The allocation of time and welfare within rural households: Evidence from Tanzania

Jennifer Golan*

Abstract

Using data on individual consumption and time use from Tanzania, this paper analyses the distribution of well-being within rural couples using Browning & Görtz’s (2007) collective household model.

We find that the relative wage has a positive impact on relative private consumption and a negative impact on leisure. The results also suggest that women are better off in richer households and that inter-generational influences, such as parental education, impact on the female position within the household.

While these findings are consistent with non-unitary household behaviour, we find little evidence in support of the collective model. Only restricting the sample to couples with individual incomes for both partners allows recovering structural parameters of the model and provides partial support of collective behaviour.

JEL Classification: D13, J22, O12

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*Department of Economics, School of Social Sciences, University of Manchester, Arthur Lewis Building, M13 9PL Manchester, UK, Email: Jennifer.Golan@manchester.ac.uk.
1 Introduction

For many years the household has been taken as one decision-making agent which maximises one utility function and has been analysed on household-level data (so-called ‘unitary model’). This model implies that once controlling for overall household income, individual income sources ought not impact on the expenditure pattern (‘income pooling’). Income pooling has been widely rejected by, for example, Bourguignon, Browning, Chiappori & Lechene (1993) for France, Thomas & Chen (1994) for Taiwan, Haddad & Hoddinott (1995) for Côte d’Ivoire, Lundberg, Pollack & Wales (1997) for United Kingdom, Phipps & Burton (1998) for certain expenditure items in Canada, Quisumbing & Maluccio (2003) for Bangladesh, Ethiopia, Indonesia, and South Africa, and Lancaster, Maitra & Ray (2006) for a set of items in India.

In consequence, in the late 1980s research started to take economic theory seriously allowing husband and wife to have different and potentially conflicting interests. In this setting household decision-making depends on each member’s utility, power and caring.

Chiappori’s (1992) collective model has been established as the ‘workhorse’ for the analysis of cooperative household behavior. This model also allows deriving testable implications which have been tested and confirmed in many of the applications. Especially in studies analyzing expenditures, such as in Bourguignon, Browning, Chiappori & Lechene (1994) using Canadian data, as well as in Thomas & Chen (1994), and in parts in Quisumbing & Maluccio (2003). There are fewer studies that aim to recover structural parameters of the model, preferences or the sharing of resources within the household. Many of the studies are applied to developed countries, although there are exceptions such as Lee (2007).

Also, most of the studies focus either on the analysis of the allocation of expenditures or time. Browning & Gørtz (2007) stress that a full picture of the intra-household allocation of well-being requires to look at the allocation of time and consumption within the same couple. Intuitively, if there are two couples that are in all respects equal but in one of them the women is working more than her husband and at the same time gets comparatively fewer goods she personally enjoys, we might think she lacks power in determining her ‘piece of the pie’. Alternatively, if she works a lot but also consumes relatively more, we might guess she prefers goods over leisure (Browning & Gørtz 2007). Only analysing these two decisions for the same couple at the same time might justify inferring whether household decision outcomes are driven by tastes or power.

In this paper, we analyse the allocation of time and expenses within rural households. We use Browning & Gørtz’s (2007) model as a generic collective model and modify it to accommodate rural households. We follow Browning & Gørtz (2007) and derive a test for collective behaviour using the structural model. We use data from Tanzania which contain information on private consumption of individual household members for a range of goods and time use information for a sub-sample of panel couples. We test whether the collective restrictions hold and we estimate the structural model.
2 Theory

The model used in this section follows very closely Browning & Gørtz’s (2007) collective model, but draws on many other papers by Singh, Squire & Strauss (1986), Chiappori (1992), Udry (1996), Bourguignon et al. (1994), Chiappori, Fortin & Lacroix (2002), and Browning, Chiappori & Weiss (forthcoming) in this literature.

The household consists of two partners, labelled A and B. In all that follows we assume that A is a woman. Partner A’s utility depends on the consumption of a good bought in the market \( q_m^A \), hours of leisure \( l_A \), a domestically produced subsistence good \( q_f^A \), a non-rival household public good \( Q \) and a vector of preference factors \( a_A \):

\[
U^A = U^A(q_m^A, l_A, q_f^A, Q; a_A).
\]

Examples of subsistence goods are maize or beans that are grown on land cultivated by the partners. Good examples of public goods are children’s welfare or a clean house. Preference factors can involve factors such as age or education.

