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May 2023

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Socio-Economic Identity and Intra-Household Distribution of Consumption in India: A Structural Approach *

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May 2023

Abstract

Using a collective household model and a new structural estimation methodology, we estimate the intra-household resource shares of individual members in both rural and urban India. Our findings indicate that men's and children's per-capita intra-household resource shares are higher in urban compared to rural areas, while the opposite is true for women. Our results suggest that urbanisation, which is a sign of economic development, is associated with lower child poverty; but significantly higher gender gap in access to consumption within the household for adults. We explore two potential channels that explain our findings. Firstly, urban locations are dominated by upper-caste households, and we find that the gender resource share gap worsens as one moves higher up the caste hierarchy. Secondly, we found that the most favorable intra-household consumption distribution for women occurs in rural areas with clayey soil textures, which traditionally foster women's participation in agriculture. However, in urban areas, even within clayey soil regions, agriculture is no longer a prominent occupation, and women's advantage in accessing intra-household consumption resources due to higher potential for labor market participation disappears. Therefore, caste identity and greater relative involvement of women in agriculture on account of exogenously varying soil textures could explain the larger gender gap in within-household resource sharing in urban compared to rural locations.

Keywords: collective households; resource shares; intra-household consumption allocation; urbanisation; soil textures; caste; India

JEL Codes: D13; D63; I31; J12; J13; J16

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*We thank participants at the 2022 Winter School of the Delhi School of Economics and the Econometric Society for helpful comments.

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1 Introduction

Traditionally, the theory of consumer behaviour has assumed that households behave as a single decision making unit. However, it is well acknowledged that unequal sharing of consumption resources within households is widely prevalent.[1] Therefore, a valuable alternative to the traditional model is the collective approach to household behaviour. The collective household model explicitly takes into account that multi-person households consist of several members who may have different preferences (Vermeulen, 2002). Shadow budgets and prices influence individual consumption demands; which are, in general, unobservable and individual shadow budgets sum to the household budget. The fraction of household expenditure allocated to each household member is defined as their resource share. Resource shares, therefore, determine within-household allocation of consumption resources following the intra-household bargaining process. Therefore, estimation of resource shares is of critical importance to understand gender gaps in access to consumption as well as prevalence of child poverty within households. In this paper, we estimate intra-household resource shares in India; differentiating across households by their location (rural vs urban) of residence. Distinguishing between households across this marker of socio-economic identity is of significance for an emerging economy such as India where increased urbanisation is expected; but where traditional social identities also remain salient. Importantly it is not clear ex-ante, whether urbanisation would imply more equal intra-household sharing of consumption resources. Therefore, computation of within household resource shares for rural vis-a-vis urban households is critical for understanding whether urbanisation, closely associated with overall economic progress, can reduce intra-household inequalities.

Unfortunately, consumption expenditure surveys rarely report consumption spending at the individual level. Therefore, computing resource shares for individual members from consumption expenditure data reported only at the household level is particularly challenging. To overcome this limitation, Browning, Chiappori, and Lewbel (2013) (henceforth, BCL) propose estimation of model parameters (shadow prices and budgets) of collective household models by utilizing consumption data of single individuals at various price vectors and budgets. Taking into account that behaviour of single individuals may not accurately capture the behaviour of married individuals, children rarely live alone and observation of consumption behaviour at multiple price vectors may not always be feasible; Dunbar, Lewbel, and Pendakur (2013) (henceforth, DLP) impose sufficient restrictions on BCL, enabling identifi-

[1] There already exists a large literature examining the impacts of unequal allocation of resources on individuals, particularly children, on account of birth order and gender discrimination using reduced form methodologies. See for example, Gupta (1987); Behrman (1988); Borooah (2004); Mishra et al. (2004); Jayachandran and Kuziemko (2011); Jayachandran and Pande (2017).

cation of shadow prices and budgets of collective households by observing their consumption demands at a given price vector. However, the estimation of nonlinear structural models as proposed by BCL and DLP over bounded parameter spaces can be computationally intensive and involve opaqueness in terms of identifying variation. This can potentially explain why these have not gained significant popularity among policymakers despite the importance of computing within-household resource shares (Lechene, Pendakur, and Wolf, 2022). Therefore, the need for a linear reframing of complex nonlinear structural models to encourage their usage in estimating resource shares and consequently intra-household inequality cannot be understated.

Given this context, Lechene, Pendakur, and Wolf (2022) (henceforth, LPW) recently proposed a linear reframing of the nonlinear structural model of DLP that is both transparent and computationally straightforward to implement. In this paper, we follow this new methodology of LPW and apply it to Indian household consumption expenditure data. Following LPW, we estimate a system of linear Engel curves of assignable goods for different types of household members, defined by their genders and age (adult men, women and children), across different types of household compositions (with and without children) where multiple types of members may be present (multiple men, women, children) and recover resource shares from the estimated coefficients.[2]

Using the National Sample Survey (NSS) on household consumption expenditure (2011) we find that for all households, per man resource share is the largest while per child resource share is the smallest.[3] In particular, we find that resource shares for men is around 52%, that for women is around 32% and for children is around 16% across Indian households. In households without children, we continue to find significant gender differences in resource shares among adults. Men's and women's overall resource shares are around 71% and 29% respectively in these households. Assuming equal sharing within each type of individual, our findings indicate significant gender gaps in per person resource shares among adults, and when present, children are found to have the lowest per person resource share. We then focus on our main research question - how resource shares for each type of individual varies across rural and urban households.

We focus on a key indicator of household socio-economic identity, that is, household lo-

[2]Assignable goods are commodities whose expenditures can be observed at the individual instead of at the household level such as children's clothing or women's footwear.

[3]The NSS consumption expenditure surveys are large, nationally representative surveys with detailed consumption expenditure modules at the household level. The 2011 round is the latest round that is publicly available and contains more detailed information on assignable goods for adult men, women, and children compared to the previous consumer expenditure surveys. We follow the classification of assignable goods by types of Calvi (2020) who also uses this round for analysis.

cation of residence and obtain several interesting findings. While per man and child resource shares are found to be higher in urban households relative to their rural counterparts by 5 and 2 percentage points respectively; per woman resource shares are higher in rural households relative to urban households by nearly 5 percentage points. Relatedly, the gender gap in per person resource shares among adults is around 12 percentage points in rural households; while it is 22 percentage points in urban households. In households without children, the gender gap in per person resource shares is found to be 22 and 32 percentage points in rural and urban households respectively. In the presence of children, the difference between men's and children's resource shares increases with urbanisation; while the gap between women's and children's resource shares decline substantially. Therefore, per person resource shares appear to largely favour men and then children with urbanisation at the expense of women. These findings can also be used to assess the extent to which per person expenditure is expected to rise when households move from rural to urban areas. For instance, if there were equal sharing within households (the standard per capita expenditure measure used to judge household welfare), then per person per day expenditure for urban households is expected to be 43% larger than rural households in the presence of children and 52% higher than their rural counterparts when no children are present in the household. However, if we take into account unequal sharing within the household as predicted by the model; we find that while per man and child daily expenditures are expected to be 54% and 65% higher in urban households relative to rural households; per woman expenditure is expected to increase by only 5.5% in urban households. The resource share estimates yield similar predictions for households that have no children. Therefore, per man and child expenditures are predicted to be higher by a larger magnitude while per woman expenditures are predicted to be higher by a substantially lower magnitude relative to an increase in per capita household expenditure (or, under the assumption of equal sharing) with improvement of household socio-economic status as proxied by urbanisation. Although it is certainly assuring to find that resource share for children (who have the lowest within-household resource share) are likely to increase with urbanisation; the falling per woman resource share in urban households is particularly worrisome. Our findings echo some studies in the existing literature that show that better economic condition/ access to social services (that are also usually associated with urban location of residence) may not readily translate to gender equality in human capital investments (health, consumption) within households and it is possible to find a significant number of disadvantaged individuals even within households characterized by better socio-economic condition (Oster (2009); Brown, Ravallion, and van de Walle (2019); Brown, Calvi, and Penglase (2021)).

We investigate two potential channels of our findings - cultural factors, namely the role of caste and economic factors, such as the role of women in agriculture and the negligible importance of agriculture itself in urban locations. We find that urban households, irrespective of household composition, are dominated by upper caste groups. Estimating intra-household resource shares by caste groups shows that the gender gap in resource shares among adults is significantly larger in upper caste households relative to their lower caste counterparts. Interestingly, the magnitude of the gender gap in resource shares among adults in upper caste households is close to the corresponding magnitude for urban households for all types of household composition. Additionally, the difference in resource shares between adults and children also follows a similar pattern. The existing literature has demonstrated that gender gaps along various dimensions are significantly larger among upper caste groups on account of social norms that mandate relatively stricter restrictions on women's behaviour and mobility (Maharatna (2000); Mitra (2008); Eswaran, Ramaswami, and Wadhwa (2013); Anukriti and Kumler (2019)). Hence, our findings on the gender gap in within household sharing among adults, in particular, largely follows the predictions from the existing literature. Therefore, it is possible that, to some extent, caste based norms play an important role in influencing the differences in intra-household resource allocation across rural and urban areas.

