)'$. Let $z_{s_{ab}} = (z^1_{s_{ab}}, ..., z^K_{s_{ab}})$ be the K - vectors of observed quantities consumed by the household. The household-level quantities are converted into private good equivalents $x_t = (x^1_t, ..., x^K_t)$ using a linear consumption technology as follows: $z_{s_{ab}} = A(x_f + x_m + s_a x_a + s_b x_b)$ where A is a $K \times K$ matrix which accounts for economies of scale in consumption.[10] The use of private good equivalents is necessary since individuals will receive utility from goods they consume, not from what the household purchases.

Each individual member has a monotonically increasing, continuously twice differentiable strictly quasi-concave utility function over a bundle of goods. Let $U_t(x_t)$ be the utility of an individual of type t who consumes x_t goods while living in the household. This utility function is assumed to be separable from leisure, savings, or any other goods not included in the commodity bundle. Individuals of the same type are assumed to have the same utility function. For the empirical results, the utility function for each person type is allowed to differ over observable characteristics such as age and education.

Using this framework, I am giving children their own utility function and thus am assuming they have their own preferences. However, given that these are oftentimes young

[7] Data limitations prevent me from dividing children into more than two groups, i.e. I am unable to have orphaned foster children, and non-orphaned foster children as different child types. However, the estimation will still allow foster child resource shares to vary with the proportion of orphaned foster children in the household.

[8] Pareto efficiency in household allocations has been analyzed in many different contexts and usually cannot be rejected. Notable papers that analyze this assumption include Browning and Chiappori (1998), Bobonis (2009), and Attanasio and Lechene (2014).

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

[10] 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.

children, I would not like to assume these children are making their own consumption decisions or that they are participants in some household bargaining game. Thus, a better and more realistic interpretation of this model is that the child's utility function is actually what the mother and father (or other caretaker) imagine the child's utility function to be.

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

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

The household then solves the following maximization problem:

$$\begin{aligned} \max_{x_m, x_f, x_a, x_b} \tilde{U}(U_m, U_f, U_a, U_b, p/y) \quad & \text{such that} \\ & z_{s_{ab}} = A(x_f + x_m + s_a x_a + s_b x_b) \\ & y = z'_{s_{ab}} p \end{aligned} \tag{2}$$

Solving this system results in bundles of private good equivalents. If these goods are priced at the shadow prices $A'p$, I obtain the resource share $\eta^t_{s_{ab}}$, which is defined as the fraction of total resources that are allocated to each individual of type t.[11][12] Note by definition men's, women's, foster, and non-foster children's resources must sum to one. I will ultimately compare resource shares of foster and non-foster children to test for intrahousehold discrimination.

With Pareto efficiency, I can reformulate the household's problem as a two step 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 personal utility function U_t subject to a Lindahl type shadow budget constraint $\sum_k A_k p^k x^k_t = \eta^t_{s_{ab}} y$.

Identification of resource shares relies on Engel curve estimation. I therefore now write household demand for a certain subset of goods whose properties substantially reduce the data requirements necessary for identification. Define these goods as *private assignable goods*, which are goods that are not shared across household member types (private), and that are consumed by a known type t (assignable). Examples of private goods include food and

[11] The shadow price vector will be different than the market prices faced by the household since some goods are jointly consumed.

[12] 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.

clothing; if the father drinks a glass of milk, the mother cannot consume that same glass of milk. Food however is not assignable; The data provides information on the total amount of food consumed, but not who in the household consumed it. On the contrary, clothing is both private and assignable, in the sense that men's clothing is observable in the data, and can safely assumed to be consumed by men.

The motivation for relying on private assignable goods is that their demand functions are substantially simpler than the demand functions for the other goods. Intuitively, household demand for men's clothing will behave fairly similarly to men's demand for men's clothing. On the other hand, the household's demand for non-private goods, such as gasoline, depends on the degree to which gasoline is shared within the household, and also on each individual's preferences for gasoline. A key contribution of DLP is that they require only household demand functions for private assignable goods to identify resource shares.

Let $W^t_{s_{ab}}(y, p)$ be the share of household expenditure y spent on person t's private assignable good. DLP derive the household demand functions for the private assignable goods, which can be written as follows:[13]

$$W^t_{s_{ab}}(y, p) = s_t \eta^t_{s_{ab}} w^t_{s_{ab}}(A'p, \eta^t_{s_{ab}} y) \tag{3}$$

where $w^t_{s_{ab}}$ is the amount of the private assignable good that a person of type t living in household type s_{ab} would hypothetically demand had they lived alone with income $\eta^t_{s_{ab}} y$ at the Lindahl price vector $A'p$. The number of each person type within the household is denoted by s_t. Note that the resource shares and the individual demand functions are unobservable, and hence the system is not identified without more assumptions (for each equation there are two unknowns).[14] In what follows I discuss how to identify the parameters of interest.

4 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 an assignable good (clothing) for each person type within the household. In this context, that would mean observing foster child clothing and non-foster child clothing, neither of which are available in the data. Thus, a direct application

[13] See section A1 in the appendix for the details of this derivation.

[14] BCL achieve identification by assuming $w^t_{s_{ab}}$ is "observed" using data from households that have only men, or only women. In households with only single men, or only single women, the household and individual demand functions are the same. This clearly does not work in a context where children are present.

of the DLP methodology is infeasible in this context. I work around this data limitation by making use of partially assignable goods; child clothing in particular, which is partially assignable to both foster and non-foster children. I demonstrate how resource shares can still be identified in the absence of assignable goods for each person type, if partially assignable goods are available in the data. The identification theorem is similar to DLP and I therefore will discuss their method in Section 4.1, and in Section 4.2 I will illustrate my alternative approach, emphasizing where and why I differ.

4.1 Identification with Private Assignable Goods

For DLP, resource shares are identified by observing the Engel curve for assignable clothing for each person type. Following equation (3), this system can be written as follows:

$$\begin{aligned}
W^m_{s_{ab}}(y) =& \eta^m_{s_{ab}} w^m_{s_{ab}}(\eta^m_{s_{ab}} y) \\
W^f_{s_{ab}}(y) =& \eta^f_{s_{ab}} w^f_{s_{ab}}(\eta^f_{s_{ab}} y) \\
W^a_{s_{ab}}(y) =& s_a \eta^a_{s_{ab}} w^a_{s_{ab}}(\eta^a_{s_{ab}} y) \\
W^b_{s_{ab}}(y) =& s_b \eta^b_{s_{ab}} w^b_{s_{ab}}(\eta^b_{s_{ab}} y)
\end{aligned} \tag{4}$$

The number of foster and non-foster children in the household is given by s_a and s_b and this determines the household type. For now the household is assumed to have only one man ($s_m = 1$) and one woman ($s_f = 1$). To achieve identification, resource shares are assumed to be independent of expenditures at low levels of expenditure.[15] This is the key identifying assumption. Resource shares can however be allowed to depend on variables highly correlated with expenditures, such as household member wages, remittances, or wealth.

Assuming individuals have Muellbauer's Piglog preferences over clothing and footwear at all levels of expenditure is used in the empirical section and facilitates discussion of identification, so it is used henceforth. No preference restriction is made on the other goods.

[15] Menon et al. (2012) show this assumption to be quite reasonable. Specifically, 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 women's resource shares and also finds that they do not vary with household expenditure.

With these preferences, Engel curves are linear in the logarithm of household expenditure.

$$\begin{aligned} W^m_{s_{ab}} &= \eta^m_{s_{ab}}[\delta^m_{s_{ab}} + \beta^m \ln(\eta^m_{s_{ab}})] + \eta^m_{s_{ab}}\beta^m \ln y \\ W^f_{s_{ab}} &= \eta^f_{s_{ab}}[\delta^f_{s_{ab}} + \beta^f \ln(\eta^f_{s_{ab}})] + \eta^f_{s_{ab}}\beta^f \ln y \\ W^a_{s_{ab}} &= s_a\eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_a\eta^a_{s_{ab}}\beta^a \ln y \\ W^b_{s_{ab}} &= s_b\eta^b_{s_{ab}}[\delta^b_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] + s_b\eta^b_{s_{ab}}\beta^b \ln y \end{aligned} \tag{5}$$

where $W^t_{s_{ab}}$ are budget shares for the private assignable good for person t in a household s_{ab}. The preference parameters are given by $\delta^t_{s_{ab}}$ and β^t. The second assumption needed for identification is that Engel curves have the same shape across household types, that is, β^t is assumed to not vary with s_{ab}.[16] This restriction is equivalent to assuming price differences across household types can be absorbed into an income deflator.[17] Type specific resource shares sum to one: $\eta^m_{s_{ab}} + \eta^f_{s_{ab}} + s_a\eta^a_{s_{ab}} + s_b\eta^b_{s_{ab}} = 1$. Note again that for simplicity I am assuming households consist of only one man and one woman.

With four household types, resource shares $\eta^t_{s_{ab}}$ are identified, which can be seen with a simple counting exercise. With four Engel curves for each household type, and four household types, there are 16 Engel curves. Moreover, for each of the four household types resource shares must sum to 1, so this results in a system of 20 equations in total. Furthermore, each Engel curve has a resource share $\eta^t_{s_{ab}}$ that needs to be identified (16 total), and there are four shape parameters β^t that need to be identified. This leads to 20 unknowns, and with 20 equations, the system is exactly identified. A formal proof is provided in DLP.

The key complication with this identification method for my purposes is the absence of separate private assignable goods for foster and non-foster children in the data; I do not observe the budget shares for foster and non-foster child clothing, $W^a_{s_{ab}}$ and $W^b_{s_{ab}}$, but rather their sum $W^c_{s_{ab}} = W^a_{s_{ab}} + W^b_{s_{ab}}$ where $W^c_{s_{ab}}$ is the budget share for *child* clothing. To work around the lack of sufficient data, I now develop a new methodology to identify resource shares in the absence of private assignable goods using private partially assignable goods.

[16] This is the Similar Across Types restriction in DLP. Alternatively, identification could be achieved by assuming preferences are Similar Across People (SAP), in which case the shape preference parameter would vary with household size, but not across person types, i.e. $\beta_{s_{ab}}$ would be substituted in for β^t for each Engel curve in equation 5.

[17] It is important to note that this restriction does *not* imply homothetic preferences. As discussed in DLP, this restriction is only applied to the cross-price effects of the non-private goods on the private goods.

4.2 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 equation (5) as a single Engel curve for children's clothing:

$$\begin{aligned}
W^m_{s_{ab}} =& \eta^m_{s_{ab}}[\delta^m_{s_{ab}} + \beta^m \ln(\eta^m_{s_{ab}})] + \eta^m_{s_{ab}}\beta^m \ln y \\
W^f_{s_{ab}} =& \eta^f_{s_{ab}}[\delta^f_{s_{ab}} + \beta^f \ln(\eta^f_{s_{ab}})] + \eta^f_{s_{ab}}\beta^f \ln y \\
W^c_{s_{ab}} =& s_a\eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_b\eta^b_{s_{ab}}[\delta^b_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] \\
& + \ln y(s_a\eta^a_{s_{ab}}\beta^a + s_b\eta^b_{s_{ab}}\beta^b)
\end{aligned} \tag{6}$$

Here the Engel curve for children's clothing is given as the sum of the Engel curves for foster and non-foster child clothing. I've simply taken the bottom two equations from equation (5) and summed them.[18] As before, I allow preferences to vary considerably by person type through both the intercept parameter $\delta^t_{s_{ab}}$ and the slope parameter β^t.