Partner B’s utility \( U^B \) depends on exactly the same arguments but for him:

\[
U^B = U^B(q_m^B, l_B, q_f^B, Q; a_B).
\]

A cares about B in the sense that she derives utility from B’s utility. Her total utility comprises her own \( U^A \) plus a proportion \( \lambda_A \) of B’s. The weight A attaches to B’s utility \( \lambda_A \) summarizes the degree of caring. We assume that the partners do not dislike or hate each other so that \( \lambda_A \geq 0 \). Her felicity function is defined as

\[
\Psi_A = U^A + \lambda_A U^B.
\]

The same considerations apply for B:

\[
\Psi_B = U^B + \lambda_B U^A.
\]

The household welfare function \( \Psi_h \) is a weighted average of both individual welfare functions:

\[
\Psi_h = \tilde{\mu} \Psi_A + (1 - \tilde{\mu}) \Psi_B \quad \text{with} \quad \tilde{\mu} \in [0, 1].
\]

The weight \( \tilde{\mu} \) reflects the so-called balance of power within the household. Substituting \( \Psi_A \) and \( \Psi_B \) into household welfare, we can redefine \( \Psi_h \) as:

\[
\mu u^A + u^B \quad \text{with} \quad \mu \equiv \tilde{\mu} + (1 - \tilde{\mu}) \lambda_B \frac{1}{1 + (1 + \lambda_A) \mu}. \tag{1}
\]

The Pareto weight \( \mu \) is a composite index of \( \tilde{\mu} \), \( \lambda_A \) and \( \lambda_B \). It captures the relative weight of partner A in the decision process. If \( \mu \) is equal to zero, then B is determining household choices. It is only the parameter \( \mu \) that is identified in the model and we never know
whether a high $\mu$ is the result of a high $\tilde{\mu}$ or a high $\lambda_B$, or low $\lambda_A$.

Economic theory does not provide a framework explaining the content of $\tilde{\mu}$, but it is said to be a function of ‘distribution factors’ (also called ‘$z$-factors’), relative wages $w_A/w_B$, prices and total household income:

$$\mu(z_1, z_2, w_A/w_B, \lambda_A, \lambda_B) = \mu[\tilde{\mu}(z_1, z_2, w_A/w_B), \lambda_A, \lambda_B],$$

where we abstracted from prices and household income for the sake of illustration.

Distribution factors $(z_1, z_2)$ are exogenous factors that impact on the allocation of power within the household but not on preferences, like $a_A$ or $a_B$, or the budget constraint, like prices or total income (Browning & Chiappori 1998). The existence of $z$-factors is crucial for identifying the collective model. Some examples of such factors are governmental transfers conditional on being single (McElroy 1990), divorce laws and sex ratios in the marriage market (Chiappori et al. 2002), relative wages, age or education differences (Bourguignon et al. (1993), Browning & Gørtz (2007)), assets brought to marriage (Quisumbing & Maluccio 2003) or changes in sex-specific earnings (Qian 2008).

In the Unitary model $\tilde{\mu}$ is constant in the sense that it does not depend on $z_1, z_2, w_A/w_B$ or prices and incomes. This means, if we estimate the impact of $\mu$ on household decision outcomes, for which $\tilde{\mu}$ ought to matter, then none of these factors should have an impact.

Figure 1 is taken from Browning et al. (forthcoming) and illustrates how distribution factors operate. Efficiency requires the solution of the household choice problem to lie on the Pareto frontier (i.e. on the contract curve of the Edgeworth box). The marginal rate of substitution of A and B’s private welfare depends on $\mu$ and so does the slope of the Utility possibility frontier. Distribution factors do not impact on the shape or position of the Pareto frontier, like prices or incomes, but impact via $\mu$ on the final allocation chosen on this frontier (Browning & Chiappori 1998).

In our model $0 \leq \mu \leq \infty$. If $\mu$ is zero, then we are at the point $0A$ in the figure. This means A does not have any power and B doesn’t care for her either, so household welfare...
is determined by B’s utility. At the point of intersection of the 45°-line with the Utility possibility frontier $\mu = 1$ and both partners have the same say in the household decision process. Increasing $\mu$ results in a move along the frontier, which means A’s utility gains more weight in household welfare.