We, then, study whether the relative importance of women in agriculture can potentially explain our findings. Following the literature, we consider districts with dominantly clayey soil textures as places with greater relative involvement of women in agriculture (Carranza, 2014). Soil texture is exogenously determined through millennia of geographical metamorphism. Clayey soils, in contrast to loamy soil textures, are not amenable to deep tillage that reduces overall female labour demand in agriculture (Carranza, 2014). We, therefore, test how intra-household resource allocation varies with soil texture and find that while complete gender equality in resource allocation is ruled out across soil textures, clayey soil textures have more gender equal resource allocation for adults relative to households in dominantly loamy soil regions. In households with children, resource allocation for children are also higher in clayey soil regions, potentially indicating the positive influence of higher women's bargaining power in these regions on child outcomes. Specifically investigating the rural-urban differences by soil textures, we find that the gender gap in resource allocation is the lowest in rural areas of clayey soil regions. In contrast, urban areas of loamy soil regions have the highest gender gap in within-household resource allocation. Interestingly, urban households in clayey soil regions are found to have a higher gender gap in resource shares among adults than even rural households in loamy soil regions. Especially in the absence of children, the gender gap in urban households in clayey soil regions is marginally higher than the corresponding figure for urban households located in loamy soil regions. These findings indicate that while overall relatively higher involvement of women in agriculture in clayey soil regions influences lower gender gap in resource shares; these beneficial impacts of traditionally higher female labour force participation do not sustain through urbanisation as the importance of agriculture itself declines.

Our analysis contributes to the literature in three major ways. Firstly, we use the method of linearization of the nonlinear structural model of DLP as proposed by LPW. This methodology is significantly simpler, more transparent in terms of implementation and involves simple and intuitive tests for model identification; but remains capable of modelling complex household compositions and consumption technologies. As LPW's methodology is quite new, analysis using this methodology is relatively scarce. To the best of our knowledge, this paper is the first to use this methodology using Indian data.[4] Secondly, unlike previous studies, our key motivation is to understand how intra-household resource shares across adult men, women and children (if present) vary by socio-economic identity of households as proxied by their location of residence. This exercise is of significant interest in its own right as urbanisation is topical and of great relevance for any emerging economy. In addition, we discuss potential mechanisms such as the salience of traditional social identities, that is, caste despite urbanisation and the changing role of women in the labour market when agriculture ceases to be an important occupation on account of an urban location. Lastly, we go beyond gender gaps in within household sharing and also focus on children's resource shares; which has remained largely understudied in the Indian context.

This paper is organized as follows: Section 2 briefly describes the LPW methodology that we have used; Section 3 describes the data; Section 4 discusses the key findings; Section 5 includes the potential mechanisms of our findings while Section 6 concludes.

2 Methodology

Measuring access to consumption at the individual level is critically important for identifying individuals who need to be targeted by anti-poverty policies. However, measuring poverty at the individual level is nearly impossible as consumption expenditure data are usually collected at the household level. To circumvent this problem, researchers have relied on the collective household framework to model household consumption allocation decisions in an environment where within household unequal sharing and consumption externalities may be

[4] The only analysis involving structural estimation of intra-household resource shares in the context of India is Calvi (2020) who undertakes estimation of the nonlinear structural model of DLP. Calvi (2020) has found gender gaps in resource shares and has importantly demonstrated the decline in women's bargaining power within Indian households with age to understand the phenomenon of "missing women" in post-reproductive ages in India.

common.[5] Following LPW, we briefly discuss the methodology here. At first, we describe the collective household model following BCL. DLP extends BCL's model that focused on households comprised of childless couples to include households where children are present. Extension to collective household models with multiple adults and children is conceptually straightforward and enables modelling household behaviour in developing countries where complex household compositions beyond nuclear families are common (see for example, Calvi (2020)). Secondly, we describe the sufficient restrictions imposed by DLP on BCL's model that enable identification of model parameters through observation of consumption behaviour of collective households at a single price vector. Lastly, we describe that LPW propose less restrictive restrictions relative to DLP and provide a linear reframing of DLP which is simpler to estimate than existing collective household models.

2.1 Theoretical Framework

In collective household models, each household is assumed to allocate resources among its members. Let t index the types of individuals in the household, in our case, m for adult male, f for adult female and c for children. We assume that the household consists of N_t individuals of each type t, and N is the household size, so that $\Sigma_t N_t = N$. Household members may consume both shareable and non-shareable goods. The quantity consumed by individuals sum up to total household consumption for a non-shareable good, while the sum exceeds the household purchase when the good is shareable. Mathematically this implies if q_t is the quantity vector consumed by each individual of type t, the household purchases a quantity vector given by:

$$Q = A\Sigma_t N_t q_t \tag{1}$$

where, **A** is a square matrix which summarizes the consumption technology relating quantities purchased to goods consumed by individuals.

Now, each person's budget constraint is characterized by a shadow budget and a shadow price vector. They are termed as "shadow" as they are unobserved but determine the consumption demand for each individual within a household. Shadow prices may be different from the market prices depending on the nature of the goods consumed. Clearly, while shadow prices equal the corresponding market prices for non-shareable goods, they are lower than the market prices for shareable goods. The diagonal elements of **A** have a direct effect on the size of the shadow price relative to the market price, while the off-diagonal elements

[5] See Brown et al. (2022) for a non-technical discussion of measuring intra-household poverty.

capture complementarities in the household consumption technology.[6] The consumption technology matrix **A** can, therefore, be used to relate the shadow and market prices. If p and $\tilde{p}$ denote the market and shadow price vectors of goods respectively, we have:

$$\tilde{p} = Ap \tag{2}$$

Individual shadow budgets sum up to household budget, I. Resource share of any type of members is defined as the share of total household budget allocated to that type. If we denote the resource share for type t as θ_t, then:

$$\Sigma_t \theta_t = 1 \tag{3}$$

Resource shares vary across types and depend on household budget, prices and various individual characteristics. We assume that within a type, resource shares are distributed equally. Therefore, the shadow budget for each person of type t is:

$$\frac{\theta_t I}{N_t} \tag{4}$$

Estimation of individual resource shares are equivalent to identifying these shadow budgets. A crucial assumption in collective household models is that within household decision making is Pareto efficient. Conceptually, therefore, one can think of the problem in two steps. At first, the household allocates resources among its members and subsequently each member of type t chooses q_t subject to their shadow budget constraint given by equation (4). Formally, the household's problem is as follows:

$$max_{\{Q,q_m,q_f,q_c\}} \Sigma_t \mu_t \tilde{U_t} \quad subject \quad to \quad Q = A\Sigma_t N_t q_t \quad and \quad Q^{'}p = I \tag{5}$$

Here, μ_t are Pareto weights that are considered measures of intra-household bargaining power, bearing a monotonic correspondence to resource shares (BCL, Calvi (2020)). U_t represents the utility function of type t individual over the consumption of q_t with usual properties. One can allow that type t individual's utility depend on the utility of other types of household members (but no direct consumption externalities) so that $\tilde{U_t} = \tilde{U_t}(U_m(q_m), U_f(q_f), U_c(q_c))$. The solution to the two-step problem of the household would, then, involve substituting the indirect utility functions obtained from the second step of the problem into the household's problem in equation (5) and solve for the optimal resource shares under the constraint that the sum of the resources shares must equal 1.

LPW describe that identification of resource shares and shadow prices from consumption

[6] See LPW for an example of the consumption technology matrix **A**.

data is achievable according to BCL if one observes Engel curves at many observed price vectors, assumes that single individuals have the same preferences as individuals who live in collective households and can observe the Engel curves of single individuals. However, these assumptions may not hold in reality as Engel curve for a household may not be available for various price vectors, children usually do not live alone and single men/women are unlikely to live alone especially in developing countries. Therefore, DLP provide sufficient restrictions on BCL's model such that resource shares can be identified with data on the consumption behaviour of assignable goods of collective households observed at a single price vector, where an assignable good is one whose expenditure can be observed for each type of individual. These sufficient restrictions include:

a) The consumption technology matrix **A** is diagonal such that 1 appears corresponding to the assignable good for each person; indicating that each person's assignable good is non-shareable, its shadow price being equal to its market price and lack of complementarities in household consumption technology.

b) Resource shares do not depend on the household budget, i.e. $\theta_t(I) = \theta_t$.

c) Individual Engel curve functions are linear in lnI and we can write it down as $s_t(I) = \alpha_t + \beta_t I$

d) Preferences are similar but not identical across people such that $\beta_t = \beta$.