Define a *one type only* household as a household that has only foster children, or only non-foster children ($s_a = 0$ or $s_b = 0$). For these households, resource shares for men, women, foster and non-foster children can be identified. This follows directly from DLP, as this setting contains private assignable goods; if the household only has foster children, then children's clothing is equivalent to foster children's clothing.

I would also like to identify foster and non-foster child resource shares in what I call *composite* households, or households with both types of children. The above identification strategy fails as there are not private assignable goods for each child type. In particular, DLP identify resource shares off of the slope of the Engel curves, which is the coefficient on $\ln y$. Whereas before this contained two unknowns (β^t and $\eta^t_{s_{ab}}$), this slope now contains 4 unknowns (β^a, β^b, $\eta^a_{s_{ab}}$, and $\eta^b_{s_{ab}}$) and I will be unable to separately identify each parameter. To solve 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 type. The restrictions are somewhat arbitrary as they are not originating from a model, but they are intuitive in the sense that they require resource shares to behave in a similar fashion in composite households as they do in one type only households. Restriction 1 is given below:

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

[18] Implicit in summing the two Engel curves is the assumption that foster and non-foster children do not share clothing. The validity of this assumption is analyzed in section 9.2.

In words, (1) the ratio of foster child resource shares in households with s_a and s_{a+1} foster children is constant across household types, (2) the ratio of non-foster child resource shares in households with s_b and s_{b+1} non-foster children is constant across household types. This restriction can be understood as an independence assumption, in that the percent change in foster child resources shares as foster children are added to the household is independent of the number of *non-foster* children present, and vice versa. To illustrate this restriction, consider the example given below:

Household	s_a	s_b	$\eta^a_{s_{ab}}$	$\eta^b_{s_{ab}}$	Restriction 1
A	1	0	20	0	
B	2	0	15	0	
C	1	1	η^a_{11}	η^b_{11}	$\frac{\eta^a_{11}}{\eta^a_{21}} = \frac{20}{15}$
D	2	1	η^a_{21}	η^b_{21}	$\frac{\eta^a_{11}}{\eta^a_{21}} = \frac{20}{15}$

The above chart is a demonstration of Restriction 1 in regards to foster child resource shares in composite households with either one of each child type (Household C), or two foster children and one non-foster child (Household D). Since Households A and B are one type only households, they are identified using solely the DLP assumptions, and can therefore be used to restrict resource shares in Households C and D. The restriction that the above chart represents can be written as $\frac{\eta^a_{s_{11}}}{\eta^a_{s_{21}}} = \frac{\eta^a_{s_{10}}}{\eta^a_{s_{20}}} = \frac{20}{15}$.

Next, I make an additional assumption, 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 says 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. To better understand this restriction, consider the following example given below:

Household	s_a	s_b	$\eta^a_{s_{ab}}$	$\eta^b_{s_{ab}}$	Restriction 2
A	1	0	20	0	
B	0	1	0	25	
C	1	1	η^a_{11}	η^b_{11}	$\frac{\eta^a_{11}}{\eta^b_{11}} = \frac{20}{25}$

Here, Household's A and B are one type only households and are identified using the DLP restrictions, whereas Household C is a composite household and resource shares are not identified without additional assumptions. Restriction 2 requires that foster and non-foster child resource shares in Household C, $\eta^a_{11}$and η^b_{11}, are proportional to foster and non-foster child resource shares in Household's A and B. In particular, if $\eta_{11}^{a} = 20$, and $\eta_{11}^{b} = 25$, then $\frac{\eta_{11}^{a}}{\eta_{11}^{b}} = \frac{20}{25}$.

In summary, I am weakening the data requirements of DLP, and to remain identified, I need to make the model slightly less flexible. With the above two restrictions, the number of parameters needed to be identified declines substantially, and the model parameters can be identified by OLS-type regressions of clothing budget shares on log expenditure. The proof for identification amounts to demonstrating a rank condition holds, and is provided formally in the appendix. I comment on the validity of these restrictions in section 9.1.

5 Data

I use the Malawi Integrated Households Survey (IHS3) 2010 and the Malawi Integrated Panel Survey 2013. The IHS3 consists of 12,288 households, of which, 4,000 were resurveyed in 2013. Both are nationally representative household surveys and contain detailed information on individual education, employment, migration, health, and other demographic characteristics as well as household-level expenditure data. I rely primarily on the expenditure module in the estimation of the structural model.

Given that I am interested in how resource shares vary with fostering and orphan status, I use a sequence of questions relating to the presence and mortality status of the parents of all children age 14 and under. This allows me to identify children living away from one or both parents, and also whether the child is a maternal, paternal, or double orphan. Unfortunately I do not observe the prior household for children living away from their parents.

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

From the data, I select a sample of 9,859 households. I exclude households that have less than one or more than four men and women, or more than five children. I also exclude households that are in the top or bottom percentile of expenditure to eliminate outliers. Households are dropped if they have missing information on any of the covariates listed in table 1. Sample sizes for each household type are provided in the appendix in table A1.

Table 1 reports descriptive statistics for the estimation sample. Households are large, with an average of 5.27 individuals. The average age of foster children in the household (9.26) is significantly higher than that of non-foster children (5.80). This is consistent with child labor and education being reasons households foster children. Roughly 38 percent of foster children have lost at least one parent, indicating a majority of foster children are voluntarily sent away by their biological parents.Households in Malawi are very poor, with the annual per capita household expenditure equal to 126,580 MWK (approximately 1,147 US$).[19] Lastly, households spend a large fraction of their income on food (62 percent), which is unsurprising given the amount of poverty in Malawi.

Table 1: Descriptive Statistics

Household Characteristics	Mean	SD	Min	Max	Sample Size
Household Size	5.273	1.712	1	13	10771
Men	1.394	0.713	1	4	10771
Women	1.344	0.646	1	4	10771
Children	2.580	1.254	1	5	10771
non-Foster	2.305	1.370	0	5	10771
Foster	0.275	0.696	0	5	10771
Per Capita Total Expenditures (1000s MWK)	126.58	106.58	145.63	1,266.38	10771
Men's Clothing Budget Shares	0.006	0.014	0	0.164	10771
Women's Clothing Budget Shares	0.009	0.016	0	0.330	10771
Child's Clothing Budget Shares	0.009	0.017	0	0.312	10771
Food Budget Shares	0.623	0.137	0.077	0.957	10771
Preference Factors					
Year=2010	0.744	0.436	0	1	10771
Foster Child Age	9.255	3.343	0	14	1935
non-Foster Child Age	5.803	3.397	0	14	9872
Proportion Orphaned of Foster Children	0.376	0.467	0	1	1935
Proportion One Parent Absent of Non-Foster Children	0.139	0.330	0	1	9872
Proportion Female of non-Foster	0.502	0.365	0	1	9872
Proportion Female of Foster	0.554	0.447	0	1	1935
Average Age Women	30.560	10.831	15	75	10771
Average Age Difference	1.947	12.488	15	75	10771
Education Men	6.666	3.719	0	14	10771
Education Women	5.180	3.646	0	14	10771
Share Women Age 15-18	0.077	0.183	0	1	10771
Share Men Age 15-18	0.114	0.247	0	1	10771
Rural	0.804	0.397	0	1	10771
Matrilineal Village	0.608	0.488	0	1	10771
North	0.200	0.400	0	1	10771
Central	0.369	0.483	0	1	10771
South	0.431	0.495	0	1	10771

Notes: Out of all households with 1-4 men, women, and children. Malawi Third Integrated Household Survey and Integrated Household Panel Survey.

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

6 Estimation

To estimate the model, I add an error term to each Engel curve in equation 6. Since the error terms of the Engel curves are likely to be correlated across equations, the system is estimated using Non-linear Seemingly Unrelated Regression. To match the data used in the empirical analysis, I now explicitly account for households with multiple men and women with s_f and s_m giving the number of women and men respectively.

$$\begin{aligned} W^m_{s_{ab}} =& s_m\eta^m_{s_{ab}}[\delta^m_{s_{ab}} + \beta^m \ln(\eta^m_{s_{ab}})] + s_m\eta^m_{s_{ab}}\beta^m \ln y + \epsilon_m \\ W^f_{s_{ab}} =& s_f\eta^f_{s_{ab}}[\delta^f_{s_{ab}} + \beta^f \ln(\eta^f_{s_{ab}})] + s_f\eta^f_{s_{ab}}\beta^f \ln y + \epsilon_f \\ W^c_{s_{ab}} =& s_a\eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_b\eta^b_{s_{ab}}[\delta^b_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] \\ &+ \ln y(s_a\eta^a_{s_{ab}}\beta^a + s_b\eta^b_{s_{ab}}\beta^b) + \epsilon_c \\ W^{food}_{s_{ab}} =& \tilde{\delta}_{s_{ab}} + \tilde{\beta}\ln y + \epsilon_{food} \end{aligned} \tag{9}$$

The objects of interest are the resource shares for foster and non-foster children, given by $\eta^a_{s_{ab}}$ and $\eta^b_{s_{ab}}$ respectively. I identify resource shares for both composite and one type only households. Resource shares are restricted to sum to one: $s_f\eta^f_{s_{ab}} + s_m\eta^m_{s_{ab}} + s_a\eta^a_{s_{ab}} + s_b\eta^b_{s_{ab}} = 1$. The estimation allows for considerable heterogeneity with each parameter being a linear function of household characteristics. One caveat is that the Engel curve shape parameter, β^t, is not allowed to vary by the household composition, s_{ab}, which is the Similar Across Types restriction from DLP. The other preference parameters $\delta^t_{s_{ab}}$ are allowed to vary by household type. To estimate the way in which resource shares differ by household composition, I include indicator variables for household type in the parameterization of the foster and non-foster child resource share functions. I therefore omit constant terms, as that is already captured by the household type indicators. The parameter restrictions on foster and non-foster child resource shares are substituted directly into the resource share functions. For example, resource shares for non-foster children are parameterized as follows:

$$\begin{aligned} \eta^b_{s_{ab}} =& \overbrace{\Big(\sum_{j=1}^{4}\eta^b_{s_{1j}} I\{s_{ab} = s_{1j}\}\Big) + \Big(\sum_{j=1}^{3}\eta^b_{s_{2j}} I\{s_{ab} = s_{2j}\}\Big) + \Big(\sum_{j=1}^{2}\eta^b_{s_{3j}} I\{s_{ab} = s_{3j}\}\Big)}^{\text{Composite Households}} \\ &+ \underbrace{\eta^b_{41} I\{s_{ab} = s_{41}\}}_{\text{Composite Household}} + \underbrace{\Big(\sum_{j=1}^{5}\eta^b_{s_{0j}} I\{s_{ab} = s_{0j}\}\Big)}_{\text{One Type Only Households}} + \mathbf{X}'\gamma \end{aligned} \tag{10}$$

where the first set of terms are the indicators for household types, which can be classified as either composite or one type only. The vector of household characteristics is given by X, and the following parameter restrictions are substituted directly into the resource share function:

$$\text{Restriction 1:} \quad \eta^b_{14} = \tfrac{\eta^b_{04} \times \eta^b_{11}}{\eta^b_{01}}, \quad \eta^b_{13} = \tfrac{\eta^b_{03} \times \eta^b_{11}}{\eta^b_{01}}, \quad \eta^b_{12} = \tfrac{\eta^b_{02} \times \eta^b_{11}}{\eta^b_{01}}, \quad \eta^b_{22} = \tfrac{\eta^b_{02} \times \eta^b_{21}}{\eta^b_{01}}$$

$$\eta^b_{23} = \tfrac{\eta^b_{03} \times \eta^b_{21}}{\eta^b_{01}}, \quad \eta^b_{32} = \tfrac{\eta^b_{02} \times \eta^b_{31}}{\eta^b_{01}}$$

$$\text{Restriction 2:} \quad \eta^b_{11} = \tfrac{\eta^a_{11} \times \eta^b_{01}}{\eta^a_{10}}$$

The resource shares for foster children are parameterized similarly.

