

Children Costs in a One-Adult Household: Empirical Evidence from the UK.

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Abstract

This paper addresses two central questions in family and economic policy. First, to what extent are estimates of the cost of children derived from two-parent households applicable to single-parent families? Second, are estimated patterns of intra-household resource allocation consistent with benefit rules that condition support uniformly on family size? To address these questions, I propose a collective consumption model for one-adult households, apply it to three datasets—the Family Expenditure Survey, the Expenditures and Food Survey, and the Living Costs and Food Survey in the UK—and present two key findings. First, child cost estimates derived from two-parent households remain externally valid for single-parent families, at least for single mothers. Second, the results find no evidence of per-child resource dilution by family size once estimation uncertainty is accounted for, with differences for fathers appearing only among households at the bottom of the expenditure distribution.

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JEL Classification: C30, D11, D12, D36, D63, I31, J12, J13

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1 Introduction

As debates over the equity and efficiency of social benefits intensify, a central yet underexplored question concerns how child costs are measured and interpreted in single-parent households. Although single-parent families account for a growing share of households with children [Skinner et al., 2008, Nieuwenhuis and Maldonado, 2018], empirical evidence on intra-household resource allocation in these families remains limited.¹ By contrast, the economic literature on child costs and intra-household allocation has made substantial progress using collective models estimated on couple households. See, e.g., Bourguignon [1999], Dunbar et al. [2013], Bargain and Donni [2012a], Bargain et al. [2014], Dunbar et al. [2021], Bargain et al. [2022, 2021], Lechene et al. [2022], among others. These contributions deliberately focus on two-adult households, where bargaining, public-good provision, and economies of scale can be structurally identified. At the same time, the absence of empirical counterparts for one-parent families has practical implications. In applied work and policy design, child cost estimates derived from couple-based models are often used—explicitly or implicitly—as reference points when evaluating living standards and transfer adequacy for single-parent households. Whether such benchmarks remain informative in the absence of a second adult—when production complementarities, time constraints, and resource allocation mechanisms differ fundamentally—remains an open empirical question. The family structure of single-parent households², combined with their heightened economic vulnerability, raises concerns about the external validity of child cost estimates extrapolated from couple households [DeLeire and Levy, 2004, Nieuwenhuis and Maldonado, 2018].³

Alongside these empirical concerns, rising attention to child poverty and the implementation of structural reforms such as the *two-child limit*—which caps family benefits to the first two children in the United Kingdom (UK)—have fundamentally reshaped the issues of targeting and fairness in social policy.⁴ While existing research consistently shows that the *two-child limit* has raised child poverty by lowering household income, it does not address the underlying mechanisms through which the policy may exacerbate inequality and poverty [González and Trommlerová, 2023, Chzhen and Bradshaw, 2025, Stewart et al., 2025a,b].⁵

Against this backdrop, this paper questions the validity of applying results from collective models estimated on couples to single-parent families. It also examines how family size and parents’ position in the income distribution shape children’s well-being. Two main questions guide the analysis: (i) To what extent are estimates of the cost of children derived from couples relevant for single parents? (ii) Are estimated patterns of intra-household resource allocation consistent with benefit rules that

¹A few notable exceptions examining resource allocation in single-parent households include Bargain et al. [2014], Echeverría et al. (2019), Bose-Duker et al. [2021], and Lechene et al. [2022].

²In this paper, single parents are defined as follows: a) widowed, divorced, or separated parents with dependent children living in their household; b) a child is defined as any biological child of the household head aged 0 to 15 years. The expression “living in the household” denotes children who regularly spend at least four nights per week at the parent’s residence. This definition ensures the inclusion of households where children reside primarily, which is critical for analyzing costs.

³Nieuwenhuis and Maldonado [2018] describe the “triple bind” of single-parent families: limited resources, barriers to stable and well-paid employment, and policy frameworks that often fail to offset these disadvantages. Although single mothers frequently achieve relatively high employment rates [Meyer and Sullivan, 2004], they remain overrepresented in precarious, low-wage jobs, and the lack of a second parent combined with atypical working hours exacerbates the challenge of balancing work and family responsibilities.

⁴The *two-child limit*, introduced in the United Kingdom in April 2017, restricts means-tested child-related benefits (Child Tax Credit and the child element of Universal Credit) to the first two children. For any additional child born after that date, no supplement is paid, implying a loss of about £244 per month (roughly £3,000 per year) per child [Chzhen and Bradshaw, 2025, Reader et al., 2025]. Adopted in a context of fiscal austerity, the reform was intended both to reduce social spending and to encourage families to finance the cost of a third child without public support. By 2023, around 1.5 million children were already affected (57% in working families and 50% in single-parent households), a figure expected to rise to nearly 2.8 million once the policy is fully phased in (HMRC statistics).

⁵Recent poverty statistics reveal that the number of children living in relative poverty (after housing costs) rose from 3.6 million in 2010 to 4.2 million by 2022. The report is available on the [Child Poverty Action Group website](#).

condition support uniformly on family size?

To address these questions, the paper extends collective models to the analysis of single-parent households in the UK, using expenditure surveys spanning four decades. The empirical validation is conducted on a collective consumption model inspired by [Bargain, Donni, and Hentati \[2022\]](#), hereafter [BDH](#). The identification strategy relies on the allocation of resources to children based on assignable goods, under the assumption of preference stability. The empirical approach also incorporates a set of exclusion restrictions to identify the intra-household sharing rule.

This study develops and estimates a static model of intra-household allocation to analyze how parental and child characteristics affect the distribution of resources within the household. The theoretical framework rests on three main components: (1) an additive utility function, positing parental altruism towards children; (2) a consumption technology describing how households transform purchased goods into individual consumption; and (3) a sharing rule determining the allocation of resources among household members, defined as the share of total household resources assigned to each individual.

To identify the sharing rule, I use clothing as the assignable good—that is, a good for which individual consumption is directly observable by the researcher within the household. This choice enables the analysis of how adult demand for such good varies with the presence and number of children in the household. Identification further relies on a parametric characterization of preferences: adults with similar observable characteristics are assumed to share similar preferences for assignable goods, independent of parental status. In other words, becoming a parent does not substantially alter individual preferences for clothing; rather, it is primarily the overall budget constraint and the resource allocation—affected by the arrival of children and associated expenditures—that may change. This assumption, widely discussed in the literature, offers a relevant framework for identifying Engel curves. See, e.g., [Bargain et al. \[2014\]](#), [Bargain et al. \[2021\]](#) and [BDH](#). Moreover, it is also adopted by the benchmark studies —[BDH](#)— against which my results are compared to assess their generalizability to single parents. Finally, the empirical strategy relies on an exclusion restriction. Certain explanatory variables influence demand for assignable good but do not directly affect either the shadow price or the intra-household sharing rule. The model is estimated using a sample of one-adult households, with and without children, from the UK Family Expenditure Survey (FES) over the period 1978–2022.⁶

The results show that the collective model predicts individual resource shares satisfactorily, while revealing significant heterogeneity by parent gender and household size. Notably, the analysis indicates male-headed single-parent households allocate a higher share of resources to children than female-headed ones. *Ceteris paribus*, single fathers with one child allocate, on average, 22.2% of their total resources to the child, compared to 14.7% for single mothers. For comparison, [BDH](#) estimate that in two-parent households with one child, the share allocated to children is 14.2%. Regardless of the identification strategy, the collective approach accurately captures the effects of family size and child age on the child’s share. Furthermore, estimated intra-household allocation patterns do not show strong, systematic per-child disadvantage by family size, suggesting that uniform family-size-based caps are not clearly contradicted by allocation behavior, while also highlighting heterogeneity in low-resource households.

This work makes four main contributions to the literature. First, the paper provides one of the few empirical estimates of the cost of children in single-parent households and, to my knowledge, the first based on data from a high-income country. By contrast, the limited existing literature—such as [Bargain et al. \[2014\]](#) for Côte d’Ivoire, [Echeverria et al. \[2019\]](#) for Argentina, and [Bose-Duker et al.](#)

⁶Family Expenditure Survey (FES) has been replaced by Expenditure and Food Survey (EFS) in 2001, then Living Costs and Food Survey from 2008 onwards. For convenience, all three are referred to as FES in this paper.

[2021] for Jamaica—focuses mainly on low- and middle-income countries with substantially different economic and social contexts. Moreover, the last two studies are based on the methodology developed by Dunbar, Lewbel, and Pendakur [2013, hereafter DLP], which does not require data on childless single adults and uses less restrictive homogeneity assumptions on preferences (Similarity Across Type—SAT—and Similarity Across People—SAP).⁷ While the former —SAT— assumes that, for a given person type (man, woman, child), the slope of individual Engel curves does not depend on the number of children, the latter —SAP— posits that for a given household type, individual Engel curves have the same slope. The present study follows the approach of Bargain et al. [2014], who identify the intra-household sharing rule using information from adults without children. However, it departs significantly by exploiting longitudinal data over multiple years, whereas Bargain et al. [2014] rely solely on cross-sectional data, which compels them to assume “independence of base”—that is, that economies of scale are independent of household resource level. Finally, this study provides new empirical evidence on the applicability of the collective approach for estimating the sharing rule and suggests that, under certain conditions, child cost estimates from couple-based models remain transferable to single-parent households.

Second, it proposes several identification tests for the sharing rule and economies of scale. Unlike BDH, I exploit price variability in the sharing rule and show that the estimates are robust to alternative functional forms for both the sharing rule and economies of scale.

Third, it sheds new light on the heterogeneity of resource shares allocated to children by parental gender. Although point estimates suggest that single fathers allocate a larger share of total expenditures to their children than single mothers, the differences are not statistically significant at conventional levels.⁸ This conclusion holds both when resource shares are evaluated at the characteristics of a representative parent and when they are computed as averages of individual predicted shares. Taken together, these findings contrast with the prevailing consensus in the literature, which emphasizes women’s stronger child-oriented preferences. For example, Duflo [2003], Duflo and Udry [2004] and Caiumi and Perali [2015] find that women allocate a larger proportion of their resources to child-related goods (food, health, education), whereas men tend to spend more on adult-oriented goods, such as tobacco and alcohol. Similarly, Bose-Duker et al. [2021] observe, in the Jamaican context, that children in female-headed households receive a larger share of household resources than those in male-headed households.

Finally, this paper advances the literature on household behavior and the design of child-related transfers [González and Trommlerová, 2023, Chzhen and Bradshaw, 2025, Reader et al., 2025, Stewart et al., 2025a,b] by examining whether family size is an empirically informative criterion for differentiating child support. Using estimated intra-household sharing rules, the analysis finds no statistically significant variation in per-child resource allocations with family size across the total expenditure distribution, even though households allocate a larger total share of resources to children as family size increases.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework and identification assumptions. Section 3 details the empirical strategy. Section 4 describes the data. Section 5 discusses the main results and their implications. Section 6 concludes.

⁷A growing body of research applies and extends these approaches in various contexts. See, e.g., Tommasi and Wolf [2018], Tommasi [2019], Calvi [2020], Brown et al. [2021], Dunbar et al. [2021], Penglase [2020], Bargain et al. [2021], Lechene et al. [2022], Lewbel and Pendakur [2022], Calvi et al. [2023], Lewbel and Pendakur [2024].

⁸A similar absence of statistically significant gender differences in child resource allocation is reported by BDH.

2 Theoretical Framework

A central objective of this study is to evaluate whether sharing rule estimated from a collective model—originally developed for couples with or without children—remains valid when applied to single-parent households. To address this, I develop a static model of household consumption inspired by BDH, enabling direct comparison with analyses of couples in the same UK data. The theoretical analysis proceeds in two steps: first, by characterizing the consumption behavior of a single adult (without children), which serves as the baseline; and second, by extending the model to single adults living with children.

2.1 The Consumption Behavior of a Single Adult without Children

Consider a household consisting of a childless single adult (either male or female), who maximizes a well-behaved utility function $u(x^a, x^c)$, where x^a denotes consumption of an assignable good (e.g., adult clothing) and x^c denotes a composite good.⁹ The utility function is assumed to be twice continuously differentiable, strictly increasing, and strictly concave.¹⁰

Let p denote the price of the assignable good, and let the price of the composite good be normalized to unity. The individual faces the following budget constraint:

$$x^a p + x^c = y \quad (1)$$

where y is total household expenditure.¹¹

The household's optimization problem is:

$$\max_{x^a, x^c} u(x^a, x^c) \text{ subject to (1)} \quad (2)$$

The first-order conditions yield the demand for the assignable good as a function of prices and total expenditure:

$$\omega = g(p, y) \quad (3)$$

where $\omega = px^a/y$ is the budget share allocated to the assignable good. Since the utility function is strictly increasing, the budget constraint binds at the optimum.

2.2 The Consumption Behavior of a Single-Adult with Children

Now consider a single adult living with $n \geq 1$ children under 16.¹² In line with established convention, the parent is assumed to exhibit Beckerian altruism, such that utility is a function of both the parent's own consumption and the utility of the children.

The utility function is specified as:

⁹ Assignable good and exclusive good are used interchangeably. See BCL for more details about exclusive and assignable goods.

¹⁰ Individual utility is further influenced by preference-driven factors, which are incorporated into the budget share function in the empirical section. Preferences are assumed to be stable, enabling predictions about household behavior.

¹¹ As is standard in the literature, only non-durable goods are considered. When the proportion of purchased goods that remains unconsumed is negligible, purchased quantities can be taken as a proxy for actual consumption.

¹² In contrast to Penglase [2020], the model treats foster and non-foster children indiscriminately. Penglase [2020] explicitly separates the two groups of children, focusing on whether there is differential treatment in the allocation of resources for the consumption of foster and non-foster children. At this point, no distinction is made regarding the characteristics of the children. My assumption is limited to the child residing with either the father or the mother and younger than 16 years old.

$$W = u(x^a, x^c) + \delta(\mathbf{n})u_k(x^k) \quad (4)$$

where x^a and x^c are as before, x^k denotes the composite good consumed by a representative child (intra-sibling allocation is not identified), and $\delta(\mathbf{n})$ captures the weight placed by the parent on child consumption, as a function of $\mathbf{n}$.¹³ This formulation is consistent with [Bargain and Donni \[2012b\]](#).

For simplicity, household income is treated as exogenous and entirely allocated to consumption; neither labor supply nor home production is modeled.¹⁴ Total expenditure y is allocated across purchased quantities q^a (exclusive good) and Q (composite good), subject to:

$$q^a p + Q = y \quad (5)$$

Here, q^a and Q denote, respectively, the purchased quantities of the household's exclusive goods and household composite goods.

Several clarifications are warranted. First, children's consumption is included in Q . Second, two types of goods are considered: an adult-exclusive good (x^a), and composite goods (x^c, x^k), the latter of which may comprise both private non-assignable and public components. Third, household survey data typically do not record individual consumption within household. As a result, information on composite goods provides limited insights into the allocation of resources to children. Nevertheless, observing adult-exclusive goods can reveal relevant aspects of household behavior.