LPW, however, impose weaker restrictions on **A** relative to DLP; assuming it to be block diagonal instead. This allows the possibility for (dis)economies of scale in consumption of assignable goods as well as complementarities in consumption of non-assignable goods; unlike DLP. Similar to DLP, LPW continue to assume no complementarities between the consumption of assignable goods and all other goods. The authors are, therefore, able to derive the same demand equations as DLP, but with a less restrictive consumption technology matrix **A**.

Following the assumptions and restrictions imposed by LPW on assignable goods and the consumption technology matrix **A**, the Engel curve for assignable good is derived as follows:

$$S_t(I) = \theta_t(I) s_t(\frac{\theta_t(I) I}{N_t}) \tag{6}$$

Here, S_t and s_t represent household and individual Engel curve functions respectively for assignable goods corresponding to type t members. The above relationship says that the household's Engel curves (at market prices, held fixed) for the assignable goods are equal to the resource share of the relevant type times the Engel curve of a person of that type facing the shadow price vector and their shadow budget.[7] Additionally, using the assumptions b), c) and d), equation (6) can be rewritten as :

$$S_t(I) = \theta_t[\alpha_t + \beta(lnI + ln\theta_t - lnN_t)] \tag{7}$$

Equation (7) is non-linear because of the presence of the terms $\theta_t * \alpha_t$ and $\theta_t * \beta$. Equation (7) also requires that resource shares be positive because of the term $ln\theta_t$. Equation (7) has been estimated using non-linear optimization techniques on bounded parameter spaces by a number of studies (see for example, DLP; Calvi (2020); Calvi and Keskar (2021)). However, such estimation can be quite tedious. Therefore, LPW propose a linear approximation of this non-linear regression equation which is relatively straightforward to implement. We use this new methodology proposed by LPW for estimation.

2.2 Structural Estimation of Resource Shares

Following LPW, for any household $h = (1, 2, ..., H)$, the estimable version of equation (7) without any covariates and assuming $N_{th} = N_t \ \forall \ h$ can be written as:

$$S_{th} = \theta_t\alpha_t + \theta_t\beta ln\theta_t - \theta_t\beta lnN_t + \theta_t\beta lnI_h + \varepsilon_{th} \tag{8}$$

Equation (8) can be simplified further and written as:

$$S_{th} = a_t + b_t lnI_h + \varepsilon_{th} \tag{9}$$

Here, $a_t = \theta_t\alpha_t + \theta_t\beta ln\theta_t - \theta_t\beta lnN_t$ and $b_t = \theta_t\beta$.

Considering that there are three types of individuals in the household (that is, t= m, f and c) we have a system of equations:

$$\begin{aligned} S_{mh} &= a_m + b_m lnI_h + \varepsilon_{mh} \\ S_{fh} &= a_f + b_f lnI_h + \varepsilon_{fh} \\ S_{ch} &= a_c + b_c lnI_h + \varepsilon_{ch} \end{aligned} \tag{10}$$

subject to the constraint:

[7] See LPW for a detailed derivation. Also, note that using $S_t(I)$ as a measure of resource share of any type of individual would not be appropriate as $S_t(I)$ is also likely to be influenced by differences in preferences (Calvi (2020); Calvi and Keskar (2021))

$$\theta_m + \theta_f + \theta_c = 1 \tag{11}$$

The above system of equations given by (10) can be estimated using linear SUR; regressing household budget share on the assignable goods on a constant and log of the household budget. If $\widehat{a_t}$ and $\widehat{b_t}$ are the estimated regression coefficients, we can recover the estimated resource shares $\widehat{\theta_t}$ from the constraint (11) as follows:

$$\widehat{\theta_t} = \frac{\widehat{b_t}}{\widehat{\beta}} = \frac{\widehat{b_t}}{\Sigma_t \widehat{b_t}}$$

Incorporating demographic covariates is conceptually straightforward, but involves additional notations. Following LPW, let z denote the set of all demographic covariates, $\tilde{z}$ the set of covariates excluding N and $N = \{N_t\}$ the number of household members of each type; such that $z = [N\ \tilde{z}]$. Household Engel curves for assignable goods become functions of z when θ_t, α_t and β depend on z. After introducing the demographic covariates, we can write down the Engel curve of assignable goods for type t for household h as:

$$S_{th}(I, z) = \theta_t(z)\alpha_t(z) + \theta_t(z)\beta(z)ln\theta_t(z) - \theta_t(z)\beta(z)lnN_t + \theta_t(z)\beta(z)lnI_h + \varepsilon_{th} \tag{12}$$

Denoting $a_{th} = \theta_t(z_h)\alpha_t(z_h) + \theta_t(z_h)\beta(z_h)ln\theta_t(z_h) - \theta_t(z_h)\beta(z_h)lnN_{th}$ and $b_{th} = \theta_t(z_h)\beta(z_h)$, the non-linear regression equation in (12) can be linearized and rewritten as:

$$S_{th} = a_{th} + b_{th}lnI_h + \varepsilon_{th} \tag{13}$$

$\forall\ h = 1, 2, ..., H.$

If α_t, β_t and θ_t are linear indices in z_h, then a_{th} is a third order function of z_h and b_{th} is a quadratic in z_h. If Z_h contains all the level and interaction terms in z_h upto the third order, then one can estimate equation (13) through an OLS regression of S_{th} on a constant, Z_h, lnI_h and $Z_h * lnI_h$. Alternatively, if α_t, β_t and θ_t are unknown functions of z_h one can consider a_{th}, b_{th} as non-parametric functions of z_h. A standard semi-parametric method can be used to estimate the model in that case. However when there are enough conditioning variables in z_h, there are too many regressors and hence the estimation suffers from dimensionality problem. LPW propose that this problem can be avoided by further linearly approximating the model as follows:

$$a_{th} = a_{t0} + a_{tlnN_t} lnN_{th} + a_{tz} z_h$$
$$b_{th} = b_{t0} + b_{tz} z_h$$

Combining the above, the Engel curve function of assignable goods for type t can be written as:

$$S_{th} = a_{t0} + a_{tlnN_t} lnN_{th} + a_{tz} z_h + b_{t0} lnI_h + b_{tz} z_h lnI_h + \varepsilon_{th} \quad (14)$$

Now, equation (14) can be estimated via equation-by-equation OLS regression of S_{th} on a constant, lnN_{th}, z_h, lnI_h and $z_h * lnI_h$ for each type t (but, ideally through SUR). The estimated coefficients can be used to construct an estimate of b_{th} denoted by $\widehat{b_{th}} = \widehat{b_{t0}} + \widehat{b_{tz}} z_h$. As $\Sigma_t \theta_t(z_h) = 1$ and $b_{th} = \theta_t(z_h)\beta(z_h)$, $\Sigma_t \widehat{b_{tz}}(z_h)$ can be used as an estimate of $\beta(z_h)$. Resource share for members of type t can, therefore, be estimated as:

$$\widehat{\theta_t(z_h)} = \frac{\widehat{b_{th}}}{\widehat{\beta}(z_h)} = \frac{\widehat{b_{th}}}{\Sigma_t \widehat{b}_t(z_h)} = \frac{\widehat{b_{t0}} + \widehat{b_{tz}} z_h}{\Sigma_t [\widehat{b_{t0}} + \widehat{b_{tz}} z_h]} \quad (15)$$

However, if there is a lot of variability in the denominator in equation (15) or if it is close to 0, then estimated resource shares may not be meaningful. For this purpose, LPW propose imposing a linear restriction as follows:

$$\Sigma_t b_{t\bar{z}} = 0$$

This restriction implies that:

$$\Sigma_t b_{th} = \Sigma_t [b_{t0} + b_{tN_m} N_{mh} + b_{tN_f} N_{fh} + b_{tN_c} N_{ch}] \quad (16)$$

Estimated resource share can then be written as:

$$\widehat{\theta_t(z_h)} = \frac{\widehat{b_{th}}}{\Sigma_t \widehat{b_{tz}}(z_h)} = \frac{\widehat{b_{th}} + \widehat{b_{tz}} z_h}{\Sigma_t [\widehat{b_{t0}} + \widehat{b_{tN_m}} N_{mh} + \widehat{b_{tN_f}} N_{fh} + \widehat{b_{tN_c}} N_{ch}]} \quad (17)$$

The b_{tN_t}s are all expected to have the same signs. Like LPW, we too impose the restriction as in equation (16) in our empirical analysis to obtain reasonable estimates of resource shares.

3 Data

We use the National Sample Survey (NSS) on consumption expenditure for 2011-12 for our analysis. The NSS consumer expenditure survey is a quinquennial nationally representative survey that collects detailed information on the consumption of several food and non-food items at the household level. The sample consists of 101,662 households covering both rural and urban India. We consider households with two different compositions for our empirical analysis: households with adult men, women and children (denoted by MWC) and households with only adult men and women (denoted by MW) as these two types of household compositions constitute almost 90% of the sample.

