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Estimating household resource shares: A shrinkage approach☆

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HIGHLIGHTS

- Collective models show great promise in the analysis of intra-household welfare.
- But their empirical application has proven difficult in practice.
- We show how a common feature of these models makes the task so difficult.
- We propose an empirical strategy involving shrinkage to stabilize the estimates.

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ABSTRACT

Collective models identifying resource shares are promising tools to analyze intra-household welfare and poverty. However, their empirical application has proven difficult in practice as authors contend with large standard errors and unstable estimates. This paper uses a prominent framework to show how a common feature of the structure of these models makes the task so difficult and proposes an empirical strategy to stabilize the estimates.

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1. Introduction

Collective models of the household (Chiappori, 1988, 1992) have become the go-to approach to study intra-household allocations. The ability of models based on Browning et al. (2013, hereafter BCL) to identify *resource shares*, that is, the fraction of household resources devoted to each member, has made them attractive to researchers investigating intra-household welfare and poverty.[1] . However, their estimation has proven difficult in practice. Authors have to contend with large standard errors, unstable estimates and difficult optimization procedures.[2] The source of these difficulties lies in the complexity of the task at hand: to learn about resource allocation among individuals from household-level consumption data. To do this, models have to account for other

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1 See Lewbel and Pendakur (2008), Bargain and Donni (2012), Dunbar et al. (2013) and applications by Cherchye et al. (2012), Bargain et al. (2014), Calvi (2016), Calvi et al. (2017), Tommasi (2017).

2 See Wolf (2016) for a more detailed discussion of these problems.

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drivers of patterns in the data, such as preferences and consumption technologies.

Demand systems derived from BCL share the following structure, where demand for a good k is expressed in household budget shares w^k as a function of resource shares η_j for members $j = 1, 2$ of a couple's household and of *desired budget shares* w_j^k, which describe member j's preferences:

$$w^k(p, y) = \sum_{j=1,2} \eta_j(p, y) w_j^k(\pi(p), y\eta_j(p, y)) \quad (1)$$

where y is total household expenditure, p are market prices and $\pi(p)$ are intra-household shadow prices.[3] A key difficulty for estimation can be spotted in Eq. (1): each summand is a product of an individual's resource share and her desired budget share. This *multiplicative feature* induces trade-offs between parameters and makes it hard to pin down the value of the parameter of interest: the resource share η_j.

In this paper, we use the Dunbar et al. (2013, hereafter DLP) model to discuss the consequences for estimation caused by this multiplicative feature and offer a simple solution. The simplified structure of this model has not only made it the most popular approach among practitioners, but also makes it well-suited for our exposition, as the consequences of the above structure emerge clearly.

2. Trade-offs in the model

Starting from (1), DLP make the following identifying assumptions. First, they focus only on household demand for private assignable goods, that is, goods for which we can assume that only one member consumes them and for which there are no economies of scale. Second, they assume that preferences of household members are similar across people (SAP), instead of identical to singles (a common assumption in BCL-type models), and that $\eta_j \perp y$ (Menon et al., 2012). Then, under PIGLOG utility functions, the resulting system maintains the multiplicative feature and takes the following form:

$$\begin{aligned} w^1(y) &= \eta \quad && (\delta + \Delta \quad + \beta \ln(\eta y)) \\ w^2(y) &= (1-\eta) \quad && (\delta \quad + \beta \ln((1-\eta)y)) \end{aligned} \quad (2)$$

where the desired budget share functions, for each member, are linear Engel curves in log *individual resources* ηy (or $(1-\eta)y$ for member 2), and η, δ, Δ, and β, are parameters to be estimated. In applications, these are typically replaced by linear indexes in characteristics to account for observed heterogeneity. By the SAP assumption, and importantly for us, the constant terms of these curves are allowed to differ by Δ between the two members, whereas the slope β is constrained to be the same.