For a purely private assignable good:

$$q^a = x^a \quad (6)$$

However, in a household with at least two members—such as an adult and a child—certain goods exhibit public or shared properties, such that their effective consumption cannot be directly inferred from purchased quantities alone. To address the resulting economies of scale, two main modeling approaches are used.

The Independence of Base (IB) approach posits that the cost savings from joint consumption of public goods are independent of both market prices and the total level of household expenditure. Under this assumption, the mapping from purchased quantities to effective consumption depends solely on household composition (e.g., number and type of members), but is invariant to economic variables. This restriction is appropriate in studies based on cross-sectional data with little or no price variation [[Lewbel and Pendakur, 2008](#), [Bargain and Donni, 2012a](#), [Dunbar et al., 2013](#)].

The Barten scales approach, in contrast, relaxes the IB restriction by allowing the transformation from purchases to effective consumption to depend on household composition as well as economic factors such as prices and total expenditure. Specifically, the vector of market prices is rescaled by a transformation function, which captures how economies of scale vary with total expenditure, prices, and household composition [[BCL](#)]. This approach, as in [BCL](#) and [BDH](#), is particularly suited to analyses with multi-year data and substantial price variation.

Assumption 1 (*Barten prices*). *For any adult in a household with $n \geq 1$ children, there exists a differentiable scalar function $\pi(y, p, \mathbf{z}^\pi, \mathbf{n})$ such that composite good purchases satisfy:*

$$Q = \pi(y, p, \mathbf{z}^\pi, \mathbf{n})x^c + x^k \quad (7)$$

¹³Strictly speaking, the argument $\mathbf{n}$ in $\delta(\mathbf{n})$ is a vector capturing all relevant characteristics of the children (e.g., number of children, average age of children, gender composition, sibling structure, etc.).

¹⁴A broader perspective on this topic is addressed by [Apps and Rees \[2001\]](#) and [Cherchye et al. \[2012\]](#).

where $\pi(y, p, \mathbf{z}^\pi, \mathbf{n})$ is a shadow price (Barten price) associated with the parent's consumption of the composite good, and $\mathbf{z}^\pi$ is a vector of sociodemographic variables included in the Barten price. For identification, the shadow price for children is normalized to unity. The shadow price serves as a deflator that measures the gains from joint consumption experienced by an adult due to household economies of scale. The parent effectively receives a greater quantity of composite goods than the amount actually purchased, due to sharing within the household (e.g., heating). When $\pi(\cdot) = 1$, goods are purely private and one member's consumption does not affect the other's. When $\pi(\cdot) < 1$, there are positive economies of scale, since each unit of x_c is effectively less costly. When $\pi(\cdot) > 1$, this indicates diseconomies of scale or stronger preferences for private consumption.

Substituting (6) and (7) into (5) gives:

$$x^a p + \pi(y, p, \mathbf{z}^\pi, \mathbf{n}) x^c + x^k = y \quad (8)$$

The household chooses (x_a, x_c, x_k) to maximize utility subject to the new budget constraint (8). By construction, parental decisions are Pareto efficient, since the single parent makes all consumption decisions.¹⁵

The allocation problem reduces to dividing resources between the parent and the child. The resulting optimization program is:

$$\begin{aligned} \max_{x^a, x^c, x^k} \quad & u(x^a, x^c) + \delta(\mathbf{n}) u_k(x^k) \\ \text{s.t.} \quad & x^a p + \pi(y, p, \mathbf{z}^\pi, \mathbf{n}) x^c + x^k = y \end{aligned} \quad (9)$$

Adopting an additive utility function simplifies the transition to a decentralized approach. The allocation can be characterized in two steps:

1. Let φ and φ_k denote the shares of resources allocated to the parent and to the child, respectively, with $\varphi + \varphi_k = 1$. The resource allocation is obtained by solving:

$$\max_{\varphi, \varphi_k} \quad \nu\left(\frac{p}{\pi}, y \frac{\varphi}{\pi}\right) + \delta(\mathbf{n}) \nu_k(y \varphi_k) \quad \text{s.t.} \quad \varphi + \varphi_k = 1 \quad (10)$$

where ν and ν_k are the indirect utility functions for the parent and the child, respectively.

2. Given $\varphi(y, p, \mathbf{z}^\varphi, \mathbf{n}) \leq 1$ for $n \geq 1$, the parent solves:

$$\max_{x^a, x^c} \quad u(x^a, x^c) \quad \text{s.t.} \quad x^a p + \pi(y, p, \mathbf{z}^\pi, \mathbf{n}) x^c = y \cdot \varphi(y, p, \mathbf{z}^\varphi, \mathbf{n}) \quad (11)$$

where $\mathbf{z}^\varphi$ represents the vector of sociodemographic variables entering the sharing rule, and $\varphi(y, p, \mathbf{z}^\varphi, \mathbf{n})$ denotes the share of the budget retained by the parent. Accordingly, the remaining share, $1 - \varphi(y, p, \mathbf{z}^\varphi, \mathbf{n})$, is assigned to the child. In the absence of children, $\varphi = 1$, meaning the parent keeps the entire budget, as in a childless single-adult household.

The parent's demand for the assignable good is thus:

¹⁵In the context of single-parent households, the Pareto efficiency assumption is automatically satisfied, as the parent acts as a dictator, making all consumption decisions on behalf of the household. More generally, the identification of intrahousehold resource allocations traditionally relies on the assumption of collective efficiency [Chiappori, 1988] and group separability—assumptions that are widely regarded as reasonable for everyday consumption choices [Baland and Ziparo, 2018]. While the literature has documented instances of inefficiency, particularly for strategic or production decisions—especially in low-income countries [Udry, 1996]—these assumptions remain plausible for repeated and non-strategic consumption choices, as also emphasized by Baland and Ziparo [2018] and Lewbel and Pendakur [2022].

$$\frac{\omega}{\varphi(y, p, \mathbf{z}^\varphi, \mathbf{n})} = g\left(\frac{p}{\pi(y, p, \mathbf{z}^\pi, \mathbf{n})}, y \frac{\varphi(y, p, \mathbf{z}^\varphi, \mathbf{n})}{\pi(y, p, \mathbf{z}^\pi, \mathbf{n})}\right) \quad (12)$$

where $\omega = px_a/y$ is the budget share devoted to the assignable good. Notably, explicit specification of the child's utility function is not required for estimation as it does not dictate the outcome of the model.

2.3 Identification

Estimating the cost of children would be straightforward if individual-level consumption data were available. In practice, however, most household surveys provide information only at the aggregate household level, and many goods are jointly consumed within the household. A few exceptions exist, such as the Dutch LISS panel exploited by [Cherchye et al. \[2012\]](#) and the Bangladeshi survey data used by [Bargain et al. \[2021\]](#), which contain information on individual consumption. Yet these datasets remain rare and limited in scope. Consequently, the identification of both resource shares within the household and economies of scale in consumption requires the introduction of additional structure.

The identification strategy relies on three pillars. First, I assume preference stability across childless single adults and single parents.¹⁶ This assumption should be interpreted as the invariance of preferences for assignable goods when moving from a single adult without children to a single parent with comparable socio-demographic characteristics. Thus, observed differences in assignable consumption can be attributed to household composition, not preference shifts. This assumption enables effective use of information from childless adults to estimate the demand function for single parents. This is especially valuable in the case of single fathers, given small sample size.

Second, identification requires the observation of at least one assignable good. While [Chiappori and Ekeland \[2009\]](#) show that three goods are typically needed for identification, [Bourguignon \[1999\]](#) and [Bourguignon et al. \[2009\]](#) demonstrate that under specific conditions, a single assignable good suffices. In line with recent contributions (e.g., [BCL](#); [Bargain and Donni, 2012a](#); [DLP](#); [BDH](#)), I focus on clothing expenditures, which are observable at the individual level.¹⁷

Third, I exploit the nonlinearity of Engel curves. Following [Prais and Houthakker \[1971\]](#), nonlinear Engel curves, augmented with socio-demographic controls, provide sufficient flexibility to recover heterogeneous demand responses. In my empirical application, this requirement is satisfied since budget share equations are nonlinear in log expenditures.¹⁸

Finally, two normalization conditions are imposed. In households without children, both the shadow price of the composite good and the resource share allocated to the adult are normalized to one.

Conditional on the previous conditions, Proposition 1 states the additional conditions under which the sharing rule and Barten scales are generically identified.

Proposition 1 *Let the demand function for an assignable good be, respectively, for childless single adults and single parents:*

¹⁶This extends the framework of [BCL](#), who utilize a similar stability assumption to map the preferences of single individuals onto those of members of a childless couple.

¹⁷[Lechene et al. \[2022\]](#) argue that food is a preferable assignable good relative to clothing, due to its larger budget share and consistently downward-sloping Engel curves. In this paper, however, I follow [BDH](#) in using clothing in order to ensure comparability with their results. This choice is further supported by [Bargain et al. \[2021\]](#), who show that the collective model predicts individual resources reasonably well when using clothing.

¹⁸See also [Banks, Blundell, and Lewbel \[1997\]](#), who show that budget share equations are typically nonlinear.

$$\begin{aligned}\omega &= g(\mathbf{z}^\omega, p, y), \\ \omega &= g(\mathbf{z}^\omega, \pi(y, p, \mathbf{z}^\pi, \mathbf{n}) \cdot p, \varphi(y, p, \mathbf{z}^\varphi, \mathbf{n}) \cdot y),\end{aligned}$$

where $\pi(y, p, \mathbf{z}^\pi, \mathbf{n})$ represents the price transformation à la Barten, and $\varphi(y, p, \mathbf{z}^\varphi, \mathbf{n})$ denotes the sharing rule. Here, p is the price of the assignable good, y represents total expenditures, $\mathbf{n}$ is a vector of children characteristics, and $\mathbf{z}^\omega, \mathbf{z}^\pi, \mathbf{z}^\varphi$ are vectors of sociodemographic variables associated with ω , π , and φ , respectively.

The functions $\pi(\cdot)$ and $\varphi(\cdot)$ are generically identifiable if at least one of the following conditions holds:

1. At least one variable in $\mathbf{z}^\omega$ is excluded from both $\mathbf{z}^\pi$ and $\mathbf{z}^\varphi$.
2. π and φ are independent of total expenditure y .
3. π and φ are independent of price p .
4. $\pi(\cdot)$ and $\varphi(\cdot)$ are known up to some parameters (semi-parametric identification).
5. $\pi(y, p, \mathbf{z}^\pi, \mathbf{n}) = \pi_1(y, p, \mathbf{z}^\pi, \tilde{\mathbf{n}}) \cdot \pi_2(n)$ with $\pi_2(1) = 1$, and $\varphi(y, p, \mathbf{z}^\varphi, \mathbf{n}) = \varphi(y, p, \mathbf{z}^\varphi, \tilde{\mathbf{n}}) \cdot \varphi_2(n)$ with $\varphi_2(1) = 1$.

The proof is given in Online Appendix A. Here, the economic intuition is as follows:

1. $\mathbf{z}^\omega$ denotes a vector of variables that affect the demand for the assignable good ω but do not necessarily influence the shadow price π or the sharing rule φ . These variables may include socio-demographic characteristics such as age, education, or region of residence. The presence of a variable in $\mathbf{z}^\omega$ —for example, decade dummies—that impacts only the demand for the assignable good while leaving π and φ unaffected provides an exclusion restriction. Exploiting variation in such a variable allows one to identify its direct effect on demand, thereby isolating the estimation of the model’s structural parameters while holding the shadow price and sharing rule constant. For instance, decade dummies capture changes in fashion trends, relative prices of clothing, or shifts in consumption norms that affect adult clothing expenditures, without necessarily altering how resources are shared between parents and children or the degree of household economies of scale. Hence, variation across decades provides a valid exclusion restriction for identifying the demand equation.¹⁹
2. In this case, the shadow price π and sharing rule φ do not change with total expenditures y . That is, whether the household’s total expenditure is £1000 or £2000, π and φ remain unchanged. If empirical evidence shows that the allocation of resources between the parent and the child does not vary with changes in total expenditure, then it is unnecessary to model π and φ as functions of y . This invariance greatly facilitates identification.²⁰

¹⁹In the empirical analysis, this exclusion restriction is also employed to identify the sharing rule.

²⁰One alternative route to identifying the sharing rule relies on the expenditure-invariance (or proportionality) assumption proposed by DLP. In their Engel-curve framework, the sharing rule can be recovered from private assignable goods provided that individual resource shares do not depend on total household expenditure, though they may depend on closely related variables such as household income, or wealth. This restriction implies that proportional changes in household expenditure leave intra-household allocation unchanged.

Importantly, this assumption is not imposed without empirical scrutiny. DLP explicitly test expenditure invariance in an overidentified setting by allowing resource shares to vary with an expenditure proxy and report that the restriction cannot be rejected in their application to Malawi. Independent support is provided by Menon et al. [2012], who use direct survey

3. Suppose the price of the assignable good increases, but this does not affect how the parent allocates their budget between themselves and their child, as captured by the sharing rule (φ). In such a case, both π and φ remain unchanged, allowing for their separate estimation, independent of the effect of price changes on demand.
4. If the functional forms of π and φ are known up to some parameters, identification reduces to estimating these unknown parameters rather than specifying the entire functional relationship. For example, if it is known that φ depends on the number of children, but the exact magnitude of this dependence is unknown, one might assume a specific parametric structure, such as $\varphi = \psi(n)$, where ψ could be a simple linear or logistic function. The empirical task then becomes estimating the parameters that govern how φ varies as the number of children increases.
5. Assuming that π and φ can be factorized into two multiplicative components significantly simplifies their structure. This specification allows the effects of household composition (e.g., the number of children) to be separated from those of prices and sociodemographic characteristics. For example, one might express π as $\pi_1(y, p, \mathbf{z}^\pi, \bar{\mathbf{n}}) \cdot \pi_2(n)$, where π_1 captures the influence of prices and demographics, and $\pi_2(n)$ isolates the effect of the number of children. Such a formulation enables the estimation of the respective impacts independently.

3 Empirical Implementation

3.1 Econometric Specification

The empirical specification examines a demand system which is quadratic in logarithmic expenditure, as used in studies such as [Browning et al. \[1994\]](#) and [BDH](#). This quadratic parametrization relaxes the restrictive linearity assumption under which marginal budget shares are invariant to the level of expenditure. The empirical model is specified as follows:

$$\omega_i = \alpha_i \mathbf{z}_i^\omega + \beta_i \ln p_i + \gamma_i \ln y_i + \eta_i (\ln y_i)^2 + \epsilon_i \quad (13)$$

for $i = f, m$, where α_i , β_i , γ_i , and η_i are the parameters to be estimated. The vector $\mathbf{z}_i^\omega$ is a linear function of a set of covariates, including a constant, education level, adult age and its square, a set of dummies for labor force participation, home ownership, decades, and region of residence, and ϵ_i , an error term capturing unobserved heterogeneity.²¹ Notably the equations are gender-specific, with separate estimations for men and women. For each adult, the budget share devoted to clothing is defined as the ratio of weekly clothing expenditures to total weekly expenditures on non-durable goods.