To reduce the computational burden and improve precision, I assume $\beta^m = \beta^f$, or that the shape of the Engel curves for men's and women's clothing are similar.[20] I fail to reject the null hypothesis that they are statistically different. Secondly, I assume men's and women's resource shares increase linearly in the number of men, women, foster, and non-foster children in the household; 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 dramatic increase in the number of parameters needed to be estimated.

Lastly, I would ideally like to estimate resource shares separately for orphaned and non-orphaned foster children. However, given the small number of orphans in the sample, this is infeasible. Instead, I include the proportion of foster children who are orphaned as a covariate of the foster child resource share function. Moreover, I interact the proportion of foster children who are orphaned with other covariates, such as gender and an indicator for rural residence. This will allow foster child resource shares to vary somewhat flexibly with the share of foster children who are orphaned.

7 Results

Figure 2 presents estimates for the predicted resource shares for foster and non-foster children ($\hat{\eta}^a_{s_{ab}}$ and $\hat{\eta}^b_{s_{ab}}$). 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. Men's and women's resource shares are also estimated, but are omitted here to facilitate the presentation of the more relevant results. Each quadrant corresponds to a different household size, defined by the number of children in the household. Within each quadrant, predicted resource shares for foster and non-foster children are given by household composition, which

[20] Other studies that apply the DLP methodology typically assume the shape parameter β does not vary across household type and person type t. See Calvi (2015) for example. DLP suggest this approach.

is determined by the number foster and non-foster children present, where for example, "1 NF 0 F" denotes 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 set to their median value.[21] The brackets are the 95 percent confidence intervals of the predicted values.

Panel A of figure 2 provides the predicted resource shares for households with one or two total children. For households with one non-foster child, and zero foster children, the non-foster child is allocated 20.4 percent of the household budget. Similarly, for households with one foster child, and zero non-foster children, the foster child is allocated roughly 21 percent of the household budget. This result provides little evidence of unequal treatment between foster and non-foster children. A similar pattern, with few exceptions, is seen in panel's B, C, and D of figure 2. As expected, the share each child receives is decreasing in the number children present. Estimates for households with five children are considerably noisier given that there are fewer observations for those household types.[22]

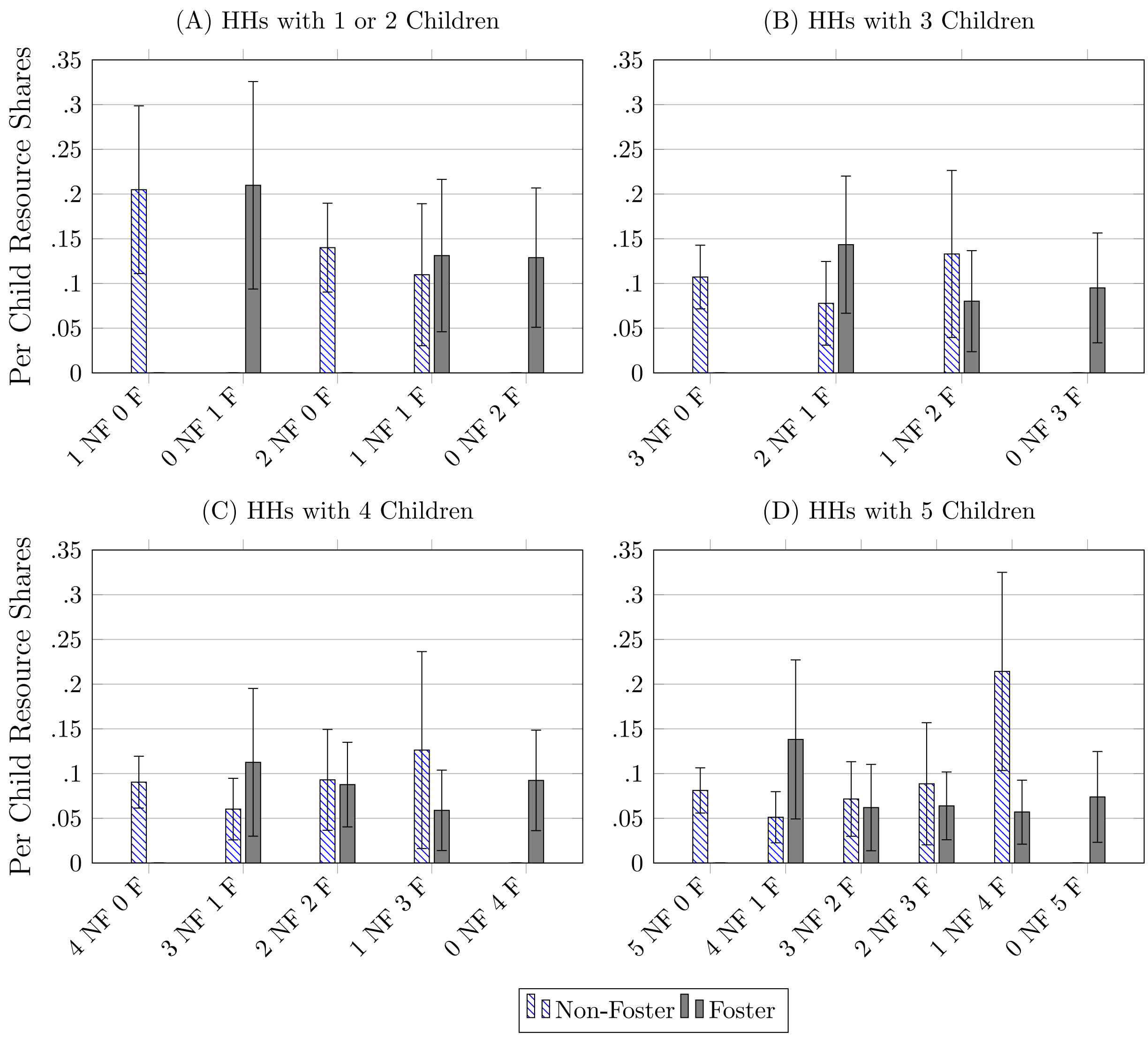
I next present the determinants of foster and non-foster child resource shares. Recall that the resource share parameters are linear functions of household characteristics, which includes indicators for household type. Table 2 presents the covariates to these functions for foster and non-foster children. I omit the coefficients on the household composition variables as those are displayed in figure 2. The results provide no evidence of gender discrimination among foster or non-foster children. Orphanhood on the other hand does seem to matter considerably for child welfare, as the results suggest that orphaned foster children are treated significantly worse than non-orphaned foster children.[23] While the number of interactions makes the interpretation of the orphan-related coefficients difficult, the results suggest, for example, that female orphaned foster children in rural areas receive resource shares that are 9.57 percentage points lower than male non-orphaned fostered children in rural areas. Female orphaned foster children seem to be particularly disadvantaged, though the interaction term is not statistically significant. These results are consistent with parents being less altruistic towards orphaned children, and diverting a smaller share of household resources to these children as a result.

The results in figure 2 are for households with covariates at their median value. Impor-

[21] 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.

[22] See table A1 for the samples sizes of each household type.

[23] An orphaned foster child is a foster child who has lost at least one parent.



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

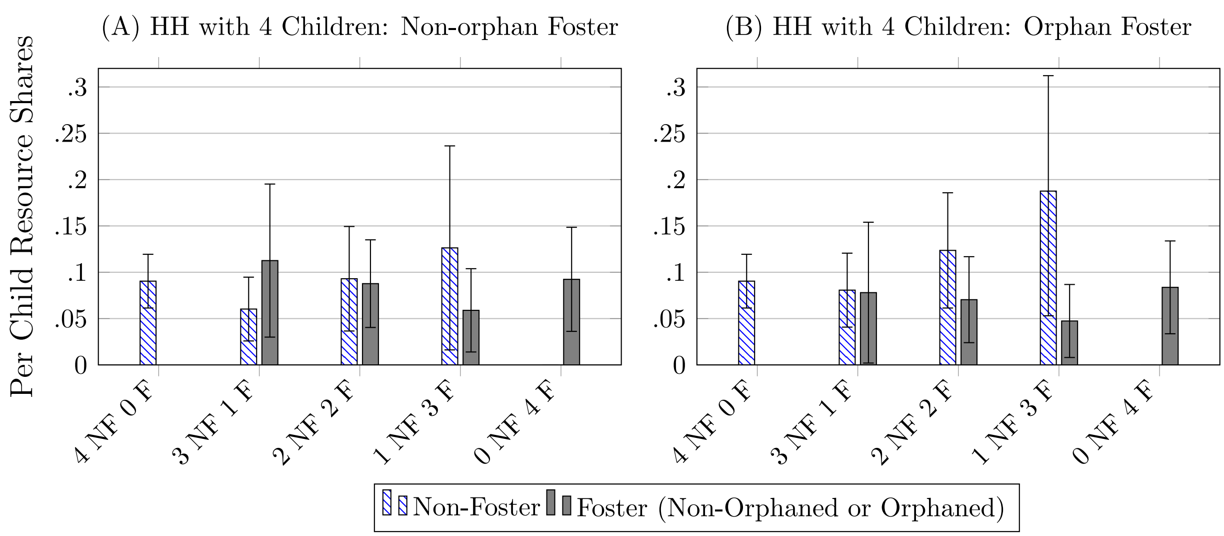
Figure 2: Predicted Resource Shares: Reference Household