Each partner has a total (exogenous) time endowment of 168 hours per week, $T$. For A, $T$ can be allocated to leisure $l_A$, food crop $f_A$, cash crop $c_A$, or public good production $h_A$ and off-farm employment activities (self- or wage employment) $m_A$. The same applies for B. In maximising household welfare, the partners therefore face the following constraints:

$$T \geq l_A + m_A + f_A + c_A + h_A \quad (2)$$
$$T \geq l_B + m_B + f_B + c_B + h_B. \quad (3)$$

Our model differs from Browning & Gørtz’s (2007) as it extends the time allocation variables to the domestic production of multiple marketable goods, in our notation, crops. Total food crop production $q^f$ can be allocated to subsistence consumption $q^l_A + q^l_B$ or traded in the local market $q^m$ at price $p^f$. For simplifying illustrations, we assume that the food crop production function $F^f$ uses only domestic labour inputs $f_A$, $f_B$. The same applies for cash crop production, except that this crop is entirely traded in the market at the cash crop price $p^c$.

The production of the household public good $Q$ depends on each partner’s time input $h_A, h_B$ and material inputs bought in the market $q_H$. All three production functions, food crop $F^f$, cash crop $F^c$ and public good $F^Q$ production function, are increasing in all inputs:

$$q^f = q^l_A + q^l_B + q^m^f = F^f(f_A, f_B) \quad (4)$$
$$q^c = F^c(c_A, c_B) \quad (5)$$
$$Q = F^Q(h_A, h_B, q_H). \quad (6)$$

The income constraint states that expenses on consumption goods bought in the market and material inputs into public good production cannot exceed domestic farm profits, non-wage income $y$ and labour incomes $m_A w_A$ and $m_B w_B$.

It is not possible to hoard time and we assume that the partners cannot afford to accumulate money. This means the inequality restrictions on time and income can be treated as equalities. We assume that both partners supply a positive amount of labour to farm and off-farm employment activities. We will lift this assumption below.

Substituting the time constraints for off-farm employment into the income constraint allows to define a ‘full-income’ constraint of the form:

$$p^m(m^m_A + m^m_B) + p^H q^H \leq p^f[F^f(f_A, f_B) - (q^f_A + q^f_B)] + p^c F^c(c_A, c_B) + y + w_A(T - l_A - f_A - c_A - h_A) + w_B(T - l_B - f_B - c_B - h_B).$$
The First Order Conditions of maximising (1) subject to the constraints in (2) to (6) by choosing private consumption and leisure, show that their distribution between the partners depends on the balance of power within the household. The marginal rate of substitution between A and B’s private welfare depends on $\mu$:

$$\frac{\partial u^B}{\partial q^m_B} \frac{\partial u^A}{\partial q^m_A} = \mu(.,) \quad (7)$$

$$\frac{\partial u^B}{\partial l_B} \frac{\partial u^A}{\partial l_A} = \mu(.,) \frac{w_B}{w_A}. \quad (8)$$

3 From Theory to Application

For a household that maximises welfare, conditions (7) and (8) determine the allocation of leisure and private consumption between the partners. To obtain an empirical expression for the intra-couple distribution of leisure and private consumption, we need to parameterize utility functions.

We follow Browning & Gørtz (2007) and assume additive separable utility functions:

$$u^A(q^m_A, l_A, q^f_A, Q; a) = \theta^A \log(q^m_A) + \tau^A \left(\frac{\rho}{1 - \rho}\right) l_A^{\left(\frac{\rho - 1}{\rho}\right)} + f(Q) \quad (9)$$

$$u^B(q^m_B, l_B, q^f_B, Q; a) = \theta^B \log(q^m_B) + \tau^B \left(\frac{\rho}{1 - \rho}\right) l_B^{\left(\frac{\rho - 1}{\rho}\right)} + f(Q), \quad (10)$$

where $\theta^A(a)$, $\tau^A(a)$, $\theta^B(a)$, $\tau^B(a)$ are preference parameters that determine the weight each partner gives to private consumption and leisure, and $a$ is a vector of observable determinants for $\theta^A$, with similar vectors for $\tau^A$, $\theta^B$ and $\tau^B$.