For childless single adults, the equation simplifies from (12) to (3). To distinguish between single parents and childless adults, I introduce a dummy variable, $\mathbb{1}_i$, which equals 1 if the adult is a parent and 0 otherwise. The stochastic structure of the budget share equations for single adults and single parents is then expressed as follows:

questions on perceived intra-household allocation in Italy and find no systematic relationship between reported resource shares and household expenditure levels. Further evidence comes from [Cherchye et al. \[2015\]](#), who develop a revealed-preference framework allowing resource shares to vary with full income—defined as potential labor income plus non-labor income—and find no systematic dependence on income. Finally, [DLP²](#) illustrate the behavioral relevance of distribution factors by examining access to credit. They show that different forms of credit have heterogeneous effects on resource allocation, and that credit received by women shifts resources toward children.

²¹Three decade dummies are included, corresponding to the periods 1991–2000, 2001–2010, and 2011–2022. Regional dummy variables are defined according to the classification detailed in the sample selection subsection 4.1.

$$\text{If } \mathbb{1}_i = 0, \quad \text{then } \epsilon_i = \omega_i - \alpha_i \mathbf{z}_i^\omega - \beta_i \ln p_i - \gamma_i \ln y_i - \eta_i (\ln y_i)^2 \quad (14)$$

$$\text{If } \mathbb{1}_i = 1, \quad \text{then } \epsilon_i = \frac{\omega_i}{\varphi_i} - \alpha_i \mathbf{z}_i^\omega - \beta_i \ln \left(\frac{p_i}{\pi_i} \right) - \gamma_i \ln \left(\frac{\varphi_i y_i}{\pi_i} \right) - \eta_i \left[\ln \left(\frac{\varphi_i y_i}{\pi_i} \right) \right]^2 \quad (15)$$

The sharing rule is modeled as a deterministic logistic function of observable parental characteristics ($\mathbf{z}^\varphi$), child characteristics ($\mathbf{n}$), total expenditures, and prices.²² Unlike some earlier contributions (Bourguignon, 1999 and BDH), the specification does not rely on a Taylor expansion for linearization:

$$\varphi_i(y, p, \mathbf{z}^\varphi, \mathbf{n}) = \frac{e^{\psi_i(y, p, \mathbf{z}^\varphi, \mathbf{n})}}{1 + e^{\psi_i(y, p, \mathbf{z}^\varphi, \mathbf{n})}}, \quad (16)$$

$$\text{with } \psi_i(y, p, \mathbf{z}^\varphi, \mathbf{n}) = \mathbf{z}_i^{\varphi'} \theta_z + \theta_y \ln y_i + \theta_p \ln p_i + \mathbf{n}_i' \theta_n$$

where θ_z , θ_y , θ_p , and θ_n are vectors of parameters. Identification is achieved using the first condition of Proposition 1, with decade dummies serving as exclusion restrictions in $\mathbf{z}^\varphi$. The parental covariates $\mathbf{z}^\varphi$ include a constant, education, age, a set of dummies for labor force status, home ownership, and region of residence. The vector of child-related variables $\mathbf{n}$ encompass the number of children and its square, the average age of the children, the proportion of boys, and a dummy for the presence of same-gender siblings, with the latter three interacted with the number of children.

It is assumed that children exert no bargaining power in the household decision process. Resource allocation is determined entirely by the parent. Nonetheless, the sharing rule links parental and child characteristics to the intrahousehold distribution of resources. For example, older children are expected to receive a larger share of household expenditures due to higher consumption needs.

To test Point V of Proposition 1, an alternative specification is also considered in which the vector of child characteristics excludes the number of children. In this case, the number of children affects the sharing rule solely through a multiplicative scale factor $n^{-\rho}$.

$$\varphi_i(y, p, \mathbf{z}^\varphi, \mathbf{n}) = \frac{e^{\psi_i(y, p, \mathbf{z}^\varphi, \tilde{\mathbf{n}})}}{1 + e^{\psi_i(y, p, \mathbf{z}^\varphi, \tilde{\mathbf{n}})}} n^{-\rho} \quad (17)$$

Following BDH, shadow prices are specified as functions of both total expenditures and the number of children, capturing potential economies of scale:

$$\pi_i(p, y, \mathbf{n}) = \kappa_i \ln y_i \sqrt{n_i} \quad (18)$$

where κ_i is a parameter to be estimated. This specification effectively combines points (1), (3), and (5) of Proposition 1. For simplicity, the intercept is assumed to be zero.²³

Relevance of decade dummies as excluded shifters. To justify the use of decade dummies as excluded shifters in the reference specification, I verify their relevance, namely, that these time indicators predict clothing demand once the influence of other covariates has been partialled out. Using the Frisch–Waugh–Lovell decomposition, the residualized outcome $M_Z \omega$ is regressed on the residualized decade dummies $M_Z D$, with inference based on a joint Wald test and standard errors clustered by year, the unit of variation of the shifters. The results, reported in Table 1, reject $H_0 : \delta =$

²²Recent work by Dunbar et al. [2021] develops a framework for identifying random resource shares, defined as varying across observationally identical households.

²³As a robustness check, I also estimate the Barten price function including an intercept.

0 at conventional levels for both genders ($F(3, 44) = 4.23$, p-value = 0.010 for men; $F(3, 44) = 3.80$, p-value = 0.017 for women), implying that decade-level variation explains a significant share of residualized demand movements.

As shown in Online Appendix B, adjusted contrasts relative to the 2011–2022 baseline point to a sizeable dip in 1991–2000 for men (≈ -0.40 percentage point) and a marked peak in 2001–2010 for women ($\approx +0.52$ percentage point). The decade-to-decade differences are not merely random noise. Men in 2001–2010 exhibit about 0.67 percentage point higher residualized clothing demand than in 1991–2000 (p-value = 0.019), while the same comparison for women yields a gap of 0.43 percentage point (p-value = 0.032). The shape of the annual means of $M_{Z\omega}$ mirrors these findings, with a pronounced trough for men in the 1990s and a clear peak for women in the early 2000s, visually corroborating the statistical evidence and reinforcing the interpretation that decade variation is an economically meaningful and empirically strong source of identifying variation.

Table 1: Joint tests by gender

	F	(df ₁ , df ₂)	p -value	Partial R^2 (%)
Women	3.16	(3, 44)	0.0339	17.73
Men	4.20	(3, 44)	0.0106	22.28

Notes: This table reports the results of joint significance tests for residualized decade indicators in the Frisch–Waugh–Lovell regression of the residualized clothing budget share $M_{Z\omega}$ on $M_Z D$, where D includes the three decade dummies (1978–1990, 1991–2000, 2001–2010). Standard errors are clustered at the year level, which corresponds to the unit of variation of the excluded shifters. The 3-df F -test assesses the conditional relevance of the temporal shifters, and the partial R^2 measures the share of residual variance explained by the decade block. Results indicate that, for both women and men, decade variation explains a substantial portion of residual demand movements conditional on controls, thereby satisfying the relevance condition in the identification strategy.

3.2 Estimation Strategy and Instruments

The demand equations are estimated separately for men and women, reflecting the focus on unpartnered adults. The structural model, which jointly specifies preferences, the sharing rule, and the shadow price, is estimated in a single step for both childless adults and single parents. Identification is then achieved through the preference stability assumption.

The model addresses two main sources of endogeneity that may bias the estimated budget shares. The first arises from measurement error in total expenditures, which may reflect the infrequency and potential under-reporting of clothing purchases, as well as recall errors in household survey. Such measurement error may induce correlation between observed total expenditure and the error term in the budget share equation, leading to biased estimates. Following DLP, total income is used as an instrumental variable for total expenditures. Total income is uncorrelated with the consumption allocation error within a given time period, but correlated with total expenditures, making it a valid instrument. Total income also serves to address endogeneity stemming from recall errors, as long as income measurement errors are orthogonal to consumption recall errors, and income remains correlated with total expenditures.

Second, the literature documents that marital expectations may influence fertility choices, creating endogeneity in the number of children [Nakamura and Nakamura, 1992, Apps and Rees, 2001].²⁴

²⁴Single women can easily have children without resorting to adoption or assisted reproductive technologies. Consequently,

To mitigate this bias, the econometric model includes a decent set of sociodemographic controls. Moreover, recent empirical evidence has shown that predicted individual resource shares—especially those derived from assignable goods such as clothing—are reliable under the preference stability assumption [Bargain et al., 2021].

To set the instruments suitably, I write the budget share equations (14) and (15) as a unique budget share equation. To do this, multiply equation (14) by $(1 - \mathbb{1}_i)$ if childless single adult and equation (15) by $\mathbb{1}_i$ if single parent to obtain:

$$\epsilon_i = (1 - \mathbb{1}_i) \left[\omega_i - \alpha_i \mathbf{z}_i^\omega - \beta_i \ln p_i - \gamma_i \ln y_i - \eta_i (\ln y_i)^2 \right] + \mathbb{1}_i \left[\frac{\omega_i}{\varphi_i} - \alpha_i \mathbf{z}_i^\omega - \beta_i \ln \left(\frac{p_i}{\pi_i} \right) - \gamma_i \ln \left(\frac{\varphi_i y_i}{\pi_i} \right) - \eta_i \left(\ln \left(\frac{\varphi_i y_i}{\pi_i} \right) \right)^2 \right]$$

Rearranging the right-hand side gives:

$$\omega_i = \alpha_i \mathbf{z}_i^\omega + \beta_i \ln p_i + \gamma_i \ln y_i + \eta_i (\ln y_i)^2 + \mathbb{1}_i A_i + \epsilon_i \quad (19)$$

with

$$A_i = \beta_i \ln \left(\frac{1}{\pi_i} \right) + \ln \left(\frac{\varphi_i}{\pi_i} \right) \left[\gamma_i + \eta_i \ln \left(\frac{y_i^2 \varphi_i}{\pi_i} \right) \right] - \omega_i \frac{1 - \varphi_i}{\varphi_i}.$$

Then, I estimate the budget share equations by setting the iterated Two Stage Least Square Method. The nonlinear estimators are iterated until the estimated parameters and error/orthogonality condition covariance matrices settle.

I use all the exogenous variables as instruments, except total expenditures which are instrumented using total income. In addition, the set of instruments includes the product of $\mathbb{1}_i$ and a second-order polynomial in all the exogenous variables included in A_i . This yields a total of 38 instruments per equation.

To obtain suitable starting values, the demand equations are first estimated on the sub-sample of childless adults. These initial estimates are then used as starting points for the estimation on the full sample (with and without children). Furthermore, the cross-equation covariance matrix from the first-stage estimation is used as the initial weighting matrix for the iterative optimization algorithm. This approach improves convergence and robustness by explicitly accounting for the correlation structure of the residuals across equations.

4 Data

4.1 Sample Selection

The analysis draws on harmonized data from the United Kingdom’s Family Expenditure Survey (FES) for the period 1978–2022, including its successors, the Expenditure and Food Survey (EFS, from 2001) and the Living Costs and Food Survey (LCF, from 2008).²⁵ These surveys provide

single parents and childless individuals may have fundamentally different preferences regarding children, which undermines the assumption of stable preferences across marital statuses. This selection issue presents a challenge to inferring single parents’ preferences from those of observably similar childless singles.

²⁵These surveys have been previously used by Lise and Seitz [2011] and BDH.

detailed socio-economic information on households, including income, expenditure structure, and regional location.²⁶

The initial sample includes 136,960 households. The analysis is restricted to single adults, both with and without children, aged 18 to 55, excluding individuals with outlier values, negative total expenditures, or missing information. The final sample consists of 40,403 households: 14,070 single men, 10,911 single women, 1,579 single fathers, and 13,843 single mothers. Notably, single fathers account for only 10% of single-parent households. Among parents, 58% of single fathers and 51% of single mothers have only one child.

Table 2: Descriptive statistics from the FES 1978-2022: Single adults with and without children

		Single		Single Mother			Single Father		
		Women	Men	Children			Children		
				1	2	3	1	2	3
Expenditure data									
Clothing	Weekly expenditure (in £)	9.46 (18.44)	5.34 (15.60)	7.53 (15.07)	6.29 (13.51)	5.15 (11.27)	4.34 (11.97)	3.56 (10.28)	2.02 (6.90)
	Percentage of zeros	0.43 (0.50)	0.72 (0.45)	0.44 (0.50)	0.46 (0.50)	0.48 (0.50)	0.71 (0.46)	0.71 (0.45)	0.81 (0.39)
Total weekly expenditure		117.31 (83.99)	124.80 (94.32)	136.44 (95.07)	143.89 (96.73)	143.73 (93.80)	158.68 (103.31)	161.80 (105.14)	158.26 (91.54)
Individual and household characteristics									
Labor participation		0.71 (0.45)	0.65 (0.48)	0.50 (0.50)	0.43 (0.49)	0.29 (0.45)	0.55 (0.50)	0.51 (0.50)	0.41 (0.49)
Education (in years)		12.49 (3.42)	12.34 (3.44)	11.77 (2.44)	11.61 (2.25)	11.32 (2.10)	11.34 (2.19)	11.49 (2.27)	11.53 (2.31)
Age		39.25 (11.14)	38.40 (10.22)	34.96 (9.21)	34.01 (7.06)	33.47 (5.92)	38.63 (9.12)	37.49 (7.84)	35.88 (7.08)
House owner		0.52 (0.50)	0.49 (0.50)	0.28 (0.45)	0.28 (0.45)	0.19 (0.39)	0.46 (0.50)	0.45 (0.50)	0.31 (0.46)
Average age of children		-	-	7.83 (4.84)	7.88 (3.74)	7.86 (3.08)	8.99 (5.18)	8.26 (3.99)	8.21 (3.22)
Proportion of boys		-	-	0.51 (0.50)	0.50 (0.35)	0.51 (0.30)	0.58 (0.49)	0.53 (0.35)	0.57 (0.30)
Number of observations		10924	14059	7084	4639	1561	910	485	135

Notes: Expenditures are in 1987 pounds. Standard deviations are in parentheses.

4.2 Descriptive Statistics

The demand system includes two assignable goods (men's and women's clothings) alongside a composite good, which represents all other goods to ensure total budget shares sum to one. Prices are measured annually at the national level.

Control variables include years of completed education, age, employment status, home ownership, region of residence (12 regions), number of children (and its square), average age of children, proportion of boys, a dummy for the presence of same-gender siblings, four decade time dummies, annual prices, and weekly total expenditures.