Table 2: Determinants of Resource Shares

	non-Foster Children (1) NLSUR	Foster Children (2) NLSUR
North	0.0206	0.0368
	(0.0220)	(0.0227)
Central	-0.0108	-0.0111
	(0.0147)	(0.0141)
Year=2010	-0.0102	-0.00816
	(0.0165)	(0.0187)
Average Age non-Foster	1.210	0.145
	(0.881)	(1.002)
Average Age non-Foster^2	-0.0193	-0.0132
	(0.0614)	(0.0723)
Average Age Foster	-1.374	-0.0710
	(1.804)	(2.525)
Average Age Foster^2	0.0900	0.0143
	(0.102)	(0.128)
Proportion of Non-Fostered One Parent Absent	0.00375	-0.0213
	(0.0256)	(0.0188)
Fraction Female non-Foster	-0.0270	0.0173
	(0.0191)	(0.0202)
Fraction Female Foster	-0.0165	0.0694
	(0.0328)	(0.0588)
Average Age Women	0.405	0.0130
	(0.367)	(0.278)
Average Age Women^2	-0.00529	-0.00109
	(0.00488)	(0.00313)
(Average Age Men - Average Age Women)	0.162*	0.0511
	(0.0849)	(0.0755)
(Average Age Men - Average Age Women)^2	-0.000964	-0.000556
	(0.00276)	(0.00169)
Average Education Men	0.00374	0.00211
	(0.00240)	(0.00342)
Average Education Women	-0.00378	-0.00388
	(0.00263)	(0.00317)
Rural	-0.0385*	-0.0421*
	(0.0204)	(0.0222)
Share of Adult Women Age 15-18	0.0285	-0.0423
	(0.0541)	(0.0379)
Share of Adult Men Age 15-18	0.0213	0.0277
	(0.0413)	(0.0478)
Matrilineal Village	0.0132	0.0385**
	(0.0178)	(0.0182)
Proportion of Fostered Orphaned	0.0206	-0.0548
	(0.0624)	(0.0420)
Proportion of Fostered Orphaned × Fraction Female Foster	0.0325	-0.0516
	(0.0633)	(0.0665)
Proportion of Fostered Orphaned × Rural	0.0113	0.0107
	(0.0520)	(0.0372)
N	10,771	
No. Parameters	259	
Log Likelihood	91543	

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

tantly, this means that the predicted foster child resource shares are for households with *no orphaned foster children*. Given that the results in table 2 demonstrate the importance of orphan status in foster child treatment, I now report predicted foster child resource shares if all covariates are at the median value for households with only orphaned foster children in figure 3. To facilitate the comparison between non-orphaned foster children and orphaned foster children, I reproduce some of the results from figure 2 alongside the predicted resource shares for orphaned foster children. For conciseness, I limit the presented results to households with four children. In figure 3, panel (A) presents the predicted resource shares for non-foster and non-orphaned foster children, while panel (B) presents the predicted resource shares for non-foster and orphaned foster children. The results illustrate a clear pattern of unequal treatment of orphaned foster children relative to non-fostered children. For example, focusing on households with two non-foster children and 2 foster children ("2 NF 2 F"), when the foster child is non-orphaned, the predicted per child resource shares for non-foster and foster children are 9.3 and 8.7 percent respectively. However, when the foster child is orphaned, the predicted per child resource shares are now 12.36 and 7.04 percent for non-foster and foster children. Similar differences are found across the different household types.



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

Figure 3: Predicted Resource Shares by Presence of Orphans

8 Poverty Analysis

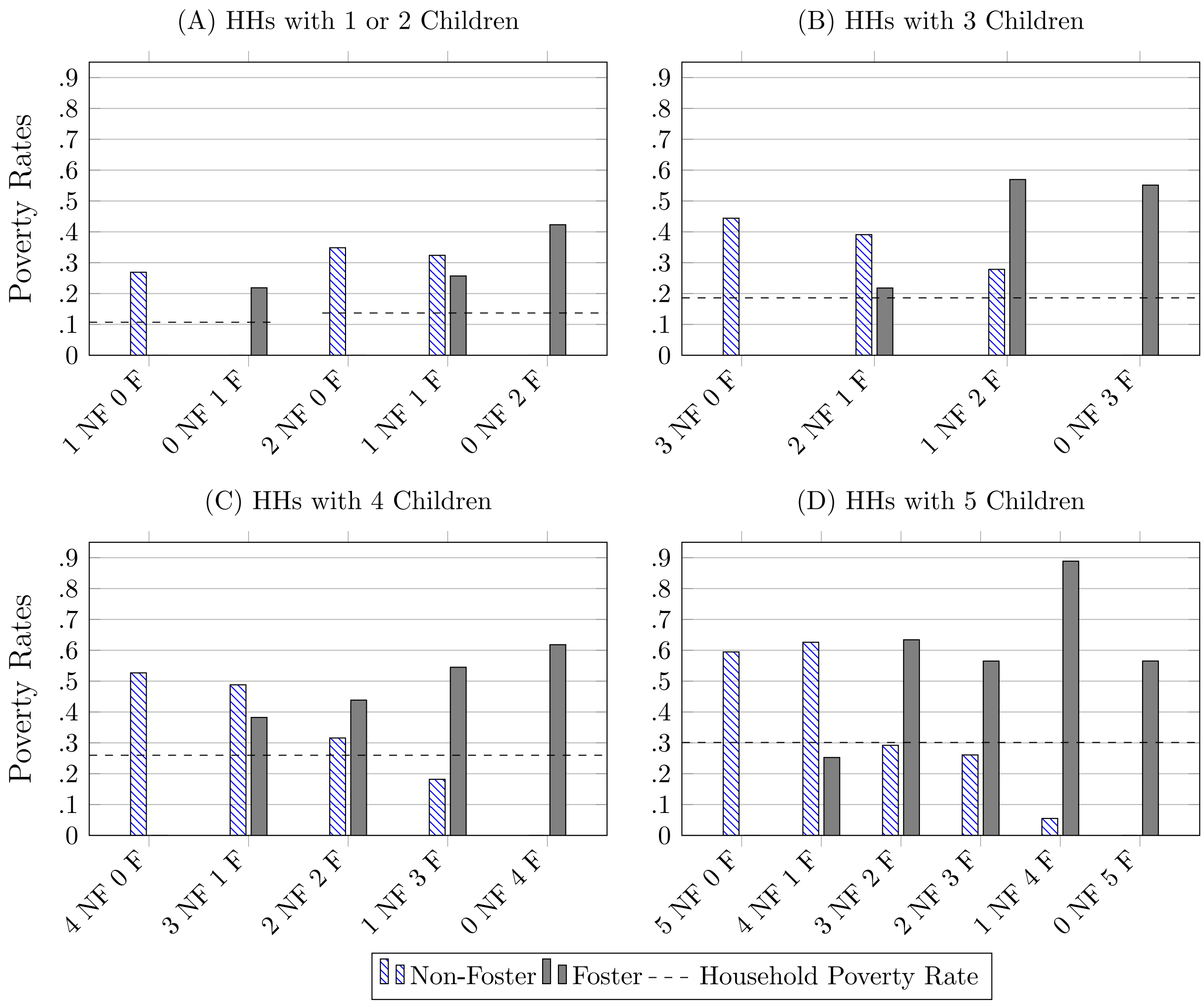
Resource shares are a desirable object to identify in part because they allow for the estimation of individual-level consumption. I can therefore use the predicted resource shares to estimate individual-level poverty rates that account for the unequal distribution of goods within the household. Importantly,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

I classify adults as poor using a 2 dollar a day poverty line and set the child poverty line to be 60 percent to that of adults. I present the results graphically in figure 4. I again divide households by size into 4 quadrants. Within each quadrant, I compare non-foster and foster poverty rates by the household composition, defined by the number of non-foster and foster children present. The solid bars correspond to foster child poverty rates and the line-patterned bars correspond to non-foster child poverty rates. The dotted line reports the household-level poverty rate for a given household size and is computed assuming an equal distribution of resources within the household.[24] The household-level poverty measures use the OECD adult equivalent scale, where the number of adult equivalents in the household is given by $1 + 0.5 \times N_c + 0.7 \times (N_a - 1)$, where N_c is the number of children and N_a is the number of adults. The choice of equivalence scale is arbitrary, and thus the main focus of the poverty analysis is to examine relative levels of poverty across foster and non-foster children within each household type, rather than levels of poverty.[25]

For each household type, child poverty rates are substantially higher than the household-level estimates. For example, in households with one non-foster, and one foster child ("1 NF 1 F"), the individual-level poverty rates for non-foster and foster children are 32 and 26 percent, respectively. On the contrary, the more traditional, household-level measures

[24] Quadrant (A) includes two household-level poverty rates: one for households with one child, and a second for households with two children.

[25] The use of adult equivalence scales is used to account for economies of scale in household consumption. The individual-level measures of poverty do not account for economies of scales; Without estimating the consumption technology function (the A - Matrix in section 3), economies of scale can not be accounted for. While the consumption technology function can in principle be identified, as in BCL, I lack sufficient price data to estimate it. As a result the household and individual levels of poverty are not directly comparable.



Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. Each quadrant presents non-foster and foster child poverty rates for different household sizes defined by the number of children. Within each quadrant, foster, and non-foster child poverty rates are presented by household type, which is defined by the number of foster and non-foster children. The dashed line corresponds to the household-level poverty rate, which assumes an equal distribution of resources within the household. A household is poor if per adult equivalent expenditures are less than 2 dollars a day. In quadrant (A), two household poverty rates are computed; one for all households with one child, and the second for households with two children. In quadrant (B) the household poverty rate is for all households with three children, and so on. Non-foster and foster child expenditure is calculated as the product of the predicted resource shares and total expenditure. The child poverty line is set at 0.6 × 2.

Figure 4: Poverty Headcount Ratios by Household Composition

of poverty would predict that in households with two children, 13.7 percent are poor. This result is consistent with DLP and recent work on using health measures to analyze the ability of household-level measures to capture individual-level poverty (Brown et al. (2016a)).

Table 3 presents the overall poverty rates for individuals by household size. Column (1) provides the distribution of household sizes defined by the number of children in the household. In the sample, there are 10,771 total households. Columns (2) - (5) provide individual poverty rates, again computed using the predicted resource shares. Comparing columns (2) and (3), the estimated poverty rates suggest foster child poverty is above non-foster child poverty, though these numbers are not directly comparable as households with non-foster children are different than households with foster children.[26] Column (6) presents the household-level rates where the poverty calculation assumes an equal distribution of resources within the household.

Table 3: Estimated Poverty Rates by Household Size

Household Size	Sample Size:	Individual Poverty Rates				Household
Number of Children	# HHs	Non-Foster	Foster	Men	Women	Poverty Rates
	(1)	(2)	(3)	(4)	(5)	(6)
1	2,643	0.307	0.425	0.168	0.257	0.107
2	2,842	0.411	0.515	0.160	0.305	0.137
3	2,597	0.515	0.551	0.185	0.335	0.186
4	1,777	0.589	0.640	0.243	0.367	0.260
5	912	0.666	0.691	0.257	0.368	0.301
All Households	10,771	0.521	0.559	0.191	0.317	0.192

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. A household is poor if per adult equivalent expenditures are less than 2 dollars a day. Individual poverty rates measure consumption as the product of predicted resource shares and total expenditure. The child poverty line is set at 0.6×2.

A caveat to this poverty analysis is that I am not making welfare statements about child fostering as an institution. It is common for parents to foster out their children due to negative income shocks, and send them to households with the financial means to take care of additional children (Akresh (2005)). Thus, children are typically moving to wealthier households. So while foster children may sometimes receive a smaller share of household resources relative to other children or the adults, 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. Unfortunately due to data limitations, I can not evaluate how foster children would be treated had they not been fostered.

[26] Table A2 in the appendix reports poverty rates by the presence and absence of foster and non-foster children within the household.