We choose clothing as an assignable good. The definition of assignable clothing for men, women and children follows Calvi (2020).[8] We use the share of monthly total household expenditure spent on assignable clothing for each type of individual as our dependent variables while estimating the Engel curves (S_{th} in equation (14)). Table 1 reports the summary statistics of these variables as well as the covariates that have been used in our analysis. While the upper panel reports the descriptive statistics for the MWC households; the lower panel reports the corresponding figures for the MW households.

We find that the average share of male, female and child assignable clothing is around 2%, 1% and 1% respectively in MWC households; while the average share of male and female assignable clothing in MW households is around 2% and 1% respectively. We also find that the monthly average total household expenditure is around Rs. 8,823 for MWC households and that it is around Rs. 8,551 for MW households with significant variations as can be seen from their standard deviations.

Equation (14) shows us that our estimation includes the logarithm of the number of individuals of each type t. The average number of adult men and women are very close to each other across household compositions. The average number of adult men is 1.68 and 1.87 in MWC and MW households respectively; whereas the average number of adult women is 1.69 in MWC households and 1.64 in MW households. The average number of children in MWC households is a little over 2.

The set of other demographic covariates, $\tilde{z}_h$, included in our analysis are the average age of men, women and children (when present), number of educated men and women, total land possessed, a dummy indicating whether a household is Muslim, is headed by a widow and state dummies to account of time invariant potentially unobserved differences (such as, culture) across states. Table 1 shows that for MWC households, the average age of adult men and women are around 38 and 36 years respectively and that for children is about 8 years. The average number of educated men is 0.75 and educated women is 0.53 in such households. On the other hand, men's and women's ages are 41 and 42 years, on average and the average number of educated men and women are found to be 1.04 and 0.65 respectively

[8] See Appendix Table A.1 for variable descriptions.

Table 1: Descriptive Statistics

Household Composition	Mean	Standard Deviation	Observations
Men, Women & Children (MWC)			
Share of male assignable clothing	0.02	0.01	62,676
Share of female assignable clothing	0.01	0.01	62,676
Share of child assignable clothing	0.01	0.01	62,676
Monthly Total Household Expenditure (Rs.)	8,823.03	7,093.10	62,676
No. of adult men	1.68	0.96	62,676
No. of adult women	1.69	0.90	62,676
No. of children	2.14	1.18	62,676
Average age of men (yrs.)	37.92	9.01	62,676
Average age of women (yrs.)	35.75	8.56	62,676
Average age of children (yrs.)	8.06	4.24	62,676
No. of educated men	0.75	0.90	62,676
No. of educated women	0.53	0.75	62,676
Non-SC/ST/OBC	0.30	0.46	62,676
Urban	0.38	0.48	62,676
Muslim	0.15	0.35	62,676
If widow headed household	0.04	0.20	62,676
Total land possessed (hectares)	0.67	1.84	62,676
Men & Women (MW)			
Share of male assignable clothing	0.02	0.01	28,524
Share of female assignable clothing	0.01	0.01	28,524
Monthly Total Household Expenditure (Rs.)	8,551.27	8,506.52	28,524
No. of adult men	1.87	0.95	28,524
No. of adult women	1.64	0.83	28,524
Average age of men (yrs.)	40.81	13.77	28,524
Average age of women (yrs.)	42.25	12.58	28,524
No. of educated men	1.04	0.99	28,524
No. of educated women	0.65	0.83	28,524
Non-SC/ST/OBC	0.36	0.48	28,524
Urban	0.44	0.50	28,524
Muslim	0.10	0.29	28,524
If widow headed household	0.08	0.26	28,524
Total land possessed (hectares)	0.59	1.68	28,524

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. Observations are at the household level. The sample covers all India.

in MW households. Around 4% MWC households are found to be headed by widows while 8% MW households have a widowed woman as head. Muslim households comprise 15% and 10% of MWC and MW households respectively. The average size of land possessed is around 0.67 hectares for MWC households and 0.59 hectares for MW households, with some variation as observed from the standard deviations. The summary statistics when the sample is confined to major states is reported in Appendix Table A.2 and appear largely similar to those reported in Table 1 here for each of the types of household compositions.[9]

Our key analysis involves estimating within-household resource shares separately for rural and urban areas for each of the MWC and MW households. We find that, 38% MWC

[9] Major states comprise Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

households are located in urban areas whereas 44% MW households are urban. As we study the role of caste identity as a plausible mechanism influencing our results, we report the caste distribution of households as well in Table 1. We find that 30% of MWC and 36% of MW households belong to the non-Scheduled Caste (SC)/Scheduled Tribe (ST)/Other Backward Classes (OBC) categories, which we broadly define as the "upper" castes. The distribution of households by location of residence and caste composition for major states is largely similar to that reported in Table 1 here (see Appendix Table A.2).

4 Results

4.1 Test of identification

Although the linear reframing of DLP proposed by LPW is simple to estimate, it requires that the data satisfy a test of identification. The discussion in Section 2 showed that while estimating resource shares, estimated $\beta(z)$ appears in the denominator (equation(15)). Therefore, identification of resource shares fail if $\beta(z_h) = 0$.

LPW propose that empirically this test can be formulated as follows. Let $S_h = \Sigma_t S_{th}$ denote the fraction of overall household budget of household h spent on assignable goods. Let us denote $a_h = \Sigma_t a_{th}$, $b_h = \Sigma_t b_{th}$ and $\varepsilon_h = \Sigma_t \varepsilon_{th}$. Consequently, the linear model in equation (13) can be rewritten as:

$$S_h = a_h + b_h lnI_h + \varepsilon_h \tag{18}$$

This equation can be estimated through an OLS regression of S_h on a constant, lnN_h (a_h includes lnN_h, where $N_h = \Sigma_t N_{th}$), z_h, lnI_h and $z_h * lnI_h$. The OLS regression estimate of b_h, denoted by $\widehat{b_h}$ provides an estimate for $\beta(z_h)$. Therefore following LPW, a convenient test would be to check whether $b_h = 0$, that is, if the overall assignable goods Engel curve is upward or downward sloping. Hence if our data is unable to reject the hypothesis that $b_h = 0$, then the linear reframing of DLP proposed by LPW cannot be used to identify resource shares.

In practice, two tests of identification have been proposed by LPW. Firstly, one can use $E[\widehat{b_h}] = \widehat{b_0} + \widehat{b_z}\overline{z_h}$ ($\overline{z_h}$ is the sample average of z_h) as a test statistic for conducting the test $b_h = 0$. This captures whether the overall assignable good Engel curve evaluated at $\overline{z_h}$ is upward or downward sloping. Alternatively, one can compute $\widehat{b_h} = \widehat{b_0} + \widehat{b_z} z_h$ for every household h in the data and report the fraction of households for which it is significantly different from 0. LPW propose that if a "reasonably" large fraction of households in the sample have an estimated Engel curve that is either upward or downward sloping, then the linear reframing of DLP can be used to identify resource shares. A threshold of 75% is taken by the authors to imply a "reasonably" large fraction of the sample.

Table 2 here implements this test of identification by estimating equation (18). Column (1) shows the sample sizes for the different compositions of households across all India and major states. Columns (2) and (3) show the mean and standard deviation of total assignable clothing budget share for households respectively. We provide the slope of the household assignable clothing Engel curve (evaluated at the average of the covariates) and associated Z value of the slopes in Columns (4) and (5). We also estimate the slope for every household and Column (6) shows the fraction of households whose estimated slope is statistically significantly different from zero (using a standard critical value of 1.96). Therefore, columns (4), (5) and (6) include the necessary results for the test of identification that would indicate whether we can use the linear reframing of DLP proposed by LPW to identify resource shares in Indian households.

Table 2: Test of Identification

Household Composition	Sample Size (1)	Mean Budget Share (2)	SD of Budget Share (3)	Slope at Average value of Covariates (4)	Z-value of Slopes (5)	% of Significant Sample (6)
Panel A: All India						
Men, Women & Children (MWC)	62,676	0.035	0.019	-0.007	-556.6	99.4%
Men & Women (MW)	28,524	0.031	0.02	-0.008	-477.7	98.9%
Panel B: Major States						
Men, Women & Children (MWC)	47,976	0.037	0.019	-0.008	-590.1	99.4%
Men & Women (MW)	22,568	0.034	0.02	-0.009	-513.2	99.1%

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. "SD" refers to standard deviation. The major states in India include Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

Table 2 shows that the average budget share of total assignable clothing across all types of members at the household level varies between 3.1% to 3.7% in our data. The high standard deviation of the assignable clothing share reflects enough dispersion in the clothing share data. For all the categories (depending on household composition and all India/major states), the slope coefficient of the assignable clothing Engel curve turns out to be significantly different from zero (see the z-value of slopes in Column (5)). Moreover, for all the 4 categories in Table 2, the percentage of households whose overall assignable clothing share Engel curve's slope is significantly different from zero turns out to be around at least 99%. Therefore, the Indian NSS data satisfies the identification criteria of LPW.