The descriptive statistics in Table 2 reveal a substantial decline in adult clothing expenditures in the presence of children: from £9.5 to £7.5 for women, and from £5.3 to £4.3 for men, with further reductions as the number of children increases (down to £2.2 for fathers and £5.3 for mothers). These results echo the Rothbarth's view, which posits that household size reduces parental well-being as measured by individual consumption. The high incidence of zero clothing expenditures supports the use of total income as an instrument for total expenditure, given the infrequency of clothing purchases [Keen, 1986].

²⁶The twelve regions of Great Britain are: Northern, Northern Ireland, York and Humberside, East Midlands, West Midlands, East Anglia, Greater London, South-East, North Western, South Western, Wales, and Scotland.

5 Estimation Results and Discussion

5.1 Resource Share Equations

A key focus of this study is the effect of children on parental resource shares. As discussed, φ_i represents the share of total expenditures retained by the parent, while $\varphi_k = 1 - \varphi_i$ corresponds to the share allocated to the children. A negative coefficient in the sharing function indicates an increase in child-related resource allocation. Table 3 presents the results corresponding to the various identification restrictions discussed in Proposition 1. For each sample group, column (I) reports the estimates from the benchmark model, where φ_i is identified using decade dummies as exclusion restrictions. Columns (I) and (II) test the first point in Proposition 1, under the assumption that decade dummies do not directly enter the sharing rule. Column (I) uses the baseline sharing rule 16, while Column (II) adopts the alternative specification 17. Column (III) jointly evaluates restrictions II and V of Proposition 1, using exogenous variation in prices. Columns (IV) and (V) implement two distinct strategies to jointly test identification restrictions II and V as outlined in Proposition 1. In column (V), I augment the demand specification by including a dummy variable—entered in both $\mathbf{z}_i^\omega$ and φ_i —that equals one for households whose total expenditure exceeds the sample median. Finally, column (VI) examines the SAT hypothesis of DLP in conjunction with restriction V of Proposition 1.

The results presented in column (I) indicate that the presence of children has an augmenting effect on parental resources, for both fathers and mothers. Specifically, the negative sign associated with the number of children implies that the marginal cost of children rises significantly with family size, while the resources allocated per child decline as family size increases. This pattern is robust across all model specifications. The estimated coefficient ρ is positive and remains stable across specifications, indicating that the per-child cost declines with additional children. These findings are consistent with previous research, including Bargain and Donni [2012a], DLP, Penglase [2020], and BDH. In addition, the results suggest that older children are associated with higher parental costs. While most coefficients related to children’s characteristics for fathers are not statistically significant, the signs are generally consistent with those observed for mothers.

As expected, the parameter associated with same-gender siblings is positive. Specifically, the coefficient indicates that mothers retain a larger share of total expenditures when the household includes siblings of the same gender, suggesting the presence of economies of scale. A similar pattern is observed for fathers, although this coefficient is not statistically significant. For example, same-gender siblings who are close in age often share clothing, thereby reducing per-child expenditures. This variable therefore captures both the effects of family size and the influence of sibling gender composition.

Table 3: Estimated parameters of the individual resource shares $-\varphi_i$ and individual prices $-\pi_i$

Parameters											
Women						Men					
Parent variables											
	I	II	III	IV	V	VI	I	II	III	IV	V
$\theta_{intercept}$	2.210*** (0.690)	1.657*** (0.731)	5.571*** (2.619)	0.333 (0.329)	9.287*** (4.624)	0.444 (1.335)	0.915 (2.029)	-1.367 (2.720)	0.075 (11.494)	3.982 (4.831)	-59.678 (55.178)
$\theta_{education}$	-0.039 (0.028)	-0.038* (0.053)	-0.032* (0.053)	-0.118** (0.053)	-0.060 (0.025)	0.068 (0.072)	-0.001 (0.141)	0.032 (0.196)	3.131 (1.978)	-0.152 (0.120)	-1.511 (1.342)
θ_{age}	0.017 (0.014)	0.022 (0.018)	0.019 (0.018)	0.012 (0.015)	0.025 (0.018)	0.074 (0.057)	0.057 (0.036)	0.095* (0.051)	0.456 (0.163)	0.039 (0.030)	0.227 (0.328)
$\theta_{labor\ participation}$	-0.058 (0.174)	-0.009 (0.217)	-0.101 (0.256)	0.120 (0.256)	-0.115 (0.251)	0.489 (0.445)	0.467 (0.520)	0.562 (0.595)	-0.366 (2.082)	0.281 (0.331)	0.664 (1.792)
$\theta_{house\ owner}$	-1.322** (0.671)	-1.427* (0.743)	-1.767*** (0.741)	-0.646 (0.636)	-1.747*** (0.577)	(0.445)	(0.520)	(0.595)	-24.694 (16.181)	3.800 (8.194)	-3.214 (3.197)
Financial variables											
θ_{lnp}	-1.026*** (0.291)	-1.320*** (0.350)	-	-5.663 (4.717)	5.676 (3.497)	-2.451* (1.325)	-0.784 (0.780)	-0.528 (0.959)	-	2.754 (7.257)	-196.715 (189.000)
θ_{lny}	0.554 (0.722)	0.783 (0.770)	1.305* (0.777)	-	-	1.424 (1.133)	2.177* (1.165)	2.192 (1.416)	41.778 (28.434)	-	2.636 (2.138)
$\theta_{dummy\ for\ y}$	-	-	-	-	2.160*** (1.010)	-	-	-	-	-	11.480 (9.373)
Child variables											
θ_n	-0.933*** (0.195)	-	-	-	-	-	-1.252* (0.711)	-	-	-	-
θ_{n^2}	0.106*** (0.032)	-	-	-	-	-	0.147 (0.128)	-	-	-	-
$\theta_{kid\ age \times n}$	-0.017 (0.011)	-0.058*** (0.023)	-0.068** (0.027)	-0.055** (0.026)	-0.076*** (0.031)	-0.131 (0.085)	-0.004 (0.024)	-0.068 (0.061)	0.738 (0.678)	-0.036 (0.042)	-0.152 (0.174)
$\theta_{proportion\ of\ boys \times n}$	-0.082 (0.059)	-0.290*** (0.138)	-0.291* (0.154)	-0.273* (0.152)	-0.282* (0.157)	-0.369 (0.377)	-0.103 (0.215)	0.367 (0.574)	6.210 (7.048)	-0.145 (0.331)	0.349 (2.328)
$\theta_{kid\ gender \times n}$	0.087 (0.046)	0.394** (0.201)	0.456* (0.247)	0.416** (0.210)	0.381* (0.224)	0.862 (0.771)	0.116 (0.156)	0.570 (0.667)	-6.345 (6.163)	0.314 (0.441)	1.171 (1.752)
ρ	-	0.347*** (0.040)	0.348*** (0.043)	0.318*** (0.025)	0.274*** (0.046)	0.315*** (0.030)	-	0.400*** (0.124)	0.459*** (0.129)	0.318*** (0.118)	0.268** (0.177)
Shadow prices											
κ	-0.446*** (0.211)	-0.341*** (0.170)	-0.465*** (0.199)	-0.260*** (0.122)	-0.608*** (0.302)	0.032 (0.118)	1.000*** (0.500)	0.874*** (0.446)	0.740* (0.406)	0.594 (0.510)	-0.169 (0.172)
Number of observations	24748	24748	24748	24748	24748	24748	15634	15634	15634	15634	15634
(Number of free parameters, Instruments)	(47,59)	(46,58)	(48,58)	(48,58)	(50,58)	(35,58)	(47,59)	(46,58)	(48,58)	(48,58)	(50,58)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. The reported coefficients correspond to the estimated parameters from the internal specification of φ_i , as defined within the budget share equation. The dependent variable is the budget share devoted to adult clothing expenditures. Results are derived from simultaneous estimation of demand functions for individuals with (15) and without (14) children using the Two-Stage Least Squares (2SLS) method, under the assumption of preference stability. Demand systems are estimated separately by gender. For brevity, parameter estimates for regional dummy variables are omitted from the table. In each group, column (I) reports results for the benchmark model. Columns (I) test point I of Proposition I, using decade dummies as exclusion restrictions. Columns (II)–(VI) provide robustness checks, all imposing restriction V of Proposition I. Specifically, columns (II) and (III) test, respectively, restrictions I and III. Columns (IV) and (V) provide two alternative approaches to jointly assessing identification restrictions II and V from Proposition 1. In column (V), the demand function is estimated with the inclusion of an additional dummy variable in both z_i^* and φ_i . This dummy takes the value one for households with total expenditure above the sample median. Column (VI) examines the SAT assumption.

5.2 The *Two-Child Limit*: Blessing or Burden?

Figure 1 presents predicted per-child resource shares across the household expenditure distribution, together with 95% confidence intervals. While point estimates suggest lower per-child resource shares in larger families at the bottom of the expenditure distribution, these differences are estimated with considerable uncertainty, and the confidence intervals overlap substantially. As such, the results do not provide statistically conclusive evidence of systematic differences in per-child resource allocation across the expenditure distribution.

Complementary formal tests of differences in predicted resource shares provide a more nuanced picture (14 in Online Appendix). As family size increases, households allocate a larger share of resources to children overall, but this does not translate into higher per-child allocations. In particular, per-child allocations are significantly lower in larger families among low-expenditure households (especially in the fathers' specification), consistent with resource dilution under binding budget constraints.

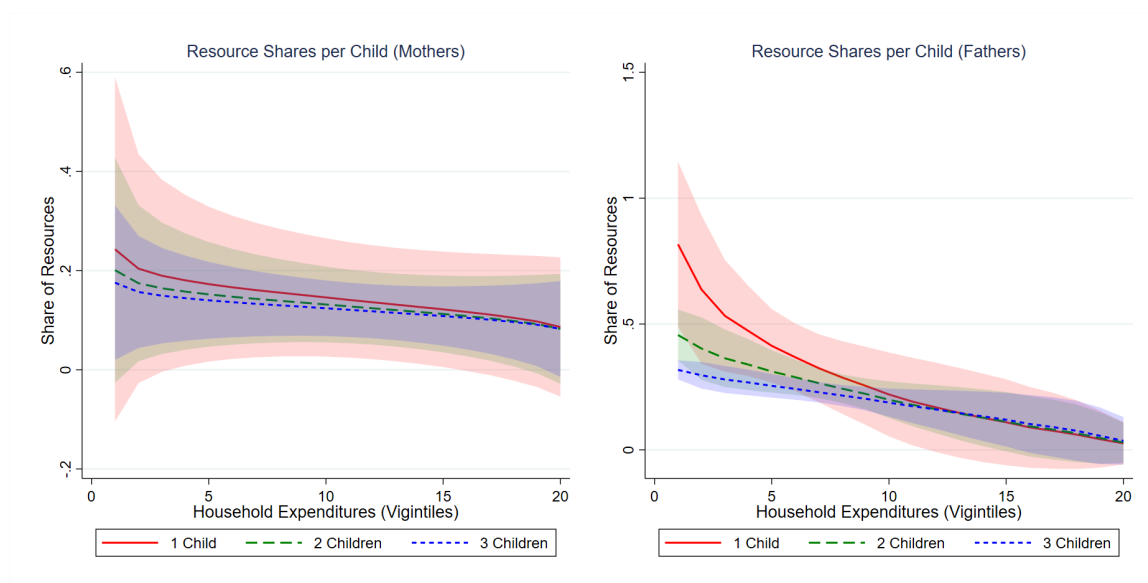


Figure 1: Children resource share by total expenditures

Notes: This figure plots the predicted per-child resource shares allocated by parents across different points of the household expenditure distribution. The x-axis shows the distribution of total household expenditures divided into 20 vigintiles, ranging from the 1st to the 20th. The y-axis displays the per-child resource shares for mothers (left panel) and fathers (right panel). The solid line represents households with one child, the dashed line indicates households with two children, and the densely dashed line corresponds to households with three children. Both panels show that family size is a key determinant of children shares in low-income families, but not in high-income families.

From the perspective of household income support, the absence of significant per-child resource dilution by family size is consistent with a policy design that does not automatically scale benefits with additional children. At the same time, the concentration of per-child constraints among low-expenditure households suggests that family-size-based rules may interact with resource scarcity in ways that merit attention when evaluating the policy from a child well-being perspective.

Table 4: Children resource share estimates – ϕ_k

Number of children	Single Mothers		Single Fathers	
	I	II	I	II
1	0.147** (0.061)	0.149*** (0.056)	0.222*** (0.085)	0.216*** (0.079)
2	0.256*** (0.076)	0.311*** (0.044)	0.383*** (0.079)	0.373*** (0.063)
3	0.357*** (0.083)	0.399*** (0.042)	0.533*** (0.097)	0.484*** (0.077)
Number of observations	13824		1575	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. This table presents estimated average expenditures on children, calculated at the average point of the sample. Column (I) reports results based on the baseline sharing rule specification, while Column (II) provides estimates using an alternative specification.

5.3 Intra-household Resource Allocation

Table 4 reports point estimates of children’s resource shares evaluated at the sample-mean covariates. Column (I) presents results under the baseline sharing rule specification, while Column (II) reports estimates from the alternative specification. Specifically, the model implies that a representative single mother with one child allocates 14.7 percent of resources to the child, whereas a representative single father allocates 22.2 percent.²⁷ For comparison, BDH estimate that a representative two-parent household with one child devote 14.2 percent of resources to that child. Given the overrepresentation of single mothers in the sample, comparisons with the couple estimates should primarily be made for this group. In this respect, the results suggest that, at least for mothers, couple-based estimates provide an externally valid reference point for single-mother households.

Point estimates from my benchmark measure—child resource shares evaluated at the characteristics of a representative parent—suggest higher child resource shares among single fathers. However, these differences are not statistically significant. An alternative approach based on averages of individual predicted shares, with inference conducted via Monte Carlo simulations, yields the same conclusion.²⁸ Taken together, these findings contrast with the prevailing consensus in the literature, which emphasizes women’s stronger child-oriented preferences.

In addition, the results highlight the nonlinear relationship between family size and the cost of children. For both genders, the marginal increase in child-related expenditures declines with family size.

²⁷Throughout, a representative single parent refers to a prediction obtained with all covariates set to their sample means (prediction-at-the-mean). Results are similar when averaging household-specific predictions over the sample distribution of covariates (average-of-predictions).

²⁸Formal inference is conducted using parametric Monte Carlo simulations that propagate the estimated variance-covariance matrix of the structural parameters through the nonlinear sharing rule. Specifically, I simulate the sampling distribution of average predicted child resource shares using 1,000 Monte Carlo replications and base statistical tests on the resulting distribution. Results on predicted mean child share resources are reported in the Online Appendix (section F).