The results demonstrate the importance of accounting for intrahousehold inequality when designing policy. Government poverty programs are by definition targeted at the poor. Accurately classifying individuals as poor is therefore essential to ensuring programs are targeted efficiently. Moreover, the results suggest it is wise for the government to target government programs at households with orphaned children, as these children appear especially vulnerable to poverty even when household-level poverty measures would suggest they are not living in poor households.

9 Robustness

9.1 Are the Restrictions Valid?

A key contribution of this paper is the extension to DLP; I demonstrate how resource shares can be identified in the absence of assignable goods using additional assumptions that limit how resource shares vary across household types. In particular, I first restrict the way in which foster child resource shares vary across household composition to be independent of the number of non-foster children present, and vice versa (Restriction 1). Secondly, I assume the extent of discrimination in a composite household with one child of each type to be the same as the extent of the discrimination across two one type only households, each with one foster or non-foster child (Restriction 2). Whether or not these two restrictions are valid is important to the reliability of this paper's findings.

One way to understand Restriction 1 is that it is an independence assumption; the ratio of non-foster child resource shares in households with different numbers of non-foster children is the same regardless of the number of foster children present (and vice versa). Thus, one way to examine whether this is a reasonable assumption is to ask, is the ratio of non-foster child resource shares in households with different numbers of non-foster children the same regardless of the number of *men or women* present? To answer this question, I drop households with foster children, and examine how non-foster child resource shares vary across household sizes in relation to the number of men or women present.[27] Neither Restriction 1 or 2 are necessary for identification with this sample.

To implement this test, define household types by s_{bmf}, or the number of non-foster children, men, and women in the household. I then estimate resource shares for non-foster children, and test whether or not the ratios of the resource shares across household types are consistent with Restriction 1. For example, Restriction 1 suggests the ratio of non-foster

[27] There are too few foster children to conduct a similar test using only households with foster children.

child resource shares between two one type only households with one and two non-foster children is equal to the ratio of non-foster child resource shares in two composite households with one and two non-foster children. To evaluate the merit of this restriction, I use a Wald-type of test the equality of the following ratio: $\frac{\eta^b_{111}}{\eta^b_{211}} = \frac{\eta^b_{121}}{\eta^b_{221}}$. In words, this says that the ratio of non-foster child resource shares in households with one or two non-foster children, is independent of the number of *men* in the household. Similar tests can be done for different combinations of men and women in the household. I consistently fail to reject the null hypothesis that ratios of the form suggested by Restriction 1 hold.

Restriction 2 requires the extent of discrimination within a composite household with one of each child type to be the same as the extent of discrimination across one type only households with either one foster or non-foster child; more concisely, $\frac{\eta^a_{11}}{\eta^a_{10}} = \frac{\eta^b_{11}}{\eta^b_{01}}$. To test this, I ask whether the extent of discrimination within a composite household with *two* of each child type is the same as the extent of discrimination across one type only households with either *two* foster or non-foster children; this equality is not required for identification. I use a Wald-type test of the following hypothesis: $\frac{\eta^a_{22}}{\eta^a_{20}} = \frac{\eta^b_{22}}{\eta^b_{02}}$. I again fail to reject the null hypothesis that this ratio is equivalent.

Overall, each test of the restrictions is meant to examine the extent to which resource shares are well-behaved; do they vary across household types in a predictable way? The above results suggest that resource shares do behave in such a way.

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 estimate the model without Restrictions 1 and 2 and compare those results to the findings recovered in this paper without having to make the additional restrictions. I leave that for future work.

9.2 Is Clothing a Private Good?

A key assumption of the model is that clothing is not shared across person types.[28] This assumption means foster children cannot share clothes with non-foster children, and vice versa.[29] While this assumption may at first seem worrisome, there are several reasons it is not of too great of a concern. First, clothing includes both shoes and school uniforms, both of which can be reasonably assumed to not be shared. Secondly, foster children are typically different ages than the non-foster children within the household. Fostering is often used to

[28] Men can share clothes with other men in the household, just not with women, foster children, or non-foster children.

[29] Hand-me-down clothing is not considered shared clothing. I define child clothing consumption as the amount the household spends on child clothing within the past year. Hand-me-down clothing is therefore not considered in the analysis and does not factor in to whether clothing is shared or not.

balance the demographic structure of the household, both in terms of child age and gender, in order to maximize household production (Akresh (2005)). 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 conduct two tests. First, I include a covariate for the age difference between foster and non-foster children in the resource share equation. If this parameter is statistically significant, then that suggests there could be sharing, however this proves not to be the case. To be even more cautious, I drop all households that have foster and non-foster children in the same age-gender bracket, and estimate the model using this restricted sample. The results are qualitatively the same and available upon request.

10 Child Labor and School Enrollment

To provide context to the above consumption results, I next examine intrahousehold inequality among foster and non-foster children along two other dimensions of welfare: education and child labor. As discussed in Section 2, education and child labor 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 the farm work. This suggests child labor may be higher among foster children.

10.1 Empirical Strategy

Unlike consumption, both school enrollment and work hours are observable at the individual level using standard household-level survey data. This facilitates a direct comparison of enrollment rates and child labor between foster and non-foster children. I begin by assigning children to two mutually exclusive groups: both biological parents absent (g=1); at least one parent present (g=2). I am therefore ignoring orphan status for now.

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

$$Y_{ihst} = \alpha + \gamma Foster_i + \pi_h + \psi_{st} + X_i\delta + \epsilon_{ihst} \tag{11}$$

where Y_{ihst} is an indicator for school enrollment or some measure of child labor. The parameter of interest is γ, which captures the effect of the absence of a child's parents on the various outcomes of interest. The omitted category is children with at least one biological parent present. In some specifications I include household fixed effects to control for any unobserved heterogeneity that does not vary over time. Household fixed effects allow for the direct examination of unequal treatment between foster and non-foster children. Lastly, I include region-year fixed effects to account for any region specific year effects that are common across foster status and households. There are four years of data and three regions so I cluster standard errors at the region-year level.

The consumption results suggest orphanhood is an important factor in how children are treated. I modify the above estimation to account for orphan status in order to examine whether a similar pattern emerges here. I now assign children into four mutually exclusive groups consistent with the consumption analysis: Non-orphaned children with at least one parent present (g=1); one parent present, and one dead (g=2); both absent and alive (g=3); both absent and at least one dead (g=4).

$$Y_{ihstg} = \alpha + \sum_{g=1}^{g=3} \gamma_g \times 1[OrphanFosterGroup_i = g] + \pi_h + \psi_{st} + X_i\delta + \epsilon_{ihstg} \tag{12}$$

The parameters of interest are now the coefficients on $OrphanFosterGroup_i$, which capture the differential effects of the child's foster and orphan status on school enrollment or child labor. The omitted category is non-orphaned children with at least one biological parent present. I again use the Malawi Integrated Households Survey (IHS3) 2010 and the Malawi Integrated Panel Survey 2013. Descriptive statistics are presented in table A3 in the appendix.

10.2 Results

I begin by analyzing the difference in school enrollment rates between foster and non-foster children. I estimate equation (11) and present the results in table 4. The coefficient of interest is γ where describes the difference in treatment for foster and non-foster children. Column 1 provides an estimate of differences in means by foster status, controlling for child age and gender. This specification ignores any household characteristics that may be associated with both school enrollment rates and the types of households that foster in children. Columns 2 and 3 attempt to uncover evidence of intrahousehold discrimination of foster children. In column 2, I account for observable household characteristics, including the education, age, and gender of the household head, household composition measures, and log per capita household expenditure. In column 3, I include household fixed effects, which accounts for any unobservable household characteristics that do not vary across time. The results provide no evidence of discrimination based on foster status. This is largely consistent with the consumption analysis.

Table 4: School Enrollment by Foster Status

	OLS			Probit
	(1)	(2)	(3)	(4)
Foster Child	-0.029	-0.020	-0.047	-0.132
	(0.013)	(0.019)	(0.036)	(0.110)
Sample Size	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes	Yes
Household Fixed Effects			Yes	

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Notes: The sample includes all children age 6-14. The omitted fostering category are children with at least one biological parent present. Standard errors are clustered at the region-year level. Individual controls include age age^2, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head.

The consumption results imply orphans are particularly mistreated within the household. To examine whether this pattern holds for education, I estimate equation (12) with four foster categories that account for orphanhood. The results are presented in table 5. The results provide evidence orphanhood matters greatly for foster child treatment; Each specification demonstrates that foster children who are orphans have enrollment rates that are statistically lower than children whose biological parents are present in the household. Column (1), which reports differences in means between foster groups controlling for child age and gender shows that on average, orphaned foster children have school enrollment rates that are 4 percentage points lower than non-orphaned, non-foster children. The results in column (2) are lower in magnitude than the results in column (1) at 2.7 percentage points, suggesting the lower school enrollment rates are partially due to differences in observable household characteristics. However the difference in school enrollment rates is still statistically significant. Once I account for household fixed effects in column (3), the estimated coefficient is negative and significant, suggesting that orphaned foster children are subject to intrahousehold discrimination.

Table 6 provides the child labor results. In columns 1 to 3, I examine the relationship

Table 5: School Enrollment by Foster Status (Detailed Categories)

	OLS			Probit
	(1)	(2)	(3)	(4)
Fostering Categories				
Orphan with One Parent Present (Non-Foster)	-0.022	-0.013	0.016	-0.080
	(0.013)	(0.012)	(0.029)	(0.050)
Both Absent and Alive (Foster)	-0.025	-0.019	-0.053	-0.131
	(0.022)	(0.028)	(0.054)	(0.160)
Both Absent Orphan (Foster)	-0.040***	-0.027**	-0.033***	-0.167***
	(0.003)	(0.003)	(0.001)	(0.027)
Sample Size	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes	Yes
Household Fixed Effects			Yes	

* p<0.1, ** p<0.05, *** p<0.01. Notes: The sample includes all children age 6-14. The omitted fostering category are non-orphaned children with at least one biological parent present. Standard errors are clustered at the region-year level. Individual controls include age age^2, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head.

between foster status and hours worked doing chores[30], while columns 4 to 6 focus on hours worked for a household farm, household enterprise, or wage work outside the household. I add controls moving from left to right; Column 1 accounts for child age and gender in examining the effect of foster status on hours worked; Column 2 adds household characteristics to the specification, while in column 3 I include household fixed effects. The results again provide little evidence that work around the house differs substantially between foster and non-foster children, which is contrary to what the literature suggests (Serra (2009)). This lack of any result is partially due to the limited definition of chores (only fetching wood and water), and possible measurement error in the data, as parents may be unwilling to reveal that their children work. The same lack of an association is apparent in examining the relationship foster status on work hours in columns 4 to 6. Table 7 accounts for orphanhood when examining the effect of foster status on child labor. The results demonstrate little difference by foster or orphan status in terms of child labor, which again is likely due to data issues.

[30] Chores include fetching wood and fetching water.

Table 6: Weekly Hours Worked by Fostering Status

	Chores			Work Outside HH		
	(1)	(2)	(3)	(4)	(5)	(6)
Fostering Categories						
Foster Child	0.077	0.007	-0.215	0.134	-0.163	-0.070
	(0.085)	(0.095)	(0.095)	(0.141)	(0.087)	(0.201)
Sample Size	20,371	20,371	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes		Yes	Yes
Household Fixed Effects			Yes			Yes

* p<0.1, ** p<0.05, *** p<0.01. Notes: The sample includes all children age 6-14. The omitted fostering category are children with both biological parents present. Standard errors are clustered at the region-year level. Individual controls include age age^2, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head.