System (2) allows us to reason fairly straightforwardly about *trade-offs* in the model. Suppose an optimal fit to data has been found. If we now slightly modify Δ, we can obtain a fit that is nearly as good as before by also modifying η in the opposite direction. This is illustrated in Fig. 1, where, for different pairs (η, Δ), we plot minimal values of the root sum of squares (RSS) associated with a toy example of (2). A dashed red line marks the floor of a valley along which the two parameters can be traded off cheaply (in RSS sense), making recovery of either value hard in practice. Though similar trade-offs characterize other BCL-type models, it is especially easy to show in DLP, where it is linear. Put another way, a strong correlation between pseudo-regressors is induced in our system (Greene, 2003, Chapter 17), inducing a corresponding correlation in parameter estimates. This problem can be seen as analogous to multicollinearity, though crucially ours is a feature of the model rather than of the data (See Appendix).

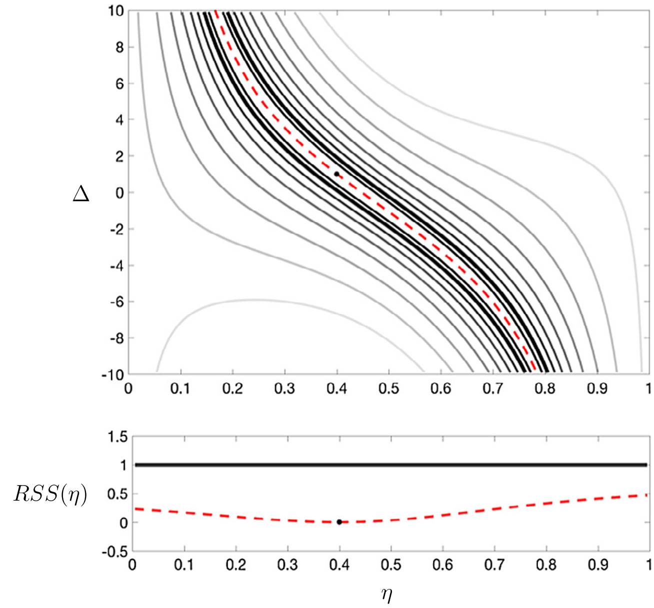

Fig. 1. RSS minima as a function of (fixed) η and Δ.

Parameter estimates are affected in two ways, which are illustrated by the black dots in Fig. 2. First, it makes the location of the sample mean η_0 of the sharing rule more uncertain (Fig. 2(a)).[4] Second, when parameters are replaced by linear indexes in household characteristics to capture observed heterogeneity, the estimated indexes for each household h, $\hat{\eta}_h$ and $\hat{\Delta}_h$, have a strong negative correlation across households (Fig. 2(b)), where $\hat{\eta}_h = \hat{\eta}_0 + \hat{\eta}_1 x_1 + \cdots + \hat{\eta}_k x_k$ and $\hat{\Delta}_h = \hat{\Delta}_0 + \hat{\Delta}_1 x_1 + \cdots + \hat{\Delta}_k x_k$. This occurs reliably even when the true correlation is large and positive. Since the model is identified, estimates by nonlinear least squares are consistent. However, at common sample sizes in household surveys, the issue described here is an important obstacle, yielding large standard errors and unstable estimates.

3. Stabilization

In order to achieve stabilization of the estimates at minimal cost, we proceed in two acts. First, the analogy with multicollinearity suggests that a shrinkage method may be beneficial in reducing the uncertainty around the location of the mean resource share. Second, we restrict the (artificial) correlation between the indexes η_h and Δ_h to address their distortion. These two issues turn out to be independent from one another in the sense that the remedy to one has no effect on the other.

We use data on singles to introduce prior information and design our shrinkage term. We formalize our rationale for shrinkage by assuming similarities between singles' budget shares w_s^j (which are estimated in a first step) and married individuals' desired budget shares. While DLP emphasize that they do not assume such similarities, we will do so in a minimal fashion which bears little resemblance to BCL's assumption of identical preferences. This amounts to using economic theory to motivate and construct

[3] Eq. (1) holds only if the shadow consumption z is linear in purchased quantities q, with $z = Aq$, where A is a diagonal matrix describing a linear consumption technology. This technology is common to all BCL-type models and notably disallows complementarities and overheads in scale economies.

[4] This comparison needs a reference point where these effects are attenuated by means of limiting the extent of these trade-offs. Our approach, detailed below, provides this reference point.

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