4.2 Baseline Findings

We estimate the system of equations represented by equation (14) using SUR and recover resource shares given by equation (17) using equations (15) and (16). Equation (15) indicates that there are two approaches for computing resource shares. One could compute resource shares for the average household in the sample (that is, at $\overline{z_h}$). Alternatively, one could compute the resource share of men, women, and children for each household, h, and report the average of the estimated resource shares across all h.[10] Under this approach, one can also report the fraction of households for which estimated resource shares lie outside the $[0, 1]$ interval.

Table 3: Estimated Resource Share and Resource Share Per-Person Evaluated at the Covariate Vector of All Households (Panel A) & at the Average of Covariates (Panel B)

Household Composition	Sample Size	Men's Resource Share	Women's Resource Share	Children's Resource Share	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Resource Share Outside [0,1] Interval (% of HHs)
Panel A: All HHs								
MWC	62,676	0.505	0.317	0.179	0.378	0.217	0.110	11.77%
		(0.155)	(0.130)	(0.113)	(0.201)	(0.118)	(0.096)	
MW	28,524	0.708	0.292	-	0.469	0.209	-	1.25%
		(0.125)	(0.125)	-	(0.218)	(0.12)	-	
Panel B: Average HH								
MWC	62,676	0.527	0.316	0.157	0.315	0.187	0.073	-
		(0.0007)	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0003)	-
MW	28,524	0.717	0.283	-	0.383	0.172	-	-
		(0.001)	(0.0009)	-	(0.0006)	(0.0005)	-	-

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. Mean of the resource shares and per person resource shares across all households are reported in Panel A while resource shares and per person resource shares at the average value of the covariates is reported in Panel B. Standard deviations of the resource shares are reported in the parentheses in Panel A while standard errors of the estimated resource shares are reported in the parentheses in Panel B. Outliers i.e., households with any type of members (men/women/children) with a resource share below 0 or above 1 are excluded from the computation of resource shares and per person resource shares.

Panel A of Table 3 reports the mean of the resource shares and per person resource shares computed by averaging across all households along with the standard deviations; while Panel B presents the estimated resource shares and standard errors evaluated at the average of the covariates (or, the average household) for all types of household compositions. Panel A shows that men have the highest resource share, on average, relative to women and when children are present, they have the lowest average resource share within the the household. In particular, in MWC households, the average men's, women's and children's resource shares

[10] Figure A.1 and A.2 in the Appendix shows that there is no correlation/weak correlation between women's resource share and total expenditure in households with and without children. The same can be shown for men's resource share also. These findings support the assumption that resource shares do not vary with total expenditure of the household, required for identification.

are 50%, 32% and 18% respectively. This translates to per man, woman and child resource shares of 38%, 22% and 11% respectively. In MW households, the resource share for men is found to be 71% and for women around 29%, on average. Per man and woman resource shares, respectively, are 47% and 21% in these households. We find that only about 12% of MWC and 1% of MW households overall have estimated resource shares outside the $[0, 1]$ interval (such households are termed "outliers" following LPW). Estimated resource shares and resource shares per person of each type for the average household reported in Panel B are close in magnitude to those reported in Panel A for all types of household compositions.[11] [12] Therefore, our baseline findings reveal significant gender gap in resource allocation among adults and low levels of children's resource share within Indian households.

4.3 Main Findings

We discuss the main findings of our paper here, where we estimate intra-household resource shares by differentiating households on the basis of their location of residence. For each of rural and urban households, we compute the resource share per person for all households h and then the average across all such households within that type of individual (that is, analogous to Panel A of Table 3). We then test whether the estimated mean resource share per person for each type of individual - adult men, women and children (if present) is significantly different across rural and urban households. We also report whether and to what extent significant gender gap among adults and gap between adult's and children's resource shares exist within rural and urban households.

Table 4 here reports these findings for MWC (Panel A) and MW households (Panel B). From Panel A we find that while per man and child resource shares are significantly higher within households of urban India, the opposite is true for per woman resource shares. Per man and child resource shares are higher in urban households by nearly 5 and 2 percentage points respectively relatively to rural households. However, women's resource share per woman is higher by nearly 5 percentage points in rural households than their urban counterparts. Therefore, relative to rural households; men's and children's resource shares are respectively found to be 13% and 22% higher whereas women's resource allocation is found to be 22% lower in urban households. Additionally, we find that the gender gap in per person resource shares is around 12 percentage points in rural households; while it is nearly double of that for urban households (22 percentage points). This finding implies that relative to men, women's

[11] It is to be noted that resource shares estimated here are non-linear functions of OLS coefficients. Therefore, resource share evaluated at $\overline{z_h}$ may not exactly equal the mean of the resource share computed over all z_h.

[12] Appendix Table A.3 reports analogous findings from the sample of major states.

resource share is 34% lower in rural MWC households while it is 55% lower in their urban counterparts. The gap between per man and child resource shares are higher in urban relative to rural households; while the gap between per woman and child resource shares in urban households is nearly half of the corresponding gap in rural households. This follows from our earlier finding that men's and children's resource allocation improve while that of women is found to fall with urbanisation. Our findings indicate that while children's resource share and consequently child poverty is likely to improve; widening of the gender gap in resource allocation among adults in urban areas is particularly worrisome.

Table 4: Estimated Differences in Per-Person Resource Shares: Rural vs Urban Locations

Household Composition	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Difference (m-w)	Difference (m-c)	Difference (w-c)
Panel A:						
MWC: Rural	0.360	0.236	0.102	0.124***	0.259***	0.134***
	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)
MWC: Urban	0.407	0.183	0.124	0.224***	0.283***	0.059***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Difference (Rural - Urban)	-0.047***	0.053***	-0.022***			
	(0.002)	(0.001)	(0.001)			
Panel B:						
MW: Rural	0.447	0.230	-	0.217***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
MW: Urban	0.496	0.181	-	0.315***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
Difference (Rural - Urban)	-0.049***	0.049***	-			
	(0.003)	(0.001)	-			

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. The figures in the parentheses are the standard errors of the estimated mean resource shares or the standard errors of the difference in estimated mean resource shares. Differences of means are calculated for each column. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels of significance respectively.

In the absence of children, we continue to observe similar patterns in terms of resource shares of adult men and women in MW households in Panel B. Men's resource share is nearly 11% higher while women's resource share is 21% lower in urban households, relative to their rural counterparts. This implies that the gender gap in resource allocation increases substantially on account of urbanisation. In particular relative to men, women's resource share is around 49% and 64% lower in rural and urban MW households respectively. Appendix Table A.4 presents analogous findings when the sample is restricted to include only major states.

Table 5: Per Person Per Day Consumption Expenditures for the Average Household by Socio-Economic Category under Equal Sharing and Model Predictions

Household Composition	Expenditure Per Person (Assuming Equal Sharing)	Men's Expenditure Per Man (Model Prediction)	Women's Expenditure Per Woman (Model Prediction)	Children's Expenditure Per Child (Model Prediction)
Panel A:				
MWC: rural	46.17	93.24	61.12	26.42
MWC: urban	66.01	143.47	64.51	43.71
% change from rural to urban	42.9%	53.8%	5.5%	65%
Panel B:				
MW: rural	65.98	103.82	53.42	-
MW: urban	100.59	174.62	63.72	-
% change from rural to urban	52.4%	68%	19%	-

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. Expenditures are reported in Indian rupees in 2011. Predicted per person daily consumption expenditure is obtained as the product of the estimated resource share per person of a particular type and the daily household consumption expenditure.

The estimated resource shares in Table 4 can be used to compute the predicted daily expenditure per type of individual for each of the rural and urban households. This is simply given by the product of the per person of resource share of a given type t and the daily household consumption expenditure reported in the data. These computations can then be compared to the standard per capita daily expenditure figure, widely used by policymakers, which is simply obtained by computing the ratio of the daily household consumption expenditure to the number of individuals in the household.[13] It is to be noted that the standard per capita measure assumes equal sharing, whereas the model predicted daily expenditure per person explicitly takes into account unequal sharing within the household. Table 5 reports these findings. We find that under the assumption of equal sharing, daily per capita household spending for urban households is 43% and 52% higher than their rural counterparts for MWC (Panel A) and MW (Panel B) households respectively. Now, model predictions indicate that per man daily expenditure would increase by 54% and per child daily spending would increase by 65% on account of urbanisation in MWC households. On the other hand, per woman daily expenditure is predicted to be higher by only around 5% for urban relative to rural MWC households. Additionally, in MW households, per man daily spending is predicted to be higher in urban households by 68% while per woman daily spending is expected to be higher by only 19% on account of urbanisation. Therefore, under

[13] In particular, we took the average daily household expenditure and the average household size in each of rural and urban India for our computations.

within-household inequality; men's and children's (when present) expenditure are found to increase by a larger magnitude than what is found under equal sharing; whereas women's daily spending is predicted to have only a modest increase and is found to be significantly lower than that under equal sharing on account of urbanisation. Therefore, urbanisation associated with structural transformation is unlikely to translate into more equitable distribution of consumption resources within the household; although access to within-household consumption appears to improve significantly only for children.[14]

5 Possible Channels

We study two potential channels for our findings. The first channel we consider is the role of culture, specifically caste, in explaining our findings. The second channel we consider is the role of economic factors, namely exogenous variation in soil endowments, that influenced the relative participation of women in agriculture and its significance given the low importance of agriculture itself in urban areas.