Table 7: Weekly Hours Worked by Fostering Status (Detailed Categories)

	Chores			Work Outside HH		
	(1)	(2)	(3)	(4)	(5)	(6)
Fostering Categories						
Orphan with One Parent Present (Non-Foster)	-0.033	-0.032	-0.100	0.113	-0.097	-0.028
	(0.084)	(0.051)	(0.068)	(0.057)	(0.119)	(0.430)
Both Absent and Alive (Foster)	-0.041	-0.140	-0.334*	0.034	-0.298	-0.068
	(0.099)	(0.100)	(0.114)	(0.187)	(0.137)	(0.294)
Both Absent Orphan (Foster)	0.253	0.211	-0.089	0.325*	0.018	-0.068
Sample Size	20,371	20,371	20,371	20,371	20,371	20,371
Region-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls		Yes	Yes		Yes	Yes
Household Fixed Effects			Yes			Yes

* p<0.1, ** p<0.05, *** p<0.01. Notes: The sample includes all children age 6-14. The omitted fostering category are non-orphaned children with at least one parent present. Standard errors are clustered at the region-year level. Individual controls include age age^2, and gender. Household controls include the number of male and female siblings age 0-6 and 7-14, the number of adult men and women, log household expenditure, and demographic characteristics of the household head.

11 Conclusion

In parts of Africa, child commonly live away from both of their parents. These foster children are living in situations that may leave them particularly susceptible to impoverishment. To examine the level of well-being of foster children, I estimate a collective model of the household using Malawian data to identify the share of household resources allocated to each household member. The findings of this paper suggest that for the most part, foster children are treated the same as other children, and that extended family members are capable caretakers. A notable exception is that orphaned foster children seem to be mistreated at higher rates than other children. The results suggest orphaned foster child poverty is being substantially understated by poverty measures that rely on household-level measures of consumption. This result emphasizes the importance of designing government programs that target not just poor households, but also orphan children, regardless of the poverty level of the household.

Secondly, this paper adds to the literature on identifying intrahousehold inequality. The household is in many ways a black box to economists. Understanding the inner workings of households is hard and measuring the treatment of children within the household is far from straightforward. I build off recent work by DLP to demonstrate how resource shares can be identified using assignable and partially assignable clothing. Like DLP, I rely on observing how budget shares vary with household expenditure and structure 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.

The weaknesses of the unitary household framework are well known.[31] This study adds to the growing literature that stresses the importance of thinking about individuals within the household, as opposed to the household as a single economic agent. This distinction is even more relevant where intrahousehold inequality may be present, as the results of this paper demonstrate in regards to child fostering. This project identifies a second, less emphasized, limitation of household-level studies, in that they typically ignore kinship networks. Individuals within a kinship network interact along many dimensions, with child fostering being a central component. The finding that non-orphaned foster children are treated better than orphaned foster children suggests kinship networks play a role in child welfare; having living parents in another household influences how foster children are treated. Recognizing the role of extended families in child welfare is therefore critical to designing policies to help children. Overall, fostering is key to understanding how children are treated within the household, both in terms of schooling, labor, and as studied in this paper, consumption.

[31] See for example, Attanasio and Lechene (2002), Duflo (2003), or Bobonis (2009).

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A Appendix

A.1 Fully Specified Model (In Progress)

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

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

$$\ln V_t(p, y) = \ln[\ln(\frac{y}{G_t(p_t, \tilde{p})})] + p_t e^{-a' \ln \tilde{p}} \tag{A1}$$

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

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

$$\tilde{U}_{s_{ab}}(U_f, U_m, U_a U_b, p/y) = \sum_{t \epsilon \{m,f,a,b\}} \omega_t(p)[U_t + \rho_t(p)] \tag{A2}$$

where $\omega_t(p)$ are the Pareto weight functions and $\rho_t(p)$ are the externality functions. Individuals are allowed to get 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.

$$\max_{x_m, x_f, x_a, x_b, z_{s_{ab}}} \omega(p) + \sum_{t \epsilon \{m,f,a,b\}} \omega_t(p) U_t$$
$$\text{s.t} \quad y = z'_{s_{ab}} p \text{ and}$$
$$z^k_{s_{ab}} = A^k_{s_{ab}}(x^k_m + x^k_f + s_a x^k_a + s_b x^k_b) \text{ for each good } k$$

where the household type is given by s_{ab}, or the number of foster and non-foster children and $\omega(p) = \sum_{t\epsilon\{m,f,a,b\}} \omega_t(p)\rho_t(p)$. Matrix $A_{s_{ab}}$ is the consumption technology function. It is a $k \times k$ diagonal matrix and gives the relative publicness or privateness of good k. If good k is private, then the k,k'th element is equal to 1, and what the household purchases is exactly equal to individual consumption.

By Pareto efficiency, the household maximization can be decomposed into two step process; In the first stage, resource shares are optimally allocated, and in the second stage, each individual maximizes their individual utility subject to the budget constraint $A^k_{s_{ab}} p^k x^k_t = \eta^t_{s_{ab}} y$. Resource shares can then be defined as $\eta^t_{s_{ab}} = x^t A_{s_{ab}} p/y = \sum_k A^k_{s_{ab}} p^k x^k_t / y$ 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, $V_t(A'_{s_{ab}} p, \eta^t_{s_{ab}}, y)$.

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

$$\begin{aligned} \max_{\eta^m_{s_{ab}}, \eta^f_{s_{ab}}, \eta^a_{s_{ab}}, \eta^b_{s_{ab}}} \quad & \omega(p) + \sum_{t\epsilon\{m,f,a,b\}} \tilde{\omega}^t_{s_{ab}}(p) \ln\left(\frac{\eta^t_{s_{ab}} y}{G_t(A'_{s_{ab}} p)}\right) \\ \text{s.t} \quad & \eta^m_{s_{ab}} + \eta^f_{s_{ab}} + s_a \eta^a_{s_{ab}} + s_b \eta^b_{s_{ab}} = 1 \end{aligned} \tag{A3}$$

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

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

$$\frac{\tilde{\omega}^m_{s_{ab}}(p)}{\eta^m_{s_{ab}}} = \frac{\tilde{\omega}^f_{s_{ab}}(p)}{\eta^f_{s_{ab}}} = \frac{\tilde{\omega}^a_{s_{ab}}(p)}{s_a \eta^a_{s_{ab}}} = \frac{\tilde{\omega}^b_{s_{ab}}(p)}{s_b \eta^b_{s_{ab}}}, \quad \text{and} \sum_{t\epsilon\{m,f,a,b\}} s_t \eta^t_{s_{ab}} = 1 \tag{A4}$$

Solving for person specific resource shares gives the following equations:

$$\eta^t_{s_{ab}}(p) = \frac{\tilde{\omega}^t_{s_{ab}}(p)}{\tilde{\omega}^m_{s_{ab}} + \tilde{\omega}^f_{s_{ab}} + \tilde{\omega}^a_{s_{ab}} + \tilde{\omega}^b_{s_{ab}}} \text{for } t \,\epsilon\, \{m, f\} \tag{A5}$$

$$\eta^t_{s_{ab}}(p) = \frac{\tilde{\omega}^t_{s_{ab}}(p)/s_t}{\tilde{\omega}^m_{s_{ab}} + \tilde{\omega}^f_{s_{ab}} + \tilde{\omega}^a_{s_{ab}} + \tilde{\omega}^b_{s_{ab}}} \text{for } t \,\epsilon\, \{a, b\} \tag{A6}$$

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 will choose x_t to maximize $U_t(x_t)$ subject to $\eta^t_{s_{ab}} y = \sum_k A^k_{s_{ab}} p_k x^k_t$. Individual demand functions can be derived using Roy's Identify on the indirect utility functions given in equation (A18), where individual income is used $\eta^t_{s_{ab}} y$ and individuals face the Lindahl price vector $A_{s_{ab}} p$.

$$h_t^k(\eta_{s_{ab}}^t y, A_s p) = \frac{\eta_{s_{ab}}^t y}{G_t} \frac{\partial G_t}{\partial A_{s_{ab}} p^k} - \frac{\partial (A p^k e^{-a' \ln \tilde{p}})}{\partial A p^k} [\ln \eta_{s_{ab}}^t y - \ln G_t] \eta_{s_{ab}}^t y \tag{A7}$$

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

$$h_t^k(\eta_{s_{ab}}^t y, A'_{s_{ab}} p) = \tilde{\delta}_t^k (A'_{s_{ab}} p) \eta_{s_{ab}}^t y - \psi_t^k (A'_{s_{ab}} p) \eta_{s_{ab}}^t y \ln(\eta_{s_{ab}}^t y) \tag{A8}$$

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

$$z_{s_{ab}}^k = A_{s_{ab}} \sum_{t \epsilon \{m,f,a,b\}} h_t^k (A'_{s_{ab}} p, \eta_{s_{ab}}^t (p) y) \tag{A9}$$

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

$$\frac{h_t^k(\eta_{s_{ab}}^t y, A'_{s_{ab}} p)}{y} = \tilde{\delta}_t^k (A'_{s_{ab}} p) \eta_{s_{ab}}^t - \psi_t^k (A'_{s_{ab}} p) \eta_{s_{ab}}^t \ln(\eta_{s_{ab}}^t y) \tag{A10}$$

The analysis in this paper uses Engel curves for private goods, which will simplify the above equation even further. First, Engel curves demonstrate how budget shares vary with income holding prices constant. Thus we can drop prices 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:

$$W_{s_{ab}}^t (y) = \frac{h_{s_{ab}}^t (y)}{y} = \eta_{s_{ab}}^t \delta_{s_{ab}}^t + \eta_{s_{ab}}^t \beta^t (\ln y + \ln \eta_{s_{ab}}^t) \tag{A11}$$

A.2 Additional Tables

Table A1: Household Structure

		# Foster					
		0	1	2	3	4	5
	0	0	480	234	107	55	23
	1	2,163	284	79	22	18	0
# Non-Foster	2	2,324	243	57	23	0	0
	3	2,168	170	41	0	0	0
	4	1,473	99	0	0	0	0
	5	708	0	0	0	0	0

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

Table A2: Estimated Poverty Rates by Household Type

Household Type	Sample Size: # HHs	Individual Poverty Rates				Household Poverty Rates
		Non-Foster	Foster	Men	Women	
	(1)	(2)	(3)	(4)	(5)	(6)
All HHs	10,771	0.521	0.559	0.191	0.317	0.192
HHs with Only Foster Children	899		0.581	0.183	0.336	0.156
HHs with Only Non-Foster Children	8,836	0.534		0.195	0.312	0.200
Composite HHs	1,036	0.376	0.534	0.166	0.335	0.156
HHs with Orphaned Foster Children	799	0.420	0.657	0.184	0.345	0.188

Notes: Malawi Third Integrated Household Survey and Integrated Household Panel Survey. A household is poor if per adult equivalent expenditures are less than 2 dollars a day. Individual poverty rates measure consumption as the product of predicted resource shares and total expenditure. The child poverty line is set at 0.6×2.