5.4 Comparison with OECD-modified Equivalence Scale

The OECD-modified equivalence scale is widely used in income comparisons to adjust for differences in household size and composition. Under this scale, the first adult is assigned a weight of 1.0, additional adults a weight of 0.5, and children under 14 a weight of 0.3. Resource shares implied by the OECD scale can be directly compared to the child resource shares estimated in this paper. For example, in a single-parent household with one child under 14, the OECD scale implies that the child’s share of household resources would be $0.3/1.3 = 23\%$, which exceeds my empirical estimates for both single mothers (14.7%) and single fathers (22.2%).

The OECD equivalence scale is a normative construct that imposes fixed resource shares based solely on household size and composition, without accounting for heterogeneity in actual spending patterns related to gender, or parental preferences. In contrast, this study provides empirically grounded estimates of resource allocation, capturing variation across households that reflects consumption choices and demographic characteristics.

Therefore, relying exclusively on the OECD equivalence scale may lead to substantial mismeasurement of the resources available to children, especially in contexts where allocation patterns deviate systematically from the scale’s assumptions. This is particularly relevant for single-parent households, where observed spending behavior may diverge from the proportionality imposed by the OECD scale.

Table 5: Robustness tests

Models		Female				Male			
		Sargan statistics	LR-type statistics	Degrees of freedom	p-value	Sargan statistics	LR-type statistics	Degrees of freedom	p-value
Reference model		26.44		13		9.98		13	
Model with	region fixed effects excluded in φ	36.62	10.18	9	0.34	8.64	1.33	9	1.00
	total expenditures excluded in φ	18.83	7.61	3	0.05	6.05	3.93	3	0.27
	prices excluded in φ	16.98	9.46	3	0.02	4.32	5.66	3	0.13
	$\pi = s_0 \log y + s_1 \text{dkid}$	21.90	4.54	2	0.10	9.82	0.16	2	0.92
	$\pi = s_0 \log y \sqrt{n} + s_1 \log p$	22.95	3.49	2	0.17	8.72	1.26	2	0.53
	prices included in φ through n	23.24	3.20	3	0.36	8.54	1.43	3	0.70
	cubic term in Engel curves	23.37	3.07	2	0.22	3.45	6.53	2	0.04
Model without	economies of scale	26.08	0.36	2	0.83	12.44	2.47	2	0.29

Notes: This table reports Sargan and likelihood-ratio (LR)-type statistics for alternative model specifications. For both females and males, the first column in each panel presents the Sargan statistic, defined as the value of the objective function multiplied by the number of observations. The second column reports LR-type statistics, computed as the absolute difference between the Sargan statistic of the baseline specification and that of the corresponding alternative specification. For all alternative models, the objective function is evaluated using Alternative specifications II and III correspond to the identification alternatives described in Proposition I (points II and III).

5.5 Sensitivity Analysis

I assess identification stability using likelihood-ratio (LR)-type tests that compare the baseline model to alternatives exploiting different sources of variation and richer demand structures. In each case, I recompute the alternative model’s objective function (J) using the baseline weighting matrix, so the difference in J is χ_q^2 under the null.

Across both genders, most alternatives are not statistically different from the baseline. In particular, replacing time with regional variation in φ yields p-value far from rejection, indicating that the sharing rule parameters are not tied to a single dimension of variation. Excluding total expenditures from φ is at most marginally rejected. The only systematic tension arises when prices are excluded

from φ : the p-value rejects for women ($p \approx 0.02$) and is borderline for men ($p \approx 0.08$). This pattern is theory-consistent—price movements are informative for the mapping from observables to needs.

I also probe robustness of the Barten scale and Engel curves. Adding a preschool-child term, allowing the scale to depend on prices, enriching Engel curves with cubic terms, and even removing economies of scale all leave the J-statistic essentially unchanged ($p\text{-value} > 0.1$). Hence, the baseline results do not hinge on a particular scaling or curvature assumption, and identification does not rely on functional-form knife-edges.

Further, Table 13 in Online Appendix reports a series of robustness checks. Column I controls for child support and alimony as distribution factors, while Column II allows the sharing rule to vary by birth cohort. Columns III and IV restrict the identifying sample to childless singles observationally comparable to parents using, respectively, cell-wise capacity-constrained matching, and proportionate stratified matching. Column V further restricts the sample to the region of common support defined by propensity score overlap.²⁹ Across all specifications, the structural parameters of the sharing rule and shadow price remain stable, indicating that the baseline results are not driven by non-fungible income sources, cohort effects, or compositional differences.³⁰

6 Conclusion

Several models have attempted to assess the cost of children for parents, but most focus exclusively on two-parent households, overlooking the increasing prevalence of single-parent families in OECD countries [Skinner et al., 2008, Nieuwenhuis and Maldonado, 2018]. This paper extends the collective consumption approach to explicitly account for the decision-making processes of single-parent households. By leveraging a model that exploits the stability of preferences and the adult-exclusive goods, I estimate the sharing rule and the associated cost of children in one-adult households.

Drawing on a unique, harmonized sample of single adults—with and without children—from three waves of UK consumption survey data, covering the years 1978–2022, I demonstrate that resource share estimates commonly applied to two-parent households remain externally valid for single-parent families, at least for single mothers. Across the expenditure distribution, per-child resource shares do not vary significantly with family size once estimation uncertainty is accounted for, particularly in mothers’ allocation patterns; for fathers, statistically significant differences are confined to the lower part of the distribution. From the perspective of household income support, the absence of resource per-child dilution is consistent with a policy design that does not mechanically scale benefits with additional children. At the same time, the concentration of per-child constraints among low-expenditure households implies that family-size-based rules may have uneven implications for child well-being across the resource distribution.

A comprehensive set of LR-type tests shows that my estimates are stable to the source of identifying variation and to rich perturbations of the Barten scale and Engel-curve specification. Switching from temporal to regional variation produces statistically equivalent fit. Also, allowing for additional curvature or alternative scaling leaves the objective function unchanged.

A potential limitation of this paper concerns the endogeneity of fertility choices, which may be shaped by expectations about partnership formation and thus challenge the assumption of preference stability across marital statuses. Although this issue is mitigated by the inclusion of rich sociodemographic controls, it is not entirely resolved. To assess robustness, three complementary procedures restrict the sample of childless singles to those observably similar to single parents. The

²⁹See the Online Appendix (Section E) for details on the methods used to construct comparable samples of childless singles.

³⁰Additional empirical results on the labeling effect are presented in the Online Appendix (Section D).

resulting estimates are qualitatively unchanged. Future research could explore revealed preference approaches—such as those proposed by Cherchye et al. [2011, 2015]—to estimate bounds on intra-household sharing without relying on preference stability.

7 Statements and Declarations

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8 Online Appendix

A Identification Proof

Proof.

1. Let's write $\mathbf{z}^\omega = (z^{\omega 0}, z^{\omega 1})$ where $z^{\omega 1} \notin \mathbf{z}^\pi$ and $z^{\omega 1} \notin \mathbf{z}^\varphi$. Then consider two values of $z^{\omega 1}$, say $z_1^{\omega 1}$ and $z_2^{\omega 1}$. This provides a system of two equations with two unknowns:

$$\begin{aligned}\omega(\bar{p}, \mathbf{z}^\omega, \bar{\mathbf{z}}^\pi, \bar{\mathbf{z}}^\varphi, \bar{y}, \bar{\mathbf{n}}) &= g(\bar{p}, z_1^{\omega 1}, \pi(\bar{p}, \bar{\mathbf{z}}^\pi, \bar{y}, \bar{\mathbf{n}}) \cdot \bar{p}, \varphi(\bar{p}, \bar{\mathbf{z}}^\varphi, \bar{y}, \bar{\mathbf{n}}) \cdot \bar{y}) \\ \omega(\bar{p}, \mathbf{z}^\omega, \bar{\mathbf{z}}^\pi, \bar{\mathbf{z}}^\varphi, \bar{y}, \bar{\mathbf{n}}) &= g(\bar{p}, z_2^{\omega 1}, \pi(\bar{p}, \bar{\mathbf{z}}^\pi, \bar{y}, \bar{\mathbf{n}}) \cdot \bar{p}, \varphi(\bar{p}, \bar{\mathbf{z}}^\varphi, \bar{y}, \bar{\mathbf{n}}) \cdot \bar{y})\end{aligned}$$

Under some regularity conditions, this system of two equations generally has a unique solution for $\pi(\bar{p}, \bar{\mathbf{z}}^\pi, \bar{y}, \bar{\mathbf{n}})$ and $\varphi(\bar{p}, \bar{\mathbf{z}}^\varphi, \bar{y}, \bar{\mathbf{n}})$, and another for each choice of $(\bar{p}, \bar{\mathbf{z}}^\pi, \bar{\mathbf{z}}^\varphi, \bar{y}, \bar{\mathbf{n}})$.

- 2-3. Combine (2) and (3), the proof of this statement is similar to the previous one.³¹
4. Let's consider choosing a parametric specification for the sharing rule function, specifically a linear form that depends on k parameters. There are k degrees of freedom, representing the k identifiable parameters. The idea is that we need k equations to determine the unknown parameters.

5. Let

$$\omega = g(\mathbf{z}^\omega, \pi_1(p, \mathbf{z}^\pi, y) \cdot \pi_2(n) \cdot p, \varphi_1(p, \mathbf{z}^\varphi, y) \cdot \varphi_2(n) \cdot y)$$

By varying the values of y and n , we might obtain the following equations:

$$\begin{aligned}\omega &= g(\mathbf{z}^\omega, \pi_1(\bar{p}, \bar{\mathbf{z}}^\pi, y_1, \bar{\mathbf{n}}) \cdot \pi_2(n_1) \cdot \bar{p}, \varphi_1(\bar{p}, \bar{\mathbf{z}}^\varphi, y_1, \bar{\mathbf{n}}) \cdot \phi_2(n_1) \cdot y_1) \\ \omega &= g(\mathbf{z}^\omega, \pi_1(\bar{p}, \bar{\mathbf{z}}^\pi, y_1, \bar{\mathbf{n}}) \cdot \pi_2(n_2) \cdot \bar{p}, \varphi_1(\bar{p}, \bar{\mathbf{z}}^\varphi, y_1, \bar{\mathbf{n}}) \cdot \varphi_2(n_2) \cdot y_1) \\ \omega &= g(\mathbf{z}^\omega, \pi_1(\bar{p}, \bar{\mathbf{z}}^\pi, y_2, \bar{\mathbf{n}}) \cdot \pi_2(n_1) \cdot \bar{p}, \varphi_1(\bar{p}, \bar{\mathbf{z}}^\varphi, y_2, \bar{\mathbf{n}}) \cdot \varphi_2(n_1) \cdot y_2) \\ \omega &= g(\mathbf{z}^\omega, \pi_1(\bar{p}, \bar{\mathbf{z}}^\pi, y_2, \bar{\mathbf{n}}) \cdot \pi_2(n_2) \cdot \bar{p}, \varphi_1(\bar{p}, \bar{\mathbf{z}}^\varphi, y_2, \bar{\mathbf{n}}) \cdot \varphi_2(n_2) \cdot y_2)\end{aligned}$$

The above example shows a set of 4 equations with 4 unknowns. Then one can identify the sharing function as well as the economies of scales. This completes the proof.

■

B Relevance Tests for Time Variation in Identification

I assess the relevance of the time variation used for identification by testing whether decade dummies significantly shift residualized demand once other factors are partialled out. Using the Frisch-Waugh-Lovell theorem, I regress the residualized outcome $r_\omega = M_Z \omega$ on the residualized decade indicators (r_{D1}, r_{D2}, r_{D3}) , clustering standard errors at the year level—the unit of variation of the excluded shifters. A joint Wald test of $H_0 : \delta = 0$ provides the block-level significance, and the corresponding partial R^2 is computed from the F -statistic. As seen in Table 6 in the main text, in both the female

Table 6: Differences vs base 2011-2022, clustered year by gender

Decade dummies	Women			Men		
	Est. value	Std err.	p-value	Est. value	Std err.	p-value
1978-1990	0.003	0.002	0.188	0.002	0.003	0.561
1991-2000	0.001	0.002	0.592	-0.005	0.003	0.059
2001-2010	0.005	0.002	0.030	0.001	0.004	0.783

Notes: This table reports the adjusted means of the residual $M_{Z\omega}$ (residualized clothing budget share) by decade, controlling for the full set of covariates Z and clustering standard errors at the year level. The 2011–2022 decade serves as the reference category. Coefficients represent the average deviation (in budget share points) relative to this baseline. Among women, the 2001–2010 decade shows a higher residual demand level (+0.005, $p \approx 0.025$), while other decades are statistically equivalent from the baseline. Among men, the 1991–2000 decade displays a significantly lower level (−0.005, $p = 0.077$), with other decades showing no significant difference.

and male subsamples, the null is rejected: decade variation explains a substantial share of residual demand movements conditional on controls, satisfying the relevance condition.

To quantify the magnitude of these shifts (in budget share points) and identify which decades deviate from the baseline, I estimate decade-specific adjusted means of $M_{Z\omega}$. For women, the level is highest in the early to mid-2000s, with the 2001–2010 period being approximately +0.0052 ($p = 0.0246$) relative to the 2011–2022 baseline and +0.0043 ($p = 0.0317$) higher than 1991–2000. For men, the largest gap occurs between 2001–2010 and 1991–2000, at about +0.0067 ($p = 0.0185$), while 1991–2000 is roughly −0.0069 ($p = 0.0048$) below 1978–1990 and −0.00495 ($p = 0.077$) below the 2011–2022 baseline. These estimates indicate that for women, the early 2000s stand out as a period of high residual demand, whereas for men the 1990s exhibit markedly lower values compared to both earlier and later decades.

Table 7: Pairwise decade contrasts, clustered year by gender

Parwise decade contrast	Women			Men		
	Est. value	Std err.	p-value	Est. value	Std err.	p-value
(1991-00 vs 1978-90)	-0.002	0.002	0.352	-0.007	0.002	0.005
(2001-10 vs 1978-90)	0.002	0.002	0.244	-0.001	0.003	0.800
(2001-10 vs 1991-00)	0.004	0.002	0.053	0.006	0.003	0.039

Notes: This table reports estimated mean differences in $M_{Z\omega}$ (residualized clothing budget share) between decades, controlling for the full set of covariates Z and clustering standard errors at the year level. Coefficients represent deviations in budget share points between the indicated decades. The results highlight gender-specific temporal patterns, with a peak in the early 2000s for women and a pronounced dip in the 1990s for men.

Finally, I include a visual diagnostic by plotting the annual mean of $M_{Z\omega}$ with 95% confidence intervals, shading the background by decade blocks. This provides a direct visual check that the annual trends support the decade-level breaks detected by the statistical tests. The figures confirm the patterns: a pronounced peak for women in the early-to-mid 2000s and a deep trough for men in the mid-1990s.