5.1 The Role of Caste

The NSS (2011) data shows that non-SC/ST/OBCs (or, upper castes) comprised 37% of urban MWC households; but only 25% of rural MWC households. Further, 44% urban MW households are upper castes; whereas only 29% rural MW households belonged to this caste category. The distribution of upper castes among MWC and MW households in major states is largely analogous to that for the all-India sample reported here. The relatively larger representation of upper castes among urban households compared to their rural counterparts motivates us to understand whether caste can be one of the potential explanations of our results.

We estimate resource shares separately for SC/ST/OBC (or, lower castes) and upper castes for each of MWC and MW households and report our findings in Table 6 here. Panel A shows that among MWC households, resource shares per man and child are higher in upper caste households; while the opposite is true for per woman resource shares. Further, the estimated difference for women's and children's resource shares between lower and upper caste households are very close to the rural-urban difference reported in Panel A of Table 4. In particular, women's resource share is found to be 21% lower in upper caste households relative to their lower caste counterparts; which is exactly similar to the percentage difference found between urban and rural households. The gender gap in resource shares among adults

[14] See Appendix Table A.5 for analogous predictions for the sample of major states.

Table 6: Estimated Differences in Per-Person Resource Shares Across Caste Groups

Household Composition	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Difference (m-w)	Difference (m-c)	Difference (w-c)
Panel A:						
MWC: SC/ST/OBC	0.373	0.231	0.105	0.142***	0.268***	0.126***
	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)
MWC: Non-SC/ST/OBC	0.388	0.182	0.121	0.205***	0.267***	0.062***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Difference (SC/ST/OBC - Non-SC/ST/OBC)	-0.014***	0.049***	-0.015***			
	(0.002)	(0.001)	(0.001)			
Panel B:						
MW: SC/ST/OBC	0.463	0.219	-	0.244***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
MW: Non-SC/ST/OBC	0.479	0.191	-	0.288***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
Difference (SC/ST/OBC - Non-SC/ST/OBC)	-0.016***	0.028***	-			
	(0.003)	(0.001)	-			

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. The figures in the parentheses are the standard errors of the estimated mean resource shares or the standard errors of the difference in estimated mean resource shares. Differences of means are calculated for each column. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels of significance respectively.

is 14 percentage points for lower caste households and 21 percentage points in upper caste households, that is, consumption resources allocated to women are found to be 38% and 53% lower in lower and upper caste MWC households relative to men. Incidentally these figures are very similar to the ones obtained for rural and urban households respectively (Panel A of Table 4). Additionally the difference in resource shares between adults and children in lower and upper caste households also matches in magnitude to that found in rural and urban households respectively in Table 4. Panel B of Table 6 reports the estimated difference in resource shares between lower and upper caste MW households. The point estimates of resource shares for each type of individual and their difference between lower and upper caste household is found to be close to that obtained for rural and urban households respectively in Panel B of Table 4. Additionally, the gender gap in resource shares is found to be 24 percentage points in lower caste households and around 29 percentage points in upper caste households; indicating that these are close to our findings for rural and urban MW households respectively. Specifically, women's resource shares are 53% and 60% lower than men in lower and upper caste MW households. Especially in the context of gender gap in resource allocation, our findings indicate that, to some extent, caste based norms may be a potential explanation of why gender gap in intra-household resource sharing worsens in urban areas.

Now, higher female bargaining power as represented through higher resource allocated to women has been demonstrated to be an important factor in increasing child welfare (Maitra (2004); Reggio (2011); Chakraborty and De (2017)). However, greater potential involvement of upper caste women in the production of "status" goods which includes greater involvement in children's upbringing, may explain why children's intra-household resource shares are likely to increase even if that for women is falling.[15]

5.2 Soil Endowments & Women's Role in Agriculture

We explore the potential economic channel that could provide another possible explanation to our main results. In particular, we look at how estimated intra-household resource shares differ by exogenously varying soil textures. We use gridded data on soil textures from the National Remote Sensing Centre, Government of India (2016) for calculating the proportion of clayey (and alternatively loamy) soil in each district. Figure 1 shows the fraction of clayey soil at the district level.[16]

We rank districts by the proportion of clayey soil and categorize districts with the fraction of clayey soil at or above the median of the distribution of this variable as "clayey soil" districts. The remaining districts are, therefore, classified as "loamy soil" districts. At first we would like to examine whether and how intra-household resource allocation varies across regions with different exogenously given soil textures. We, therefore, estimate within-household resource shares differentiating households based on whether they are located in clayey vis-a-vis loamy soil texture districts. The findings are reported in Table 7 here.

Panels A and B of Table 7 show that men's resource shares are higher in predominantly loamy soil districts; while women's resource shares are found to be higher in clayey soil districts. This finding is in line with the existing literature that has documented positive relative outcomes for women in clayey soil dominated regions (Carranza, 2014). Additionally, children's resource share within the household is marginally higher in clayey soil districts relative to their loamy soil counterparts (Panel A of Table 7). Now, it is important to compare the gender gap in resource shares among adults in households across regions with different soil textures. We find that in both MWC and MW households, the gender gap in resource shares is lower in clayey soil districts. For MWC households, the gap between men's and children's resource shares is found to be higher in loamy soil districts while the gap between

[15] Eswaran et al. (2013) describes the widespread involvement of women in upper caste households in the production of "status" goods in lieu of market work. The authors provides examples of status goods which include cooking nutritious meals, greater attention towards children etc.

[16] Districts with low or no proportion of clayey soil predominantly have loamy soil textures. It is also to be noted that the same district could have both clayey and loamy soil textures

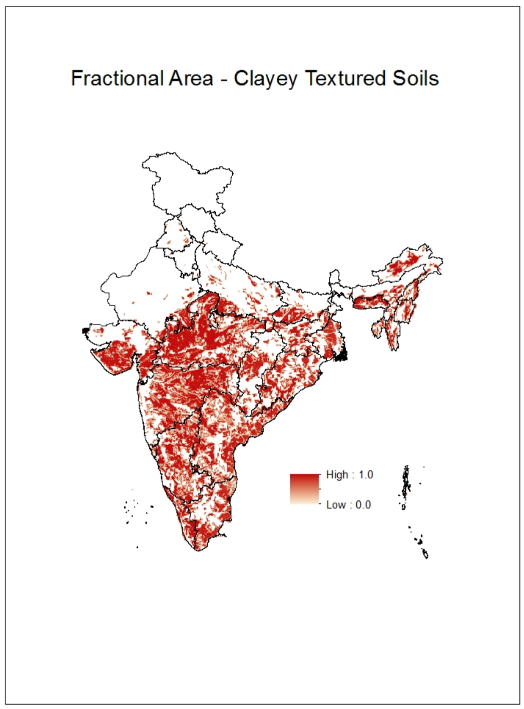

Figure 1: Source: National Remote Sensing Centre, Govt of India (2016)

Table 7: Estimated Differences in Per-Person Resource Shares Across Soil Endowments

Household Composition	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Difference (m-w)	Difference (m-c)	Difference (w-c)
Panel A:						
MWC: Clayey Soil	0.381	0.238	0.101	0.143***	0.280***	0.137***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MWC: Loamy Soil	0.402	0.208	0.090	0.193***	0.312***	0.118***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Difference (Clayey - Loamy)	-0.020***	0.030***	0.011***			
	(0.002)	(0.001)	(0.001)			
Panel B:						
MW: Clayey Soil	0.438	0.273	-	0.165***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
MW: Loamy Soil	0.430	0.251	-	0.179***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
Difference (Clayey - Loamy)	0.007***	0.022***	-			
	(0.003)	(0.002)	-			

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. The figures in the parentheses are the standard errors of the estimated mean resource shares or the standard errors of the difference in estimated mean resource shares. Differences of means are calculated for each column. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels of significance respectively. The sample is restricted to include major states - Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

women's and children's resource shares is found to be lower in loamy soil regions; driven largely by the relatively larger decline in women's resource share in loamy soil dominated regions.