Table A3: Descriptive Statistics: Education and Child Labor

	Mean	SD	Min	Max	Sample Size
Foster Status					
Both Parents Present	0.622	0.485	0	1	20371
Father Present Mother Absent and Alive	0.013	0.115	0	1	20371
Father Present Maternal Orphan	0.009	0.092	0	1	20371
Mother Present Father Absent and Alive	0.116	0.320	0	1	20371
Mother Present Paternal Orphan	0.058	0.234	0	1	20371
Both Absent and Alive	0.107	0.309	0	1	20371
Double Orphan	0.027	0.163	0	1	20371
Both Absent Paternal Orphan	0.026	0.158	0	1	20371
Both Absent Maternal Orphan	0.022	0.146	0	1	20371
Individual and Household Characteristics					
Enrolled in School	0.880	0.325	0	1	20371
Hours Worked in Chores Past Week	1.825	5.674	0	96	20371
Hours Worked (Excluding Chores) Past Week	2.166	4.021	0	49	20371
Log Expenditure per Capita	10.746	0.846	7.997	14.805	20371
Log Remmitances Per Capita	0.093	5.865	-4.605	14.376	20371
North	0.207	0.405	0	1	20371
Central	0.362	0.481	0	1	20371
South	0.432	0.495	0	1	20371
Year = 2010	0.739	0.439	0	1	20371
Male Sibling Age 0-6	0.613	0.762	0	5	20371
Female Siblings Age 0-6	0.621	0.759	0	4	20371
Male Siblings Age 7-14	0.656	0.784	0	6	20371
Female Siblings Age 7-14	0.662	0.788	0	6	20371
Men in HH	1.370	0.958	0	9	20371
Women in HH	1.485	0.810	0	7	20371
Age	9.694	2.596	6	14	20371
Female	0.508	0.500	0	1	20371
Rural	0.825	0.380	0	1	20371
Age Household Head	44.032	12.999	16	104	20371
Female Household Head	0.174	0.379	0	1	20371
Education of Household Head	5.530	4.123	0	14	20371

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

A.3 Identification Theorem

What follows is an extended version of Theorem 2 in DLP. Parts of the theorem will be similar and I will point out the parts where I differ.

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

The household solves the following maximization problem where each individual person type has their own utility function:[32]

$$\max_{x_m, x_f, x_a, x_b} \tilde{U}_{s_{ab}}[U_m(x_m), U_f(x_f), U_a(x_a), U_b(x_b), p/y] \text{ such that}$$
$$z_{s_{ab}} = A_{s_{ab}}[x_m + x_f + s_a x_a + s_b x_b] \text{ and} \tag{A12}$$
$$y = z'p$$

The household demand functions are given by $H_{s_{ab}}^k(p, y)$. Let $A_{s_{ab}}^k$ 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 $A'_{s_{ab}}$ and individual income $\eta_{s_{ab}}^t y$. Then household demand can be written as follows

$$z_{s_{ab}}^k = H_{s_{ab}}^k(p, y) = A_{s_{ab}}^k \Big[\sum_{t \epsilon \{m,f,a,b\}} s_t h_t(A'_{s_{ab}} p, \eta_{s_{ab}}^t y) \Big] \tag{A13}$$

where $\eta_{s_{ab}}^t$ are the resource shares of person t in a household with s_a foster children and s_b non-foster children. Resource shares by construction must sum to 1.

$$\eta_{s_{ab}}^m + \eta_{s_{ab}}^f + s_a \eta_{s_{ab}}^a + s_b \eta_{s_{ab}}^b = 1 \tag{A14}$$

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

ASSUMPTION A1: Equations (A12), (A13), and (A14) hold with resource shares $\eta^t_{s_{ab}}$ that do not depend on y.

Resource shares being independent of household expenditure is the key identifying assumption. An important qualification is that resource shares can still depend on other variables correlated with household expenditure such as men's or women's wages.

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.

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. For example, child clothing only appears in U_a and U_b, and so it is partially assignable to children.

Private assignable goods are central to identification in DLP and they are here as well. What makes private assignable goods unique and especially useful for identification is that by definition, the quantities that the household purchases is equivalent to what individuals in the household consume. In other words, there's no economies of scale or sharing for these goods making household-level consumption in some sense equivalent to individual-level consumption. I however must make use of goods that are not entirely assignable because I lack a private assignable good for foster and non-foster children.

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

For the mother and father, household demand functions for the private assignable good can be written as

$$z^k_{s_{ab}} = H^k_{s_{ab}} = h_k(A'_{s_{ab}}p, \eta^k_{s_{ab}}(p)y) \text{ for } k \,\epsilon\, \{m, f\} \tag{A15}$$

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

$$z^c_{s_{ab}} = H^c_{s_{ab}} = s_a h_a(A'_{s_{ab}}p, \eta^a_{s_{ab}}(p)y) + s_b h_a(A'_{s_{ab}}p, \eta^b_{s_{ab}}(p)y) \tag{A16}$$

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 I assume clothing is not shared across child types.

I now restrict utility functions in such a way that I can identify resource shares. In particular, I restrict preferences to be similar across household types, or the SAT restriction in DLP.

Browning et al. (2013) derive the following demand functions for the private assignable goods:

$$\begin{aligned}
W^m_{s_{ab}}(y,p) &= \eta^m_{s_{ab}}(y,p)w^m(\eta^m_{s_{ab}}(y,p)y, A'_{s_{ab}}p) \\
W^f_{s_{ab}}(y,p) &= \eta^f_{s_{ab}}(y,p)w^f(\eta^f_{s_{ab}}(y,p)y, A'_{s_{ab}}p) \\
W^a_{s_{ab}}(y,p) &= s_a\eta^a_{s_{ab}}(y,p)w^a(\eta^a_{s_{ab}}(y,p)y, A'_{s_{ab}}p) \\
W^b_{s_{ab}}(y,p) &= s_b\eta^b_{s_{ab}}(y,p)w^b(\eta^b_{s_{ab}}(y,p)y, A'_{s_{ab}}p)
\end{aligned} \tag{A17}$$

ASSUMPTION A3: Define $\tilde{p}$ to be the price of all non-private goods. Define $\bar{p}$ to be the vector of prices of all goods that are private other than p_t for $t \,\epsilon\, \{m, f, a, b\}$. Assume $\bar{p}$ is nonempty, and assume each person $t \,\epsilon\, \{m, f, a, b\}$ has PIGLOG preferences over goods given by the following indirect utility function:[33]

[33] PIGLOG indirect utility functions are used in the empirical application and therefore are used here. See

$$V_t(p, y) = b_t(p)[\ln y - \ln a_t(p)] \tag{A18}$$

where $b_t(p) = \bar{b}_t(\bar{p}/p_t)$ and is therefore a function of private good prices, and $a_t(p) = \bar{a}_t(\tilde{p})$ and is therefore some function of the prices of the other goods. By Roy's identity the budget share functions for person t's private assignable goods are as follows:

$$\omega_t(y, p) = d_t(p) + \beta_t(\bar{p}/p_t) \ln y \tag{A19}$$

where d_t is a function of $\bar{a}_t(\tilde{p})$ and $\bar{b}_t(\bar{p}/p_t)$, and $\beta_t(\bar{p}/p_t)$ is minus the own price elasticity of $\bar{b}(\bar{p}/p_t)$.

With the above restrictions, the budget share functions can be substituted into equation (A17) resulting in the following system:

$$\begin{aligned}
W^m_{s_{ab}} &= \eta^m_{s_{ab}}[\delta^m_{s_{ab}} + \beta^m \ln(\eta^m_{s_{ab}})] + \eta^m_{s_{ab}}\beta^m \ln y \\
W^f_{s_{ab}} &= \eta^f_{s_{ab}}[\delta^f_{s_{ab}} + \beta^f \ln(\eta^f_{s_{ab}})] + \eta^f_{s_{ab}}\beta^f \ln y \\
W^a_{s_{ab}} &= s_a\eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_a\eta^a_{s_{ab}}\beta^a \ln y \\
W^b_{s_{ab}} &= s_b\eta^b_{s_{ab}}[\delta^b_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] + s_b\eta^b_{s_{ab}}\beta^b \ln y
\end{aligned} \tag{A20}$$

where $\delta^t_{s_{ab}} = d_t(p)(A'_{s_{ab}}p)$ and $\beta^t = \beta(\bar{p}/p_t)$.

Because there is no private assignable good for foster and non-foster children, I rewrite the system of demand functions with the private partially assignable good for children in

Assumption B3 in DLP for a discussion of the class of preferences consistent with the SAT restriction.

place of $W^a_{s_{ab}}$ and $W^b_{s_{ab}}$

$$
\begin{aligned}
W^m_{s_{ab}} =& \eta^m_{s_{ab}}[\delta^m_{s_{ab}} + \beta^m \ln(\eta^m_{s_{ab}})] + \eta^m_{s_{ab}}\beta^m \ln y \\
W^f_{s_{ab}} =& \eta^f_{s_{ab}}[\delta^f_{s_{ab}} + \beta^f \ln(\eta^f_{s_{ab}})] + \eta^f_{s_{ab}}\beta^f \ln y \\
W^c_{s_{ab}} =& s_a\eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_b\eta^b_{s_{ab}}[\delta^b_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] \\
& + \ln y(s_a\eta^a_{s_{ab}}\beta^a + s_b\eta^b_{s_{ab}}\beta^b)
\end{aligned}
\tag{A21}
$$

Define the matrix Ω' by

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

ASSUMPTION A4: The matrix Ω' is finite and nonsinuglar.

Finiteness of Ω' requires that resource shares are never zero. The matrix will be non-singular 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.

Definition: A *composite* household is a household that contains at least one fostered and non-fostered child, or more concisely ($s_a > 0$ and $s_b > 0$).

Definition: A *one type only* household is a household that has children, but is not a composite household, or more concisely ($s_a > 0$ and $s_b = 0$) or ($s_a = 0$ and $s_b > 0$) .

ASSUMPTION A5; The ratio of foster and non-foster child resource shares in households with s_a and $s_{a'}$, and s_b and $s_{b'}$ foster and non-foster children is constant across household sizes.

$$\frac{\eta^a_{s_a0}}{\eta^a_{s_a+1,0}} = \frac{\eta^a_{s_ab}}{\eta^a_{s_a+1,b}} \text{ and } \frac{\eta^b_{s_0b}}{\eta^b_{s_0,b+1}} = \frac{\eta^b_{s_ab}}{\eta^b_{s_a,b+1}} \tag{A22}$$

for s_a and s_b ϵ $\{1, 2\}$.