We do not observe $q^f_A$ or $q^f_B$ at the individual level, which means we do not observe total private consumption. Both partners have the same preferences for the public good, $f(Q)$. Nothing hinges on this assumption as we assume additive separability, and the focus of the analysis is the allocation of leisure and private consumption between partners. Also, we have to assume that there is no ‘joint leisure’ i.e. that the marginal utility of A’s leisure does not depend on B’s leisure.

The parameter $\rho$ is a so-called ‘leisure curvature parameter’ and captures flexibility in time use, where $0 < \rho < 1$. It can also be interpreted as the negative of the Frisch elasticity i.e. the inter-temporal elasticity of labour supply with regard to the wage. Browning & Gørtz (2007) show that values of the parameter range between 0.05 and 0.1, which is based on labour supply elasticities between 0.1 and 0.2 that are frequently found in empirical applications.

Substituting (9) and (10) into (7), we obtain a model for relative private consumption

$$q^m_A/q^m_B = \theta \mu(.,) \quad (11)$$
and using (8), we obtain a model for relative leisure
\[
l_A/l_B = [(\tau \mu(\cdot))]^\rho (w_A/w_B)^{-\rho}.
\] (12)

To make notation less cluttered, we have defined \( \theta_A/\theta_B \equiv \theta \) and \( \tau_A/\tau_B \equiv \tau \). Also, relative private consumption and leisure are always A’s relative to B’s, thereafter.

Equations (11) and (12) are the central equations to this paper. To illustrate, suppose there are just two distribution factors \( z_1 \) and \( z_2 \). Remembering that \( \mu(z_1, z_2, w_A/w_B, \lambda_A, \lambda_B) \), in the Collective model, a change in \( z_1 \) or \( z_2 \) impacts on both leisure and relative private consumption via \( \mu \). As with \( z_1 \) and \( z_2 \), a change in the relative wage affects relative private consumption via \( \mu \), but impacts on relative leisure twice. It has a negative effect due to labour supply response: as A’s wage increases, she substitutes marketed time for leisure which decreases her relative leisure. At the same time, an increase in the relative wage has a positive impact on the Pareto weight and so increases her leisure share.

In the Unitary model, a change in \( z_1 \) or \( z_2 \) has no impact on relative consumption and leisure. A change in the relative wage does not affect relative consumption and has a standard negative effect on leisure due to labour supply response. In words, A’s relative consumption remains the same and A’s leisure share decreases although her wage has increased.

We still need to parameterize \( \theta \), \( \tau \) and \( \mu \), again following Browning & Gørtz (2007):
\[
\begin{align*}
\theta &= \exp(\gamma_0 + \gamma_\theta a + \varepsilon_\theta) \\
\tau &= \exp(\gamma_0 + \gamma_\tau a + \varepsilon_\tau) \\
\mu &= \exp(\alpha_0 + \alpha' z + \delta w \log(w_A/w_B) + \varepsilon_\mu).
\end{align*}
\]

The error terms in the relative preference equations, \( \varepsilon_\theta \) and \( \varepsilon_\tau \), comprise unobserved heterogeneity in tastes between couples such as differences in relative ability or motivation. Factors we cannot control for in determining the Pareto weight are captured by \( \varepsilon_\mu \). Good examples of such factors are the partners’ relative degree of caring and their relative physical attractiveness. Substituting these expressions into (11) and (12) and taking logs, yields a system of two structural equations:
\[
\begin{align*}
\log(q_A^m/q_B^m) &= (\alpha_0 + \gamma_\theta a) + \alpha' z + \gamma_\theta a + \delta w \log(w_A/w_B) + \varepsilon_q \quad (13) \\
\log(l_A/l_B) &= \rho(\alpha_0 + \gamma_\tau a) + \rho\alpha' z + \rho\gamma_\tau a + \rho(\delta w - 1) \log(w_A/w_B) + \varepsilon_l. \quad (14)
\end{align*}
\]

where \( \varepsilon_q \equiv \varepsilon_\theta + \varepsilon_\mu \) and \( \varepsilon_l \equiv \rho(\varepsilon_\tau + \varepsilon_\mu) \). We could have an additional error term in each equation to capture measurement errors in the consumption and leisure data. As we are in practice not able to distinguish these factors neither from latent preference nor power factors, we do not take them explicitly into consideration but assume that \( \varepsilon_\theta \) and \( \varepsilon_\tau \) comprise any measurement error.