We now examine the differences in estimated intra-household resource shares between rural and urban areas in clayey vis-a-vis loamy soil districts. Tables 8 and 9 report our findings for MWC and MW households respectively.

Table 8 shows that in clayey soil districts, the gender gap in intra-household resource allocation among adults in MWC households is 10 percentage points in rural areas; but it is around 22 percentage points in their urban counterparts. This implies that relative to men, women's resource share is 28% and 52% lower in rural and urban areas respectively of predominantly clayey soil districts. On the other hand, the gender gap in resource shares is found to be 15 percentage points for rural areas and 27 percentage points for urban areas in predominantly loamy soil districts; indicating that the share of consumption resources allocated to women is respectively 39% and 60% lower in rural and urban areas of dominantly loamy soil districts. These findings indicate that while rural areas in clayey soil regions appear to have the lowest gender gap in resource allocation; urban areas in loamy soil re-

Table 8: Model Predicted Gender gap in Resource Shares & Child Poverty: Rural & Urban Across Soil textures for MWC Households

MWC HHs	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Diff (m-w)	Diff (m-c)	Diff (w-c)
Clayey Soil:						
Rural	0.36	0.26	0.10	0.10***	0.26***	0.16***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Urban	0.42	0.20	0.11	0.22***	0.32***	0.09***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Loamy Soil:						
Rural	0.38	0.23	0.08	0.15***	0.30***	0.15***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Urban	0.43	0.17	0.11	0.27***	0.33***	0.06***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)

Note: Standard errors in parentheses. Sample comprises of major states. Outliers excluded from computations. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels of significance respectively.

gions are found to have the largest gender gap in within-household sharing among adults.[17] Additionally comparing the magnitude of the estimated differences, we find that the gap between men's and children's resource shares is lowest in rural areas of clayey soil districts and is highest in the urban areas of loamy soil districts. In contrast, children's resource shares vis-a-vis women are found to improve in urban areas across soil textures on account of overall lower resource share for women and higher resource shares for children in urban households.

Table 9 here presents similar findings as Table 8 but for the sample of MW households. In particular, relative to men, women's share of consumption resources is 24% lower in rural areas while it is 54% lower in urban areas of clayey soil districts. In predominantly loamy soil regions, women's resource allocation is 30% and 52% lower in rural and urban areas respectively, relative to that of men.

Our findings from Tables 8 and 9 show that gender gap in resource allocation is relatively lower in regions with predominantly clayey soil textures. However, the gender gap in within-household resource shares in urban areas of clayey soil dominated regions are substantial and appear to be higher than the corresponding figures estimated for rural areas in loamy soil dominated regions. In particular for urban MW households, the extent to which

[17]It is to be noted that clayey soil confers relative and not necessarily absolute advantage to women in terms of participation in agriculture. Carranza (2014) notes that women are equally unlikely to participate in soil preparation in both clayey and loamy soil regions; however women are more likely to participate in other stages of agricultural production such as fertilizing, transplanting and weeding. However, deep tillage commonly practiced in loamy soil regions is found to reduce overall labour demand in all stages of agricultural production; implying that it reduces the relative demand for women's labour (Carranza, 2014). This, therefore, gets reflected in our finding that although gender gap in resource allocation is not absent in clayey soil regions; gender gap in resource allocation is relatively lower in clayey vis-a-vis predominantly loamy soil areas.

Table 9: Model Predicted Gender Gap in Resource Shares: Rural & Urban Across Soil textures: Clayey vs Loamy for MW HHs

MW HHs	Men's Resource Share Per Man	Women's Resource Share Per Woman	Diff (m-w)
Clayey Soil:			
Rural	0.41	0.31	0.10***
	(0.002)	(0.002)	(0.003)
Urban	0.48	0.22	0.25***
	(0.003)	(0.002)	(0.003)
Loamy Soil:			
Rural	0.40	0.28	0.12***
	(0.003)	(0.002)	(0.003)
Urban	0.46	0.22	0.24***
	(0.003)	(0.002)	(0.003)

Note: Standard errors in parentheses. Sample comprises of major states. Outliers excluded from computations. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels of significance respectively.

women's resource share is lower relative to men's is identical between clayey and loamy soil regions. These results indicate that the relative valuation of women is found to fall much more sharply in urban areas of clayey soil regions. Now urbanisation is associated with declining importance of agriculture. Our findings show that when agriculture itself ceases to be an important occupation on account of urbanisation, the higher relative valuation of women stemming from women's traditional relative advantage in agriculture in clayey soil regions is not found to persist. The relative disadvantage of women in urban labour markets is, therefore, found to be more stark in clayey soil regions relative to their loamy soil counterparts. This could potentially explain the relatively low bargaining power of women within urban households.

6 Conclusion

This paper uses a new methodology proposed by LPW, which is the linearization of the non linear structural model of DLP, to estimate intra-household resource shares for adult men, women and children (if present) in Indian households differentiated by their location of residence. This linearized structural model is simple, more transparent to estimate than previous methodologies involving estimation of nonlinear structural models over bounded parameter spaces. It is, therefore, likely to have more widespread usage in estimating intra-household resource shares and poverty in the future.

Although we find that men command the highest resource shares and children the least and significant gender gaps in resource shares exist among adults for all households; we uncover an interesting finding about within-household sharing in rural vis-a-vis urban households. We find that men's and children's resource shares are higher in urban households; while the opposite is true for women's resource share. The model predicts that urbanisation, which is an integral part of structural transformation, is associated with substantially higher consumption expenditure for men and children in the average household but significantly lower increment in women's spending; even relative to the benchmark case of equal intra-household sharing. Additionally in households where no children are present, we obtain similar findings with regard to men's and women's resource shares. Higher children's resource shares in urban households is reassuring; while the continued increase in men's resource shares potentially at the expense of that for women in urban households is somewhat disturbing. As India becomes more urbanised, the model estimates predict that gender gaps in intra-household resource distribution is unlikely to disappear.

We also study two mechanisms that could potentially explain our findings. The first channel is that of cultural institutions and in particular caste. We find that the gender gap in resource allocation and gap between children's and adult's resource shares between lower and upper caste households are very close in magnitude to the corresponding figures for rural and urban households respectively. Caste based norms that impose relatively stricter restrictions on women's behaviour and mobility are likely to explain low intra-household bargaining power of women within upper caste households. However, as women are also more likely to be engaged in the production of "status" goods in upper caste households such as greater attention to children, children's resource shares are found to be higher despite lower women's resource shares in upper caste households. As India's urban areas have a relatively larger representation of upper castes relative to rural areas; caste could be a potential channel that could be explaining our key findings. The second channel that we explore is the economic channel that relies on examining how within household resource sharing varies by exogenously given soil textures. In particular clayey soil texture, which is not conducive to deep tillage for land preparation, is associated with greater relative contribution of women in agriculture and hence larger valuation of women in general. We find that rural areas in clayey soil regions have the lowest while urban areas of loamy soil regions have the largest gender gap in resource allocation. Interestingly, the gender gap in urban households of clayey soil regions are not trivial and are close in magnitude to that for urban areas of loamy soil regions. Our findings indicate that the relative valuation of women due to their greater potential contribution to economic activities do not persist on account of urbanisation as occupational sectors change and agriculture remains no longer relevant as a source of livelihood in urban areas.

Our paper makes important contributions to the literature, while being extremely policy relevant. On one hand, we use a relatively new but a simpler, straightforward methodology to estimate intra-household resource shares in the Indian context; focusing on not only gender differences in resource shares between adults but also children's resource shares. On the other hand, our results point towards the important role for policymakers in addressing continuing gender gaps in allocation of consumption resources within the household despite economic progress. As urbanisation is likely to result in improvement of children's access to consumption within the household, our analysis calls for acknowledging the limited role of growth and urbanisation in mitigating within household gender gaps in resource shares. As urban areas expand, the need for targeting urban poverty would become relevant in the future. Our analysis suggests that policymakers would need to be careful in designing transfer programmes targeting urban households. This is because household level transfers would fail to be welfare improving for everyone within urban households.