ASSUMPTION A6: 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.

$$\frac{\eta^a_{s10}}{\eta^b_{s01}} = \frac{\eta^a_{s11}}{\eta^b_{s11}} \tag{A23}$$

Define the matrix Ω'' by

$$\Omega'' = \begin{bmatrix} \beta^a & 0 & 0 & 0 & \beta^b & 0 & 0 & 0 \\ 0 & \beta^a & 0 & 0 & 0 & 2*\beta^b & 0 & 0 \\ 0 & 0 & 2*\beta^a & 0 & 0 & 0 & \beta^b & 0 \\ 0 & 0 & & 2*\beta^a & 0 & 0 & 0 & 2*\beta^b \\ -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & \frac{\eta^b_{01}}{\eta^b_{02}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & \frac{\eta^b_{01}}{\eta^b_{02}} \\ -1 & 0 & 0 & 0 & \frac{\eta^a_{10}}{\eta^b_{01}} & 0 & 0 & 0 \end{bmatrix}$$

ASSUMPTION A7: The matrix Ω'' is finite and nonsinuglar.

The matrix will be finite as long as resource shares for an individual type are never zero. For the matrix to be nonsingluar, preferences for the partially assignable good must be different, i.e. $\beta^a \neq \beta^b$.

ASSUMPTION A8: 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 type only households in the data.

For Assumption A8 to hold in this context, it is necessary to observe both one type only households with one or two foster children (s_{10} and s_{20}), and also one type only households with one or two non-foster children (s_{01} and s_{02}). This requirement is easily met but may be more difficult in other contexts. For example, if one was interested in analyzing intrahousehold inequality between widows and non-widow adult women, it is rare to have multiple widows in the same household. In this case, identification could be achieved by observing a one type only household with only a widow present, and three different household types with only non-widowed adult women present.

Theorem 1. *Let Assumptions A1, A2, A3, A4, A5, A6, A7, and A8 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 $H^t_{s_{ab}}(y)$ 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.*

A.4 Identification Proof

This proof follows the proof of Theorem 2 in DLP, and extends it to identify resource shares when a household member type does not have a private assignable good. The proof proceeds in two steps. In the first step, I demonstrate resource shares are identified in the one type only households; this follows directly from DLP. In the second step, I extend DLP to demonstrate how resource shares can be identified in the absence of private assignable goods by making parameter restrictions based on what is identified from the one type only households.

A.4.1 Identification for Households with One Child Type

DLP derive household Engel curve functions for men's, women's, and children's private assignable goods, and demonstrate the key parameters of the model are identified. Here, I differentiate between foster and non-foster children by allowing them to have different preferences and resource shares. Thus, the Engel curve for children's clothing will by different. With PigLog preferences, these Engel curves are given by

$$W^t_{s_{ab}} = \eta^t_{s_{ab}}[\delta^t_{s_{ab}} + \beta^t \ln(\eta^t_{s_{ab}})] + \eta^t_{s_{ab}}\beta^t \ln y$$

for $t \,\epsilon\, \{m, f\}$, and

$$\begin{aligned} W^c_{s_{ab}} =& s_a\eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_b\eta^b_{s_{ab}}[\delta^a_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] \\ &+ \ln y(s_a\eta^a_{s_{ab}}\beta^a + s_b\eta^b_{s_{ab}}\beta^b) \end{aligned}$$

for children. Let $s_{ab} \,\epsilon\, \{s_{10}, s_{20}, s_{01}, s_{02}\}$ be the different household types. Then since the functions W^t and W^c are identified, ζ^t_{20}, ζ^t_{02}, and ζ^t_{01} defined as $\zeta^t_{20} = \lim_{y\to 0} W^t_{10}(y)/W^t_{20}(y)$, $\zeta^t_{02} = \lim_{y\to 0} W^t_{10}(y)/W^t_{02}(y)$, and $\zeta^t_{01} = \lim_{y\to 0} W^t_{10}(y)/W^t_{01}(y)$ can all be identified. Then for $t \,\epsilon\, \{m, f\}$:

$$\zeta^t_{20} = \frac{\beta^t\eta^t_{10}y}{\beta^t\eta^t_{20}y} = \frac{\eta^t_{10}}{\eta^t_{20}} \quad \text{and} \quad \zeta^t_{02} = \frac{\beta^t\eta^t_{01}y}{\beta^t\eta^t_{02}y} = \frac{\eta^t_{01}}{\eta^t_{02}} \quad \text{and} \quad \zeta^t_{01} = \frac{\beta^t\eta^t_{10}y}{\beta^t\eta^t_{01}y} = \frac{\eta^t_{10}}{\eta^t_{01}}$$

Moreover, the same ratio for fostered and non-fostered children in households with only one child type can be identified:

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

Note $\zeta^a_{s_{0b}} = 0$ and $\zeta^b_{s_{a0}} = 0$ and are therefore omitted. Using that resource shares must sum to 1, the following equations can be written, first for households with only non-foster children:

$$\zeta^m_{s20}\eta^m_{s20} + \zeta^f_{s20}\eta^f_{s20} + \zeta^a_{s20}s_a\eta^a_{s20} = \eta^m_{10} + \eta^f_{10} + \eta^a_{10} = 1$$
$$\zeta^m_{s20}\eta^m_{s20} + \zeta^f_{s20}\eta^f_{s20} + \zeta^a_{s20}(1 - \eta^m_{s20} - \eta^f_{s20}) = 1$$
$$(\zeta^m_{s20} - \zeta^a_{s20})\eta^m_{s20} + (\zeta^f_{s20} - \zeta^a_{s20})\eta^f_{s20} = 1 - \zeta^a_{s20}$$

and then for households with only foster children:

$$\zeta^m_{s02}\eta^m_{s02} + \zeta^f_{s02}\eta^f_{s02} + \zeta^b_{s02}s_b\eta^b_{s02} = \eta^m_{01} + \eta^f_{01} + \eta^b_{01} = 1$$
$$\zeta^m_{s02}\eta^m_{s02} + \zeta^f_{s02}\eta^f_{s02} + \zeta^b_{s02}(1 - \eta^m_{s02} - \eta^f_{s02}) = 1$$
$$(\zeta^m_{s02} - \zeta^b_{s02})\eta^m_{s02} + (\zeta^f_{s02} - \zeta^b_{s02})\eta^f_{s02} = 1 - \zeta^b_{s02}$$

These above equations for $t \,\epsilon\, \{m, f\}$, 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 8×8 matrix in this equation equals the previously defined matrix Ω' which was assumed to be nonsingular. Therefore the system can be solved for $\eta^m_{s_{a0}}$, $\eta^m_{s_{0b}}$, $\eta^f_{s_{a0}}$, 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 $\eta^a_{s_{a0}} = (1 - \eta^m_{s_{a0}} - \eta^f_{s_{a0}})/s_a$ and $\eta^b_{s_{0b}} = (1 - \eta^m_{s_{0b}} - \eta^f_{s_{0b}})/s_b$. Moreover, the identified non-foster and foster child resource shares can be used to identify β^a and β^b, which is necessary to identify resource shares in composite households in what follows.

A.4.2 Identification of Resource Shares in Composite Households

I now aim to identify non-foster and foster child resource shares in households with both types of children. First recall the following system of Engel curves:

$$
\begin{aligned}
W^m_{s_{ab}} =& \eta^m_{s_{ab}}[\delta^m_{s_{ab}} + \beta^m \ln(\eta^m_{s_{ab}})] + \eta^m_{s_{ab}} \beta^m \ln y \\
W^f_{s_{ab}} =& \eta^f_{s_{ab}}[\delta^f_{s_{ab}} + \beta^f \ln(\eta^f_{s_{ab}})] + \eta^f_{s_{ab}} \beta^f \ln y \\
W^c_{s_{ab}} =& s_a \eta^a_{s_{ab}}[\delta^a_{s_{ab}} + \beta^a \ln(\eta^a_{s_{ab}})] + s_b \eta^b_{s_{ab}}[\delta^b_{s_{ab}} + \beta^b \ln(\eta^b_{s_{ab}})] \\
& + \ln y (s_a \eta^a_{s_{ab}} \beta^a + s_b \eta^b_{s_{ab}} \beta^b)
\end{aligned}
$$

Define the coefficient on $\ln y$ as $R_{s_{ab}} = s_a \eta^a_{s_{ab}} \beta^a + s_b \eta^b_{s_{ab}} \beta^b$, which is identified by an OLS type regression of clothing budget shares on the log of expenditure. Moreover, with SAT preferences, β^a and β^b are identified from the one child type only households. For four composite household types ($s_a \ \epsilon \ \{1, 2\}$ and $s_b \ \epsilon \ \{1, 2\}$), this yields the following system of equations:

$$
\begin{bmatrix}
\beta^a & & 0 & 0 & \beta^b & 0 & 0 & 0 \\
0 & \beta^a & 0 & 0 & 0 & 2 * \beta^b & 0 & 0 \\
0 & 0 & 2 * \beta^a & 0 & 0 & 0 & \beta^b & 0 \\
0 & 0 & & 2 * \beta^a & 0 & 0 & 0 & 2 * \beta^b
\end{bmatrix}
\times
\begin{bmatrix}
\eta^a_{11} \\ \eta^a_{12} \\ \eta^a_{21} \\ \eta^a_{22} \\ \eta^b_{11} \\ \eta^b_{12} \\ \eta^b_{21} \\ \eta^b_{22}
\end{bmatrix}
=
\begin{bmatrix}
R_{11} \\ R_{12} \\ R_{21} \\ R_{22}
\end{bmatrix}
$$

There are four equations in total and eight unknowns ($\eta^a_{s_{ab}}$ and $\eta^b_{s_{ab}}$) and the system is clearly underidentified. However, with Assumption A5, the following restrictions are added to the system:

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

for s_a and $s_b \ \epsilon \ \{1, 2\}$, where $\frac{\eta^a_{s_{a0}}}{\eta^a_{s_{a+1,0}}}$ and $\frac{\eta^b_{s_{0b}}}{\eta^b_{s_{0,b+1}}}$ are identified from the one child type only households. This restriction results in four additional equations in the system.

Lastly, by Assumption A6, the following equation must hold:

$$\frac{\eta^a_{s10}}{\eta^b_{s01}} = \frac{\eta^a_{s11}}{\eta^b_{s11}} \tag{A24}$$

This results in one additional equation for identification.

$$\begin{bmatrix} \beta^a & & 0 & 0 & \beta^b & 0 & 0 & 0 \\ 0 & \beta^a & 0 & 0 & 0 & 2*\beta^b & 0 & 0 \\ 0 & 0 & 2*\beta^a & 0 & 0 & 0 & \beta^b & 0 \\ 0 & 0 & & 2*\beta^a & 0 & 0 & 0 & 2*\beta^b \\ -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & \frac{\eta^a_{10}}{\eta^a_{20}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & \frac{\eta^b_{01}}{\eta^b_{02}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & \frac{\eta^b_{01}}{\eta^b_{02}} \\ -1 & 0 & 0 & 0 & \frac{\eta^a_{10}}{\eta^b_{01}} & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} \eta^a_{11} \\ \eta^a_{12} \\ \eta^a_{21} \\ \eta^a_{22} \\ \eta^b_{11} \\ \eta^b_{12} \\ \eta^b_{21} \\ \eta^b_{22} \end{bmatrix} = \begin{bmatrix} R_{11} \\ R_{12} \\ R_{21} \\ R_{22} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

The 9×8 matrix in this equation equals the previously defined matrix Ω'', which by Assumption A7 is nonsingular , and therefore the system is identified. With the foster and non-foster child resource shares in composite households identified the identification of men's and women's resource shares follows immediately using similar arguments to what was used in the identification of one child type only households.