³¹The complete proof for the statement 2 is given by [Dunbar et al., 2013, online appendix].

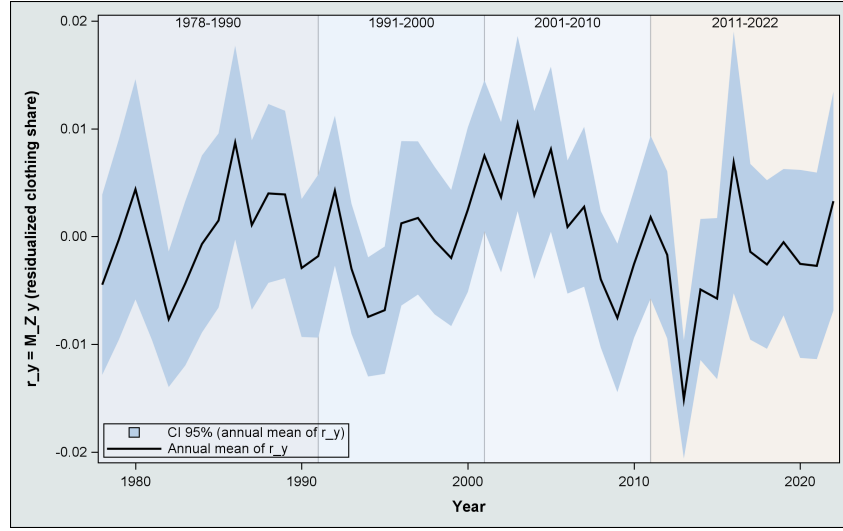


Figure 2: Annual means of $M_Z\omega$ with confidence intervals and decade segments — Women

Notes: This figure plots the annual mean of the residual $M_Z\omega$ (residualized clothing budget share) together with its 95% confidence interval, overlaid with shaded backgrounds denoting decade blocks. The graph provides a visual check on whether the annual trends align with the temporal breaks detected in the formal tests (Tables 6-7) and highlights potential peaks or troughs in the series.

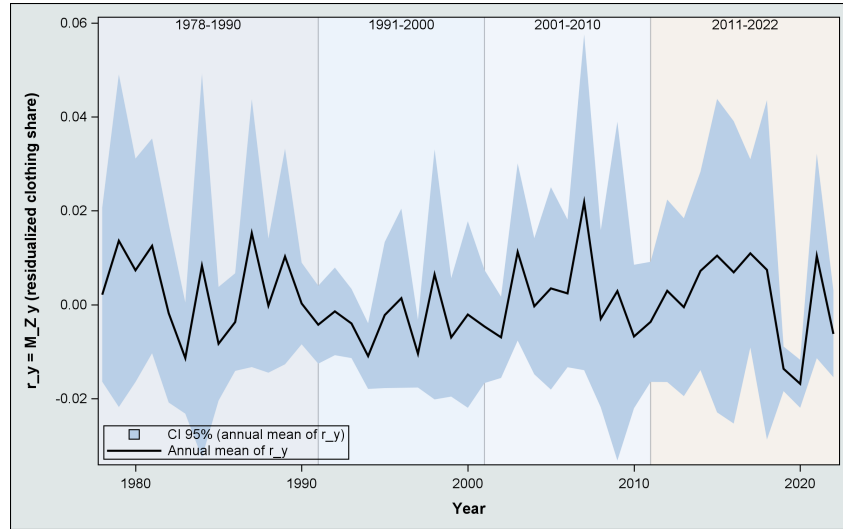


Figure 3: Annual means of $M_Z\omega$ with confidence intervals and decade segments — Men

Notes: See the notes in Figure 2.

C Budget Share Equations

Table 8 reports estimates of the clothing budget share equations for men and women. The demand estimates reveal that socio-demographic characteristics play a limited role, with age being the primary determinant of clothing budget allocation for both men and women. For both genders, age exhibits a nonlinear relationship with clothing expenditure. Specifically, the budget share decreases with age but increases at older ages, as indicated by the significantly negative coefficient on age and the positive coefficient on age squared.

D Labeling effect

This section examines whether external income sources are treated as fungible with earned income or instead exhibit behavioral “labeling” in household allocation decisions. Following the literature on income labeling [see e.g., Kooreman, 2000], I use expenditures on children’s clothing as a proxy for child-specific resource allocation.

In the United Kingdom, state transfers related to children—such as child benefit and income supplements—are largely uniform across households with children, while private transfers (maintenance and alimony payments) display substantial heterogeneity. The relative uniformity of state transfers is evidenced by their near-universality (Figure 4), limited dispersion conditional on family size (Figure 5), and compressed distributions among recipients (Figure 6). In contrast, private transfers are frequently absent and highly dispersed when positive (Figure 4). Therefore, I aggregate child benefit and income supplements into a single measure of state child-related benefits, rather than modeling them separately.

D.1 Children’s Budget Shares Specification

For each $i = f, m$, I estimate the children’s clothing budget share separately as

$$w_i^k = X_i' \alpha_i^k + \lambda_i^k \ln y_i + \lambda_{i,a}^k \ln a_i + \lambda_{i,b}^k \ln b_i + \xi_i \hat{u}_i + \sigma_i \lambda_i + \epsilon_i^k, \quad (20)$$

where w_i^k denotes the budget share of children’s clothing. Total household expenditure, y_i , is treated as endogenous. The variable a_i captures private transfers in the form of maintenance or alimony payments, while b_i denotes state-provided child-related benefits. The vector X_i includes the intercept and demographic controls such as parental age, educational attainment, and the number of children.

Endogeneity of total household expenditure is addressed using a control-function approach. Specifically, $\hat{u}_i$ denotes the residual from a first-stage regression of $\ln y_i$ on disposable income and a set of exogenous covariates. Inclusion of $\hat{u}_i$ in the budget share equation allows for correlation between total expenditure and unobserved determinants of child clothing demand. The coefficient ξ_i captures the magnitude of this correlation.

A second econometric challenge arises from the prevalence of zero reported expenditures on children’s clothing, which represent about 43% of observations among single mothers and 54% among single fathers. To account for this censoring, I estimate equation (20) within a Heckman sample selection framework.

The latent propensity to observe positive child clothing expenditure is modeled as

$$d_i^* = \Psi_i' \tau_i + D_i \delta_i + v_i \quad (21)$$

where $d_i = 1$ if $w_i^k > 0$ and $d_i = 0$ otherwise. The vector D_i contains exclusion restrictions that affect the probability of observing a purchase but are assumed not to influence the conditional budget share. I use decade dummies as exclusion restrictions, motivated by long-run changes in fashion environments and clothing prices. These factors are assumed to affect the likelihood that a purchase occurs, while remaining orthogonal to intra-household allocation decisions conditional on purchase. The resulting inverse Mills ratio, λ_i , is included in equation (20) to correct for sample selection.

D.2 Results

Table 9: Estimates of the children's clothing budget share

		Women			Men		
Parameters		I	II	III	I	II	III
Financial variables							
$\lambda_{\log(state\ benefit)}^k$		0.014*** (0.005)	0.016*** (0.004)	0.018*** (0.004)	-0.013 (0.016)	-0.006 (0.009)	0.004 (0.009)
$\lambda_{\log(alimony)}^k$		0.011 (0.007)	0.011** (0.005)	-0.002 (0.005)	0.086*** (0.031)	0.050** (0.022)	0.045** (0.021)
$\lambda_{\log(total\ expenditures)}^k$		-0.039*** (0.005)	-0.016*** (0.004)	0.021*** (0.001)	-0.048*** (0.012)	-0.010 (0.007)	0.012*** (0.003)
Parent variables							
$\alpha_{education}^k$		0.001 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.002* (0.001)	-0.001** (0.001)	-0.001** (0.001)
α_{age}^k		-0.002* (0.001)	-0.001 (0.001)	-0.001* (0.001)	0.000 (0.002)	0.001 (0.001)	0.000 (0.001)
α_{age2}^k		0.002 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.002 (0.003)	-0.001 (0.002)	-0.001 (0.002)
$\alpha_{labor\ participation}^k$		0.004 (0.002)	0.004*** (0.002)	-0.002 (0.002)	0.000 (0.006)	-0.001 (0.004)	-0.005 (0.003)
Child variables							
$\alpha_{number\ of\ kids}^k$		0.007*** (0.001)	0.010*** (0.001)	0.005*** (0.001)	0.003 (0.004)	0.006*** (0.002)	0.003* (0.002)
$\alpha_{mean\ age\ of\ kids}^k$		0.002*** (0.000)	0.001** (0.000)	0.000 (0.000)	0.003*** (0.001)	0.001 (0.000)	0.000 (0.000)
$\alpha_{ratio\ of\ boys}^k$		-0.001 (0.002)	-0.007*** (0.001)	-0.008*** (0.001)	-0.001 (0.006)	-0.002 (0.003)	-0.001 (0.003)
$\lambda_{gender\ of\ kids}^k$		0.003 (0.002)	0.001 (0.002)	0.000 (0.002)	0.008 (0.007)	0.001 (0.004)	0.001 (0.004)
Correction and selection terms							
ξ		0.040*** (0.006)	- -	- -	0.043*** (0.014)	- -	- -
Number of observations		13824	13824	13824	1575	1575	1575

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. This table reports parameter estimates for children's clothing budget share equations, estimated separately for women and men. The dependent variable is the budget share of children's clothing. Column (I) presents estimates from a Heckman selection model combined with a control function approach to simultaneously address the selection bias resulting from the high frequency of zero-expenditure observations and the endogeneity of total household expenditures. Column (II) provides Two-Stage Least Squares (2SLS) estimates to account for the endogeneity of total expenditures. Column (III) reports Ordinary Least Squares (OLS) estimates. For brevity, coefficients on region fixed effects, price controls, and selection equation covariates are not reported.

Table 9 reports estimates separately for women and men under three specifications: (i) Heckman selection with control function (preferred), (ii) two-stage least squares, and (iii) ordinary least squares. State benefits are positively and significantly associated with the child clothing budget

share for women, while private maintenance is positively and significantly associated with the child clothing budget share for men.

Table 10 reports Wald tests of coefficient differences, conducted separately for women and men. The table presents both bilateral tests of equality and unilateral tests. The bilateral tests evaluate the null hypothesis $H_0 : \lambda_{i,m}^k = \lambda_i^k$ or $\lambda_{i,b}^k = \lambda_i^k$, while the unilateral tests assess whether the marginal effects of external income sources are strictly larger than that of total household expenditure.

The bilateral Wald tests strongly reject equality between the marginal effects of external income sources and total household expenditure for both women and men. Focusing on the unilateral tests, the null hypothesis that external income sources have marginal effects on the child clothing budget share no larger than those of total household expenditure is rejected for both groups. For men, the marginal effect of private maintenance is statistically larger than that of state benefits, whereas no such conclusion can be established for women. Taken together, these results reject full income fungibility and provide evidence consistent with external income labeling, in that external income sources generate source-dependent marginal responses in child clothing expenditure shares.

Table 10: Wald tests of coefficient differences

Coefficient differences	Women				Men			
	Est. value	Wald χ^2	p-value (two-sided)	p-value (one-sided)	Est. value	Wald χ^2	p-value (two-sided)	p-value (one-sided)
$\lambda_{i,b}^k - \lambda_i^k$	0.053	53.38	0.000	0.000	0.035	4.90	0.027	0.013
$\lambda_{i,m}^k - \lambda_i^k$	0.050	25.16	0.000	0.000	0.134	14.43	0.000	0.000
$\lambda_{i,m}^k - \lambda_{i,b}^k$	-0.003	0.13	0.717	0.642	0.098	7.77	0.005	0.003

Notes: This table reports Wald tests of coefficient differences, including both bilateral and unilateral tests. For the bilateral tests, reported p -values correspond to tests of the null hypothesis $H_0 : \text{Diff} = 0$ against $H_1 : \text{Diff} \neq 0$. For the unilateral tests, reported p -values correspond to tests of $H_0 : \text{Diff} \leq 0$ against $H_1 : \text{Diff} > 0$. Wald statistics are asymptotically distributed as χ^2 .

E Construction of Comparable Samples of Childless Singles

This section describes three complementary procedures used to restrict the sample of childless singles to those who are observably similar to single parents. The primary objective is to ensure that the identification of the sharing rule does not rely on extrapolation outside the covariate support of single parents and to mitigate the risk that results are driven by compositional differences between the identifying group (childless singles) and the target group (single parents). Consistent with the empirical design of the paper, all procedures are implemented separately by gender $i \in \{f, m\}$.

E.1 Notation and Setup

Let $i \in \{f, m\}$ index gender. Let $\mathbb{1}_{ji} = 1$ indicate that individual j of gender i is a single parent, and $\mathbb{1}_{ji} = 0$ indicate a childless single. Let $\mathbf{z}_{ji}$ denote a vector of observable characteristics. The analysis focuses on a parsimonious set of covariates that exhibit the largest structural differences between parents and childless singles: labor-force participation and homeownership status. I recognize that other characteristics (e.g., age, education) exhibit substantial overlap in the data.

Cells $c \in \mathcal{C}$ are defined by the cross-classification of labor-force participation and homeownership:

$$c(j) = (\text{Participation}_{ji}, \text{Owner}_{ji}) \in \{0, 1\} \times \{0, 1\} \quad (22)$$

Let N_{ci}^P be the number of single parents in cell c and gender i , and N_{ci}^C be the number of childless singles in the same cell. Throughout these procedures, I retain the full sample of single parents and select a specific subset of childless singles.

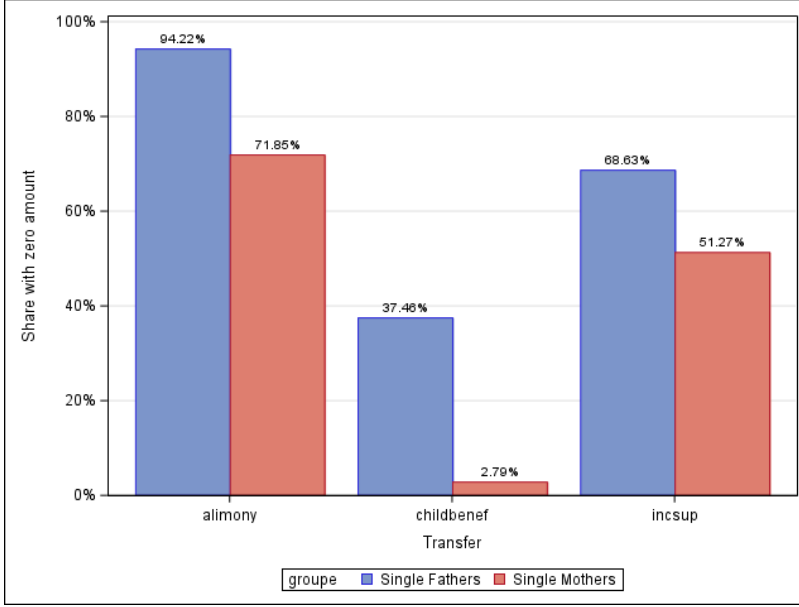


Figure 4: Share of zero transfers by transfer type and group

Notes: The bars report the proportion of individuals with zero receipt for each transfer type, separately for lone mothers and lone fathers. Zero receipt is defined as a reported amount equal to zero; observations with missing values are excluded.