The two structural equations are log-transformed and so the coefficient of the relative
wage can be interpreted as elasticity. The relative wage impacts on relative consumption only through the Pareto weight, so \( \delta_w \) must be positive. The final sign of the relative wage on leisure depends on whether \( \delta_w \gtrless 1 \). If \( \delta_w < 1 \), then the coefficient of the relative wage in the leisure equation is negative, which means that the labour supply response effect dominates the Pareto weight effect.

The Pareto weight enters both equations. If \( \varepsilon_\theta \) and \( \varepsilon_\tau \) are independent from each other and from \( \varepsilon_\mu \), then we expect the errors of the two equations to be positively correlated.

We can write a reduced form model of the two structural equations as

\[
\begin{align*}
\log\left( \frac{q_A}{q_B} \right) &= \beta_q q_0 + \beta'_q z + \beta'_q a + \beta'_q \log(w_A/w_B) + \varepsilon_q \quad (15) \\
\log\left( \frac{l_A}{l_B} \right) &= \beta_l l_0 + \beta'_l z + \beta'_l a + \beta'_l \log(w_A/w_B) + \varepsilon_l. \quad (16)
\end{align*}
\]

Equating (13) with (15) and (14) with (16) we get:

\[
\beta_w^l = \rho (\delta_w - 1) \quad \text{and} \quad \beta_w^q = \delta_w.
\]

Hence, the reduced form estimates of \( \beta_w^l \) and \( \beta_w^q \) identify uniquely the structural parameters \( \rho \) and \( \delta_w \),

\[
\delta_w \equiv \beta_w^q \quad \text{and} \quad \rho \equiv \beta_w^l / (\beta_w^q - 1).
\]

Estimates of the \( z \)-factor parameters are given by

\[
\beta'_q z = \alpha' \quad \text{and} \quad \beta'_l z = \rho \alpha'.
\]

For a given \( \rho \), the Pareto weight parameters are identified from either equation, except for the intercept \( \alpha_0 \). So, given \( \rho \) is identified above or set to a specific value, we get \( M \) overidentifying restrictions:

\[
\beta'_{lz_m} = \beta'_{qz_m} \rho \quad m = 1, ..., M, \quad (17)
\]

where \( M \) is the total number of distribution factors available.

Browning & Gørtz (2007) highlight that the restrictions in (17) satisfy an extended version of Bourguignon, Browning & Chiappori’s (2009) proportionality condition which has been shown to be necessary and sufficient for the collective model.

Hence, if \( M \) overidentifying restrictions hold, the structural model is consistent with the reduced form and therefore the collective model is consistent with the data.

If \( \rho \) is identified as above the relative wage can be treated as being exogenous; however, if it is set to a specific value, we get an additional restriction

\[
\beta_w^l = \rho (\beta_w^q - 1). \quad (18)
\]
Imposing restriction (18) can be interpreted as if we ‘forced’ exogeneity upon the relative wage. These two properties regarding exogeneity of the relative wage are very valuable because it may be difficult to claim validity for an instrument that should not be in any case in the model as it represents a distribution factor.

4 Gender Issues in Tanzania

In terms of gender equality, Tanzania performs comparatively well in the sub-Saharan setting. The new OECD Social Institution and Gender Index database for Non-OECD countries provides index measures that allow to make cross-country comparisons. The Family Code index aims to capture institutional level factors that determine the position of women within the household. It is a composite index of the proportion of young women who are married, divorced or widowed, the acceptance of polygamy, legal rights to claim parental authority and inheritance rights of women. The broader Social Institutions and Gender Index (SIGI) comprises beyond the Family Code index other indexes that capture the status of women. Both indexes lie between zero and one. A low value means that a country has a high level of gender equality. In terms of the SIGI, the best cross-country rank position, i.e. the highest level of gender equality, has Paraguay with a value of 0.002 while Sudan has the worst index value with a value of 0.678 (for more information, see [http://genderindex.org/](http://genderindex.org/)). For both indexes, Tanzania’s values lie below the Sub-Saharan averages.

This might be explained by the fact that the government implemented a set of reforms with beneficial impacts on the status of women within Tanzanian households. For instance, in 1971 the Law of Marriage Act, a law of marriage and divorce, was implemented. The law regulates the division of property upon divorce, children custody and enables women to claim maintenance (Rwezaura & Wanitzek 1988).