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Appendix Tables and Figures

Table A.1: Description of Variables Used

Variable	Description
Panel A:	
Share of male assignable clothing	Share of male assignable clothing in monthly total household expenditure
Share of female assignable clothing	Share of female assignable clothing in monthly total household expenditure
Share of child assignable clothing	Share of child assignable clothing in monthly total household expenditure
Monthly Total Household Expenditure	Total monthly expenditure of a household in rupees
No. of adult men	Total number of adult male members in a household
No. of adult women	Total number of adult number of female members in a household
No. of children	Total number of children in a household
Average age of men	Average age of adult male members in a household
Average age of women	Average age of adult female members in a household
Average age of children	Average age of children in a household
No. of educated men	Total number of adult men in a household with at least secondary education
No. of educated women	Total number of adult women in a household with at least secondary education
Non-SC/ST/OBC	Whether the household belongs to non-SC/ST/OBC category (a binary variable that takes the value 1 for a non-ST/SC/OBC household and 0 otherwise)
Urban	Whether the household belongs to urban area (a binary variable that takes the value 1 for an urban household and 0 otherwise)
Muslim	A binary variable for Muslim households (it takes the value 1 for a Muslim household and 0 otherwise)
If widow headed household	A binary variable for widow headed households (it takes the value 1 for a widow headed household and 0 otherwise)
Total land possessed	Total land possessed by a household (in hectares)
Panel B:	
Men's assignable clothing:	Dhoti, lungi, kurta-pajamas suits for males, pajamas, salwar, and cloth for coats, trousers, suit, shirt, pajama, kurta and salwar
Women's assignable clothing:	Saree, shawls, chaddar, and kurta-pajamas suits for females
Children's assignable clothing:	School uniforms and infant clothing

Note: Data source is the National Sample Survey (NSS) consumption expenditure data, 2011.

Table A.2: Descriptive Statistics: Major States

Household Composition	Mean	Standard Deviation	Observations
Men, Women & Children (mwc)			
Share of male assignable clothing	0.02	0.01	47,976
Share of female assignable clothing	0.01	0.01	47,976
Share of child assignable clothing	0.01	0.01	47,976
Monthly Total Household Expenditure (Rs.)	8,702.25	7,331.06	47,976
No. of adult men	1.68	0.96	47,976
No. of adult women	1.70	0.90	47,976
No. of children	2.16	1.21	47,976
Average age of men (yrs.)	37.78	9.09	47,976
Average age of women (yrs.)	35.69	8.64	47,976
Average age of children (yrs.)	7.96	4.26	47,976
No. of educated men	0.73	0.90	47,976
No. of educated women	0.51	0.74	47,976
Non-SC/ST/OBC	0.28	0.45	47,976
Urban	0.38	0.48	47,976
Muslim	0.13	0.34	47,976
If widow headed household	0.04	0.20	47,976
Total land possessed (hectares)	0.66	1.86	47,976
Men & Women (mw)			
Share of male assignable clothing	0.02	0.01	22,568
Share of female assignable clothing	0.02	0.01	22,568
Monthly Total Household Expenditure (Rs.)	8,462.27	8,900.58	22,568
No. of adult men	1.82	0.92	22,568
No. of adult women	1.58	0.78	22,568
Average age of men (yrs.)	41.28	14.12	22,568
Average age of women (yrs.)	42.87	12.77	22,568
No. of educated men	1.00	0.97	22,568
No. of educated women	0.60	0.79	22,568
Non-SC/ST/OBC	0.35	0.48	22,568
Urban	0.44	0.50	22,568
Muslim	0.08	0.28	22,568
If widow headed household	0.07	0.26	22,568
Total land possessed (hectares)	0.59	1.77	22,568

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. Observations are at the household level. The major states in India include Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

Table A.3: Estimated Resource Share and Resource Share Per-Person Evaluated at the Covariate Vector of All Households (Panel A) & at the Average of the Covariates (Panel B): Major States

Household Composition	Sample Size	Men's Resource Share	Women's Resource Share	Children's Resource Share	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Resource Share Outside [0,1] Interval (% of HHs)
Panel A: All HHs								
mwc	47,976	0.522	0.324	0.153	0.391	0.224	0.095	8.13%
		(0.127)	(0.119)	(0.092)	(0.190)	(0.114)	(0.081)	
mw	22,568	0.641	0.359	-	0.435	0.264	-	0.43%
		(0.144)	(0.144)	-	(0.210)	(0.143)	-	
Panel B: Average HH								
mwc	47,976	0.535	0.324	0.142	0.319	0.191	0.066	-
		(0.0007)	(0.0007)	(0.0005)	(0.0004)	(0.0004)	(0.0002)	-
mw	22,568	0.643	0.357	-	0.353	0.226	-	-
		(0.001)	(0.001)	-	(0.0006)	(0.0007)	-	-

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. Standard deviations of the resource shares are reported in the parentheses in Panel A and standard errors of the estimated resource shares are reported in the parentheses in Panel B. The estimated resource shares are the averages across households. Outliers i.e., households with any type of members (men/women/children) with a resource share below 0 or above 1 are excluded from the calculation. The major states in India include Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

Table A.4: Estimated Differences in Per-Person Resource Shares: Rural vs Urban in Major States

Household Composition	Men's Resource Share Per Man	Women's Resource Share Per Woman	Children's Resource Share Per Child	Difference (m-w)	Difference (m-c)	Difference (w-c)
Panel A:						
mwc: Rural	0.369	0.247	0.089	0.123***	0.280***	0.158***
	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)
mwc: Urban	0.429	0.185	0.106	0.244***	0.322***	0.079***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Difference (Rural - Urban)	-0.059***	0.062***	-0.017***			
	(0.002)	(0.001)	(0.001)			
Panel B:						
mw: Rural	0.407	0.300	-	0.110***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
mw: Urban	0.469	0.221	-	0.248***	-	-
	(0.002)	(0.001)	-	(0.002)	-	-
Difference (Rural - Urban)	-0.062***	0.076***	-			
	(0.003)	(0.002)	-			

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. The figures in the parentheses are the standard errors of the estimated mean resource shares or the standard errors of the difference in estimated mean resource shares. Differences of means are calculated for each column. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels of significance respectively. The major states in India include Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

Table A.5: Per Person Per Day Consumption Expenditures for the Average Household by Socio-Economic Category under Equal Sharing and Model Predictions: Major States

Household Composition	Expenditure Per Person (Assuming Equal Sharing)	Men's Expenditure Per Man (Model Prediction)	Women's Expenditure Per Woman (Model Prediction)	Children's Expenditure Per Child (Model Prediction)
Panel A:				
mwc: rural	46.17	93.24	61.12	26.42
mwc: urban	66.01	143.47	64.51	43.71
% change from rural to urban	42.9%	53.8%	5.5%	65%
Panel B:				
mw: rural	65.98	103.82	53.42	-
mw: urban	100.59	174.62	63.72	-
% change from rural to urban	52.4%	68%	19%	-

Note: Authors' estimation from the National Sample Survey (NSS) consumption expenditure data, 2011. Expenditures are reported in Indian rupees in 2011. Predicted per person daily consumption expenditure is obtained as the product of the estimated resource share per person of a particular type and the daily household consumption expenditure. The major states in India include Rajasthan, Punjab, Haryana, Madhya Pradesh, Chhattisgarh, Maharashtra, Uttar Pradesh, Uttarakhand, Gujarat, Karnataka, Andhra Pradesh (including Telengana), Odisha, Bihar, Jharkhand, Tamil Nadu, Kerala and West Bengal.

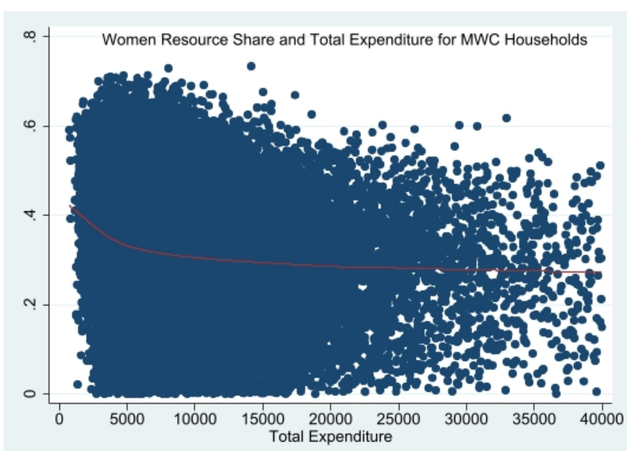

Figure A.1: Locally Estimated Scatterplot Smoothing

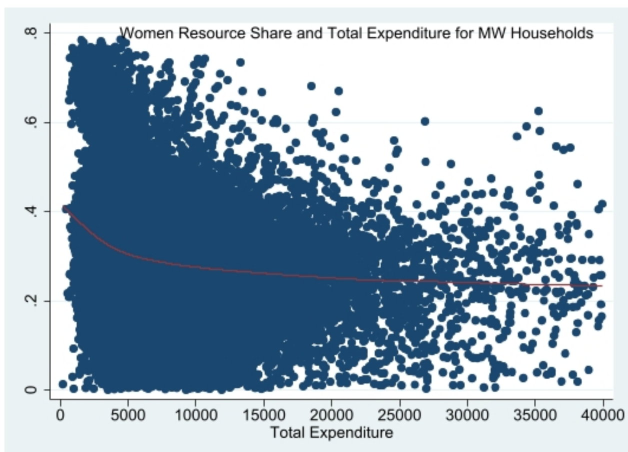

Figure A.2: Locally Estimated Scatterplot Smoothing