E.2 Method A: Cell-wise Capacity-Constrained Matching

This method constructs a childless subsample such that, within each cell c , the number of childless singles retained is proportional to the number of parents in that cell, subject to feasibility constraints. It enforces comparability on the most salient discrete dimensions while preserving statistical power.

Algorithm:

1. Compute cell counts N_{ci}^P and N_{ci}^C for each gender i .
2. Compute the feasible common multiplier k_i :

$$k_i \equiv \left\lceil \min_{c \in \mathcal{C}: N_{ci}^P > 0} \frac{N_{ci}^C}{N_{ci}^P} \right\rceil \quad (23)$$

3. For each cell c , randomly sample (without replacement) exactly $\tilde{N}_{ci}^C = k_i \cdot N_{ci}^P$ childless singles.
4. Construct the restricted dataset as the union of all parents and the sampled childless singles.
5. **Capacity Constraint:** If a cell is under-supplied ($N_{ci}^C < N_{ci}^P$, resulting in $k_i = 0$), I implement a variant where $\tilde{N}_{ci}^C = \min\{N_{ci}^C, k^{\text{fix}} \cdot N_{ci}^P\}$ with $k^{\text{fix}} = 1$. This approach retains all available childless singles in scarce cells to preserve within-cell comparability without discarding parental observations.

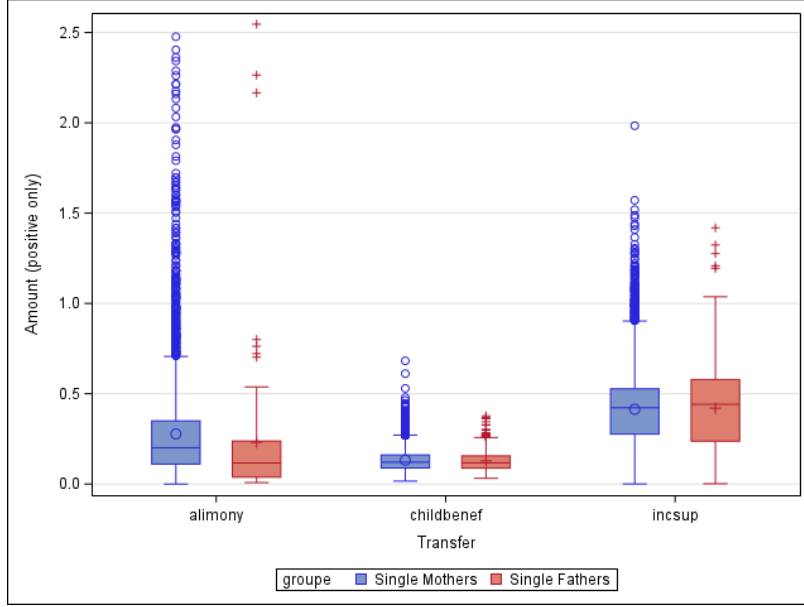


Figure 5: [Distribution of positive transfers](#)

Notes: This figure display the distribution of positive transfer amounts in levels for alimony, child benefit, and income support, separately for lone mothers and lone fathers. Boxes represent the interquartile range, with medians indicated by horizontal lines; whiskers extend to 1.5 times the interquartile range.

E.3 Method B: Proportionate Stratified Matching

Method B matches the distribution of childless singles across cells to the parental distribution as closely as possible while maximizing the feasible sample size under cell-level capacity constraints.

Target Cell Proportions: Define parental cell shares as:

$$\pi_{ci} \equiv \frac{N_{ci}^P}{\sum_{c' \in \mathcal{C}} N_{c'i}^P} \quad (24)$$

I seek an optimal childless sample size N_i^* such that the cell counts $\tilde{N}_{ci}^C \approx \pi_{ci} N_i^*$ do not exceed the available capacity N_{ci}^C . The maximal feasible sample size is determined by the tightest cell constraint:

$$N_i^* \equiv \left\lceil \min_{c \in \mathcal{C}: \pi_{ci} > 0} \frac{N_{ci}^C}{\pi_{ci}} \right\rceil \quad (25)$$

The restricted cell counts are then set as:

$$\tilde{N}_{ci}^C = \min \{N_{ci}^C, \lceil \pi_{ci} N_i^* \rceil\} \quad (26)$$

I sample $\tilde{N}_{ci}^C$ childless singles at random within each cell.

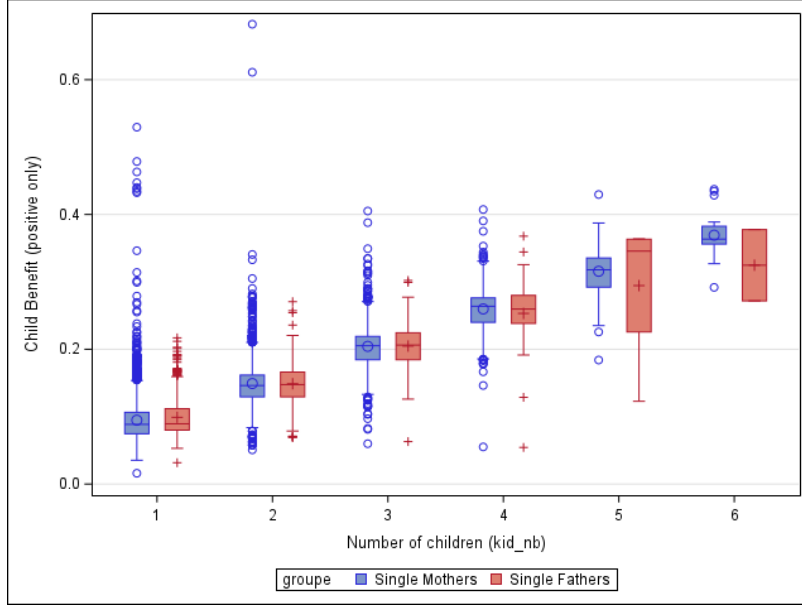


Figure 6: Child benefit by number of children (positive amounts only)

Notes: This figure reports boxplots of positive child benefit amounts by number of children, separately for single mothers and single fathers. Boxes represent the interquartile range, the horizontal line denotes the median, and whiskers extend to 1.5 times the interquartile range.

E.4 Method C: Propensity Score Common Support

This method generalizes the notion of similarity to a multivariate index based on predicted parenthood, implementing the standard overlap restriction common in the program evaluation literature.

Step 1: Propensity Score Estimation

For each gender i , I estimate a logit model:

$$\hat{p}_{ji} = \Pr(\mathbb{1}_{ji} = 1 \mid X_{ji}) \quad (27)$$

where X_{ji} includes demographics (age, education), socioeconomic characteristics, and regional fixed effects.

Step 2: Overlap Restriction

Let

$$\underline{p}_i = \min_{j:\mathbb{1}_{ji}=1} \hat{p}_{ji} \quad \text{and} \quad \bar{p}_i = \max_{j:\mathbb{1}_{ji}=1} \hat{p}_{ji}.$$

I retain all parents ($\mathbb{1}_{ji} = 1$) and childless singles ($\mathbb{1}_{ji} = 0$) whose predicted scores fall within the parental support: $\hat{p}_{ji} \in [\underline{p}_i, \bar{p}_i]$. To ensure results are not driven by outliers, I also report estimates using a trimmed support based on the $[p_5, p_{95}]$ interval of the parental propensity score distribution.

Table 11: Matching methods and resulting sample sizes

	Women				Men			
	Method A	Method B	Method C-support	Method C-trim	Method A	Method B	Method C-support	Method C-trim
Childless parents retained	8 703	4 747	10 924	8 555	1 575	9 916	13 825	11 658
Fraction of childless parents dropped	20.33%	56.55%	0.00%	21.69%	88.80%	29.47%	1.66%	17.08%
Cell exact match	Yes	Approx.	No	No	Yes	Approx.	No	No

Notes: The table reports retained childless observations and exclusion rates under alternative matching methods. Method C-support applies the common support condition, while Method C-trim trims the propensity score distribution at the 5th and 95th percentiles.

E.5 Diagnostics

Table 11 reports, for each method, the number of retained childless observations and the corresponding exclusion rates. Among women, Method B excludes the largest share of observations, removing 56.55 percent of the childless sample. Among men, Method A is the most restrictive, retaining only 11.2 percent of childless observations. The data include only 1,575 childless men, yielding an equal number of fathers and childless adult males.

Under the propensity score common support approach, no female observations are excluded when the support is defined by the minimum and maximum of the mothers’ propensity score distribution. In contrast, trimming the support to the 5th–95th percentile interval excludes 21.69 percent of female observations. A similar pattern emerges for men, although exclusion rates are substantially smaller: fewer than 2 percent of observations are lost when the support is defined using the minimum and maximum of the mothers’ propensity score distribution.

F Additional Results

Table 12 reports average predicted child resource shares among single parents, computed as averages of individual predicted shares. Inference is conducted using parametric Monte Carlo simulations that propagate estimation uncertainty in the model parameters. The results are consistent with those reported in the main text (Table 4), where child resource shares are evaluated at the characteristics of a representative parent.

Table 14 reports estimated differences in predicted child resource shares along the household expenditure distribution. Columns “Diff 2 vs 1” and “Diff 3 vs 2” report marginal differences in the total share of resources allocated to children when moving from one to two children and from two to three children, respectively, while “Diff 3 vs 1” reports the total difference between families with three and one child. Estimates are shown separately for women (Panel A) and men (Panel B) at each expenditure quintile. Brackets report 95% confidence intervals. Across the expenditure distribution, the estimated differences in total child resource shares are positive, indicating higher predicted child shares in larger families.

G Additional Figures

Figure 7 plots the non-parametric distributions of the estimated fraction of each parent’s resources devoted to children. The modal mass for mothers lies close to the lower part of the support (roughly 0.10–0.25), whereas the father distribution peaks at higher shares and appears to be more evenly distributed across a broader range. There is sizeable overlap between 0.15 and 0.60, but the father

Table 12: Predicted mean child share resources

	Women		Men	
	(1)	(2)	(1)	(2)
1 child	0.173 (0.055)	0.186 (0.049)	0.286 (0.052)	0.296 (0.052)
2 children	0.282 (0.059)	0.341 (0.041)	0.414 (0.046)	0.438 (0.048)
3 or more children	0.373 (0.065)	0.425 (0.040)	0.523 (0.066)	0.533 (0.061)

Notes: This table reports average estimated child resource shares, computed as averages of individual predicted shares among single parents. Inference is conducted using parametric Monte Carlo simulations that propagate estimation uncertainty in the structural parameters. Standard errors (reported in parentheses) are calculated as the standard deviation of the simulated estimates across 1,000 replications. Column (I) reports results based on the baseline sharing rule specification, while Column (II) provides estimates using an alternative specification.

density allocates more probability in the 0.35–0.70 range, while the mother density concentrates below 0.35. This pattern is consistent with the regression evidence reported in the main text.

Figure 8 plots the relative price trends for male and female clothing, with both indices set to 100 in the years 1978 and 2022, respectively. Both categories exhibit a marked decline between 1978 and around 2010, though the fall is substantially sharper for female clothing. By the mid-1980s, the female clothing index had dropped below 60, compared to above 70 for male clothing. The gap widened further through the 2000s, with female clothing prices reaching a trough of about 10 in 2009, relative to roughly 30 for male clothing. Since 2010, both series have rebounded, with male and female clothing prices showing a gradual recovery.

Table 13: Estimated parameters of the individual resource shares $-\varphi_i$ – and individual prices $-\pi_i$: further results