In 1993, a women development fund was established to expand access to commercial loans and participation of women in economic activities, but only in 2004 women were legally entitled to access bank loans. In 1998, a law on sexual assault was enacted to address rape and incest, although spousal rape is only marginally covered by this. In 1999, the Land Act was implemented that allows women to own, use and sell land.

Still gender and intra-household discrimination are widespread:

“More than half of Tanzanian women are thought to have been beaten by their husbands [...]. Many women are killed by their husbands or commit suicide after being subjected to domestic violence” ([http://genderindex.org/country/tanzania](http://genderindex.org/country/tanzania)).

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1 Restriction (18) can be interpreted as a test of exogeneity of relative wages. To see this assume: 
\[ \varepsilon_l = \kappa \log(\frac{w_A}{w_B}) + \tilde{\varepsilon}_l. \]

The relative wage in the reduced form equation for relative leisure is only exogenous iff \( \kappa = 0 \). Substituting \( \varepsilon_l = \kappa \log(\frac{w_A}{w_B}) + \tilde{\varepsilon}_l \) into the structural leisure equation, then \( \beta_w^L = \rho(\delta_w - 1) \) and not \( \beta_w^L = \rho(\delta_w - 1 + \kappa) \) i.e. \( \kappa = 0 \). Once we solve for \( \rho = (\beta_w^L / \delta_w - 1) \), as above, we force \( \kappa = 0 \) as \( \beta_w^L = (\beta_w^L / \delta_w - 1)(\delta_w - 1 + \kappa) \) \( \Rightarrow \kappa = 0 \). For further discussion, see Browning & Gørtz (2007).
Although the minimum legal age for marriage is 15 years for women, circumstance-
dependent exceptions are granted to girls aged 14 and below.

Case study evidence from the town Moshi in Tanzania, confirms that the likelihood
of intimate partner violence increases in low levels of female education, polygamous rela-
tionships and disproportionate child bearing or delivery problems (McCloskey, Williams
& Larsen 2005).

Taken together, the issues discussed in this section suggest that, amongst many other
factors, female decision-power within Tanzanian households might depend on the female
education level, the status of the relationship, and the age at marriage.

5 Data

The data we use come from the Kagera Health and Development Survey (KHDS) con-
ducted by the World Bank in cooperation with the University of Dar es Salaam in the
Kagera Region of Tanzania. Kagera borders with Burundi, Uganda and Rwanda in the
Northwest of Tanzania.

The survey is longitudinal and covers four waves between 1991 and 1994, which we
call the ‘base sample’. In keeping with the initial survey objective, households with an
increased probability of an adult death were over-sampled. In 2004, a fifth wave was
added in an attempt to re-interview all base respondents. The base sample contains
912 households of which 93 percent had been re-contacted in 2004. The 2004 sample is
much larger, as not only households, but individuals were tracked (Beegle, de Weerdt &
Dercon 2006).

In our case, sample attrition is very severe because for the analysis we need couples
with private consumption and leisure reported for both partners. In addition, the 2004
survey does not comprise housework in the time use questionnaire, which mitigates against
constructing a sensible leisure variable. We therefore analyse the base sample only, com-
prising a total of 3,482 partners and 1,741 couples with both private consumption and
leisure.

5.1 Dependent variables

Relative private consumption. Apart from Browning & Gørtz’s (2007) data, there
are very few data sets that have information on private consumption of individual house-
hold members. The KHDS contains information on private consumption, from which we
construct $q^m_A/q^m_B$. The individual consumption questionnaire is divided into two different
sections with different recall periods; one for goods of semi-durable and one for goods of
non-durable nature.

A problem is that the goods are already categorized into individual and household
consumption, and some of the goods in the individual questionnaire we expect to be
consumed jointly by the household members. Browning & Gørtz’s (2007) data is similar
in the sense that individuals are asked to estimate their private expenses for three types of goods during a month. While the authors can cross-validate their data against another Danish data set, we cannot do this. However, the KHDS interviewer explicitly states “By acquired, I mean items that you bought for yourself, made for yourself, or that were given to you” (KHDS Household Questionnaire, Wave 1, p.135) and asserts in the second section to be “interested only in the items you purchased for yourself or someone else with your own money, and not items purchased for you by someone else”. So, we believe the data allow to construct a valid proxy for private consumption.