Parameters	Women						Men					
	I	II	III	IV	V	VI	I	II	III	IV	V	VI
Parent variables												
$\theta_{intercept}$	2.911 (1.816)	3.088* (1.635)	5.588** (2.668)	7.188** (3.484)	3.336** (1.681)	5.747* (3.159)	1.074 (3.296)	-0.226 (3.594)	1.718 (4.462)	-1.483 (3.712)	-0.921 (3.445)	-0.821 (3.807)
$\theta_{education}$	-0.044 (0.028)	-0.032 (0.032)	-0.038* (0.032)	-0.071** (0.033)	-0.038 (0.027)	-0.096** (0.040)	0.012 (0.131)	0.022 (0.146)	-0.002 (0.132)	0.051 (0.164)	0.023 (0.147)	-0.025 (0.149)
θ_{age}	-0.018 (0.102)	-0.035 (0.094)	-0.121 (0.138)	-0.183 (0.183)	-0.055 (0.095)	-0.061 (0.161)	0.032 (0.025)	0.114 (0.175)	0.023 (0.223)	0.152 (0.169)	0.147 (0.160)	0.159 (0.181)
θ_{age^2}	0.045 (0.130)	0.120 (0.118)	0.179 (0.178)	0.245 (0.236)	0.095 (0.120)	0.089 (0.205)	0.021 (0.219)	-0.091 (0.216)	0.056 (0.300)	-0.125 (0.223)	-0.123 (0.209)	-0.133 (0.236)
$\theta_{household\ head's\ birth\ year}$	—	—	—	—	—	—	—	-0.011 (0.035)	—	—	—	—
$\theta_{labor\ participation}$	-0.100 (0.184)	-0.053 (0.176)	-0.358 (0.245)	-0.627* (0.326)	-0.056 (0.171)	-0.360 (0.287)	0.341 (0.453)	0.450 (0.513)	0.792 (0.535)	0.363 (0.544)	0.487 (0.517)	0.439 (0.520)
$\theta_{house\ owner}$	-1.275* (0.687)	-1.434* (0.768)	-1.513* (0.776)	-1.419** (0.700)	-1.172 (0.758)	-1.990** (0.951)	-0.658 (1.579)	-0.899 (1.704)	-1.641 (1.410)	-0.837 (1.666)	-0.876 (1.637)	-0.647 (1.694)
Financial variables												
θ_{inp}	-1.000*** (0.263)	-0.193 (0.419)	-1.332*** (0.392)	-1.266*** (0.346)	-1.008*** (0.297)	-1.581*** (0.783)	-0.449 (0.783)	-1.158 (1.436)	-0.173 (0.844)	-0.704 (0.794)	-0.744 (0.775)	-0.725 (0.808)
θ_{iny}	0.184 (0.704)	0.991 (0.770)	0.561 (0.583)	0.421 (0.499)	0.456 (0.751)	0.849 (0.583)	1.730 (1.108)	2.308* (1.206)	2.098* (1.126)	2.490** (1.193)	2.226* (1.200)	2.147* (1.208)
$\theta_{log\ of\ child\ benefit}$	-0.213 (1.095)	—	—	—	—	—	5.033** (2.456)	—	—	—	—	—
$\theta_{log\ of\ alimony}$	0.436 (0.324)	—	—	—	—	—	2.109 (9.082)	—	—	—	—	—
Child variables												
θ_n	-0.953*** (0.211)	-0.912*** (0.189)	-0.974*** (0.242)	-0.934*** (0.244)	-0.914*** (0.193)	-1.060*** (0.294)	-1.291* (0.756)	-1.348* (0.766)	-1.395* (0.750)	-1.285* (0.753)	-1.312* (0.748)	-1.292 (0.791)
$\theta_{n,2}$	0.105*** (0.032)	0.102*** (0.032)	0.105*** (0.038)	0.094** (0.038)	0.102*** (0.031)	0.118*** (0.045)	0.168 (0.147)	0.170 (0.143)	0.156 (0.122)	0.157 (0.137)	0.161 (0.137)	0.160 (0.147)
$\theta_{kid\ age \times n}$	-0.013 (0.012)	-0.018 (0.013)	-0.015 (0.013)	-0.012 (0.012)	-0.014 (0.012)	-0.021 (0.014)	-0.013 (0.025)	-0.003 (0.024)	-0.001 (0.025)	-0.010 (0.026)	-0.004 (0.024)	-0.005 (0.026)
$\theta_{proportion\ of\ boys \times n}$	-0.081 (0.061)	-0.079 (0.060)	-0.106 (0.074)	-0.126 (0.079)	-0.077 (0.058)	-0.130 (0.086)	-0.130 (0.216)	-0.096 (0.217)	-0.057 (0.204)	-0.074 (0.230)	-0.074 (0.217)	-0.101 (0.227)
$\theta_{kid\ gender \times n}$	0.095** (0.046)	0.082* (0.046)	0.105* (0.055)	0.109* (0.056)	0.085* (0.045)	0.113* (0.063)	0.104 (0.155)	0.097 (0.159)	0.124 (0.156)	0.109 (0.171)	0.100 (0.157)	0.077 (0.171)
Shadow prices												
κ	-0.560*** (0.191)	-0.431* (0.235)	-0.592*** (0.168)	-0.761*** (0.200)	-0.448** (0.213)	-0.561*** (0.157)	0.700 (0.492)	1.024** (0.511)	1.221** (0.505)	1.101* (0.599)	1.099** (0.555)	1.155* (0.616)
Number of observations	24748	24748	22527	18571	24748	22379	15634	15634	3150	11491	15400	13233
(Number of free parameters, Instruments)	(50,59)	(49,59)	(48,59)	(48,59)	(48,59)	(48,59)	(50,59)	(49,59)	(48,59)	(48,59)	(48,59)	(48,59)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. This table reports additional robustness checks for the estimated sharing rule in single-parent households. Columns I–II examine alternative specifications of the baseline model by (i) explicitly controlling for child support and alimony as distribution factors, and (ii) allowing the sharing rule to vary with the birth year of the household head to capture cohort-specific norms. Columns III–VI restrict the comparison group of childless singles to individuals who are observationally similar to single parents. Column III implements cell-wise capacity-constrained matching, constructing a subsample of childless singles matched to parents within employment-homeownership cells, subject to cell-level capacity constraints. Column IV applies proportionate stratified matching, selecting the largest feasible subsample of childless singles whose distribution across cells exactly replicates that of parents. Columns V and VI restrict the sample to the region of common support based on estimated propensity scores. Column VI additionally trims observations below the 5th and above the 95th percentiles of the propensity score. Across all specifications, the results remain stable, indicating that the main results are not driven by observable compositional differences between parents and non-parents. Estimates for regional dummy variables are excluded for conciseness.

Table 14: Differences in predicted child resource shares across the expenditure distribution

Vigintile	Diff 2 vs 1			Diff 3 vs 2			Diff 3 vs 1		
	Est	CI	P-value	Est	CI	P-value	Est	CI	P-value
Panel A: Women									
1	0.159	[0.040 ; 0.278]	0.009	0.125	[0.094 ; 0.157]	0.000	0.284	[0.144 ; 0.425]	0.000
2	0.145	[0.049 ; 0.241]	0.003	0.122	[0.085 ; 0.158]	0.000	0.267	[0.140 ; 0.394]	0.000
3	0.139	[0.056 ; 0.223]	0.001	0.120	[0.084 ; 0.155]	0.000	0.259	[0.144 ; 0.374]	0.000
4	0.135	[0.060 ; 0.210]	0.000	0.118	[0.084 ; 0.152]	0.000	0.253	[0.148 ; 0.358]	0.000
5	0.132	[0.064 ; 0.199]	0.000	0.116	[0.084 ; 0.149]	0.000	0.248	[0.152 ; 0.343]	0.000
6	0.128	[0.067 ; 0.189]	0.000	0.115	[0.084 ; 0.146]	0.000	0.243	[0.156 ; 0.331]	0.000
7	0.126	[0.070 ; 0.181]	0.000	0.113	[0.084 ; 0.143]	0.000	0.239	[0.159 ; 0.319]	0.000
8	0.123	[0.072 ; 0.174]	0.000	0.112	[0.084 ; 0.140]	0.000	0.235	[0.161 ; 0.309]	0.000
9	0.120	[0.074 ; 0.167]	0.000	0.111	[0.084 ; 0.137]	0.000	0.231	[0.162 ; 0.299]	0.000
10	0.118	[0.074 ; 0.161]	0.000	0.109	[0.083 ; 0.134]	0.000	0.227	[0.163 ; 0.290]	0.000
11	0.115	[0.074 ; 0.155]	0.000	0.107	[0.082 ; 0.132]	0.000	0.222	[0.161 ; 0.283]	0.000
12	0.112	[0.073 ; 0.151]	0.000	0.106	[0.081 ; 0.131]	0.000	0.218	[0.158 ; 0.277]	0.000
13	0.109	[0.070 ; 0.148]	0.000	0.104	[0.078 ; 0.130]	0.000	0.213	[0.152 ; 0.274]	0.000
14	0.106	[0.066 ; 0.146]	0.000	0.102	[0.074 ; 0.130]	0.000	0.208	[0.144 ; 0.273]	0.000
15	0.103	[0.061 ; 0.146]	0.000	0.100	[0.070 ; 0.131]	0.000	0.203	[0.133 ; 0.274]	0.000
16	0.100	[0.053 ; 0.147]	0.000	0.098	[0.063 ; 0.132]	0.000	0.198	[0.119 ; 0.277]	0.000
17	0.097	[0.044 ; 0.149]	0.000	0.095	[0.056 ; 0.135]	0.000	0.192	[0.102 ; 0.281]	0.000
18	0.092	[0.033 ; 0.152]	0.002	0.092	[0.046 ; 0.139]	0.000	0.184	[0.080 ; 0.289]	0.001
19	0.087	[0.018 ; 0.156]	0.013	0.088	[0.033 ; 0.144]	0.002	0.175	[0.053 ; 0.298]	0.005
20	0.079	[-0.004 ; 0.162]	0.063	0.082	[0.011 ; 0.153]	0.023	0.161	[0.008 ; 0.314]	0.039
Panel B: Men									
1	0.096	[-0.045 ; 0.237]	0.184	0.040	[-0.050 ; 0.131]	0.382	0.136	[-0.088 ; 0.360]	0.233
2	0.168	[0.044 ; 0.291]	0.008	0.084	[-0.016 ; 0.185]	0.101	0.252	[0.068 ; 0.435]	0.007
3	0.195	[0.057 ; 0.334]	0.006	0.111	[0.021 ; 0.200]	0.015	0.306	[0.143 ; 0.470]	0.000
4	0.205	[0.053 ; 0.357]	0.008	0.126	[0.043 ; 0.208]	0.003	0.331	[0.162 ; 0.500]	0.000
5	0.210	[0.049 ; 0.371]	0.010	0.140	[0.061 ; 0.218]	0.001	0.349	[0.169 ; 0.530]	0.000
6	0.210	[0.048 ; 0.371]	0.011	0.149	[0.070 ; 0.228]	0.000	0.359	[0.171 ; 0.547]	0.000
7	0.206	[0.050 ; 0.361]	0.010	0.157	[0.075 ; 0.238]	0.000	0.362	[0.172 ; 0.553]	0.000
8	0.199	[0.054 ; 0.344]	0.007	0.162	[0.077 ; 0.246]	0.000	0.361	[0.173 ; 0.548]	0.000
9	0.191	[0.058 ; 0.323]	0.005	0.164	[0.077 ; 0.251]	0.000	0.355	[0.174 ; 0.535]	0.000
10	0.178	[0.061 ; 0.296]	0.003	0.165	[0.076 ; 0.253]	0.000	0.343	[0.173 ; 0.513]	0.000
11	0.166	[0.061 ; 0.271]	0.002	0.162	[0.072 ; 0.253]	0.000	0.328	[0.165 ; 0.491]	0.000
12	0.154	[0.057 ; 0.252]	0.002	0.158	[0.065 ; 0.251]	0.001	0.312	[0.151 ; 0.474]	0.000
13	0.141	[0.047 ; 0.235]	0.003	0.152	[0.055 ; 0.249]	0.002	0.293	[0.128 ; 0.459]	0.001
14	0.128	[0.034 ; 0.222]	0.007	0.145	[0.041 ; 0.248]	0.006	0.273	[0.096 ; 0.449]	0.002
15	0.115	[0.019 ; 0.211]	0.019	0.136	[0.024 ; 0.247]	0.017	0.250	[0.059 ; 0.442]	0.010
16	0.098	[-0.002 ; 0.198]	0.055	0.122	[-0.001 ; 0.245]	0.051	0.220	[0.008 ; 0.431]	0.042
17	0.086	[-0.017 ; 0.188]	0.101	0.111	[-0.020 ; 0.242]	0.096	0.196	[-0.028 ; 0.421]	0.086
18	0.071	[-0.031 ; 0.173]	0.174	0.096	[-0.042 ; 0.234]	0.172	0.167	[-0.067 ; 0.401]	0.163
19	0.052	[-0.045 ; 0.148]	0.292	0.074	[-0.065 ; 0.213]	0.298	0.126	[-0.107 ; 0.358]	0.289
20	0.033	[-0.048 ; 0.113]	0.424	0.049	[-0.076 ; 0.174]	0.439	0.082	[-0.121 ; 0.286]	0.429

Notes: This table reports estimated differences in predicted child resource shares at each expenditure vigintile. Columns "Diff 2 vs 1" and "Diff 3 vs 2" present marginal differences, while "Diff 3 vs 1" presents total differences. Panel A reports estimates for women and Panel B for men. Brackets show 95% confidence intervals.

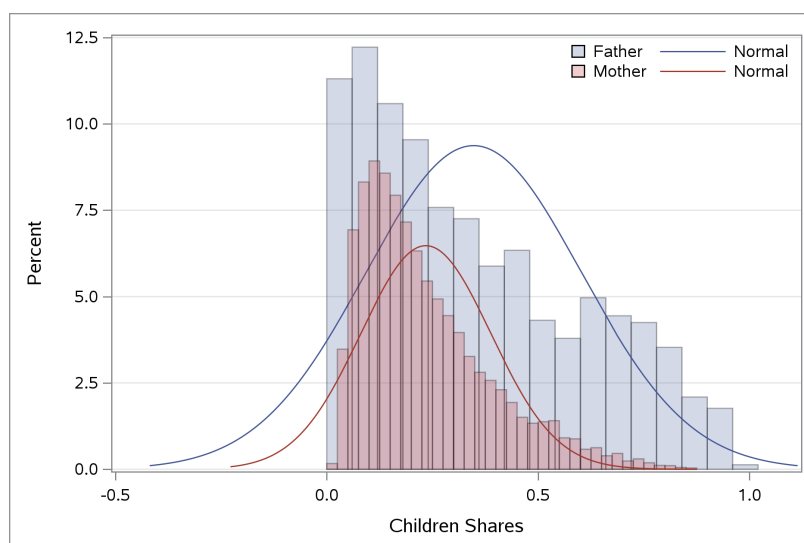


Figure 7: Non-parametric distribution of parents' resource shares allocated to children

Notes: This figure plots the density of the cost of children across parents. Based on the sharing rule estimates, the mean share of resources devoted to children is 0.28 and 0.40 respectively for mothers and fathers. The father distribution is shifted to the right and is more dispersed than the mother distribution; both depart from normality due to the bounded support $[0, 1]$.

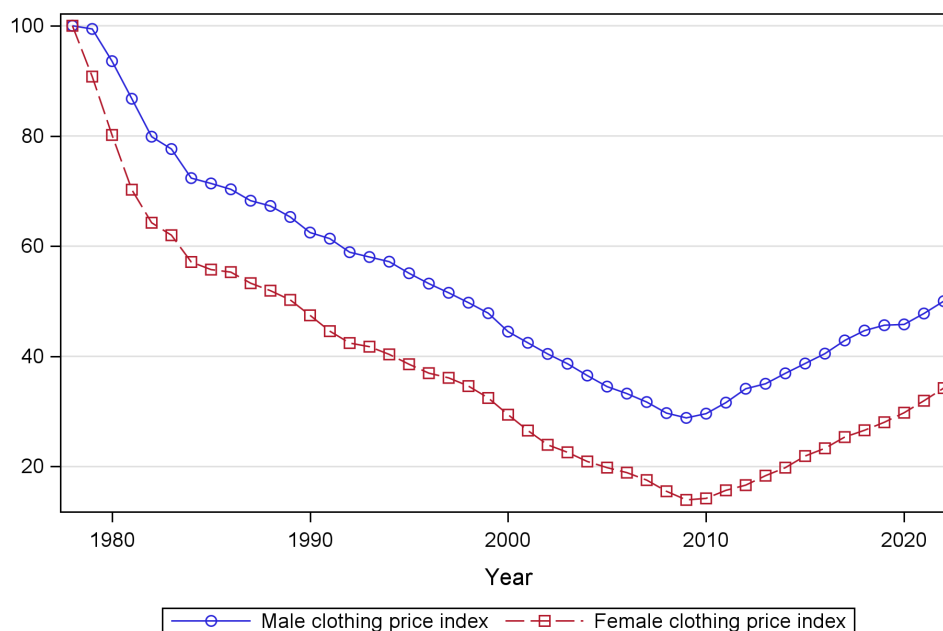


Figure 8: Relative price indexes for male and female clothing between 1978 and 2022

Notes: This figure illustrates the relative prices of male and female clothings from 1978 to 2022, represented by indices set to 100 in both 1978 and 2022, respectively.