In the first section, information is collected for khangas (traditional East African cloth worn by women), other clothing, footwear, jewelry or watches, toys, haircuts, handbags, medicines and other medical services. In the second section, information is collected for food and drinks consumed outside the household, tobacco or cigarettes, magazines, entertainment, candles, batteries, gas or motor oil, cosmetics, etc. in a two week recall period.

In order to guard against overstating the value of certain items, such as khangas, and understating expenses on other purchases, such as of cigarettes, we convert the information into yearly totals. We sum all consumption for each partner and take the ratio of the wife’s private consumption relative to her husband’s, i.e. $q^m_A/q^m_B$.

Figure 2 shows the distribution of relative private consumption. The dashed line in

![Figure 2: Relative Consumption $q^m_A/q^m_B$](image)

the picture represents $q^m_A = q^m_B$. The figure illustrates that, on average, husbands get a far
bigger share in private consumption than their spouses. The median of positive relative consumption is 0.40, which means that in 50% of the couples women receive less than 40% of their husbands consumption. Although husbands and wives are not the only people in the household that report private consumption, taken together, their private consumption amounts to 72 percent of total household private consumption.

**Relative leisure.** For constructing the relative leisure variable $l_A/l_B$, we use the time use questionnaire. This questionnaire is based on a seven day recall period of hours spent in wage employment, self-employment, livestock cultivation, crop production, domestic household duties, caring for ill household members, job seeking, and funeral attendance.

There are $T = 168$ hours in a week. We assume that 30 hours have to be spent on sleeping and hygienic care. We aggregate the time spend on the activities listed in the questionnaire and add the 30 hours. We exclude observations with more than 168 hours in total and those with no time spend on any of the listed activities. We proxy leisure by 168 minus total time spent on all activities for each partner.

A shortcoming is that we do not have diary information. Browning & Gørtz’s (2007) data contain both diary information for a week and weekend day, and information about the usual time spend on these activities during a normal week. Due to high infrequency in the diary data, i.e. that the information collected on the day of the diary deviates from the time spent on activities normally during a week, Browning & Gørtz (2007) choose the usual week information for their empirical application. Our data do not allow to make this comparison. However, using seven day recall data, we argue to get close to the variable the authors use in their empirical application.

Figure 3 illustrates the distribution of relative leisure. Compared to relative private consumption, relative leisure has a much more egalitarian distribution with a sample median of 0.9; however, there is still a slight left skew, indicating that in this dimension also husbands receive a relatively larger share. In fact, the distributions of the two dependent variables are completely different, which may indicate that leisure and private consumption are very differently valued and distributed amongst partners in Tanzanian households.

Equations (11) and (12) illustrate that relative private consumption and leisure are both a function of preferences $\theta, \tau$, wages $w_A/w_B$ and power $\mu$. Holding relative wages constant, any correlation between the two dependent variables must be driven by preferences or power. If A prefers private consumption over leisure, and there is no variation in power, we expect the two variables to be negatively correlated since women with high private consumption tend to enjoy comparatively less leisure and vice versa. If preferences for leisure and private consumption are uncorrelated then any correlation must be due to power and we would expect a positive correlation between the two variables. Women with high private consumption also enjoy comparatively more leisure. We can also illustrate this more formally. Taking logs of (11) and (12) yields:

$$\log(q^m_A/q^m_B) = \log(\theta) + \log \mu(.),$$
\log(l_A/l_B) = \rho \log \tau + \rho \log \mu(.) - \rho \log(w_A/w_B).

Holding relative wages constant and assume preference factors are uncorrelated with Pareto factors,
\[ E[\log \mu, \log \theta] = E[\log \mu, \log \tau] = 0. \]

Given these assumptions, the correlation coefficient of the two dependent variables is defined as
\[ \text{Corr}(q, l) = \frac{\text{Cov}(q, l)}{\sigma_q \sigma_l} = \frac{\rho^2 \sigma^{2}_{\log \mu} + \rho \text{Cov}(\log \theta, \log \tau)}{\sigma_q \sigma_l}, \]

where we renamed \( \log(q_A/q_B) = q \) and \( \log(l_A/l_B) = l \) for simplifying notation. In other words, the correlation depends on the variance of the Pareto weight, the covariance between preferences for private consumption and leisure, and the size of \( \rho \). So, analysing the raw correlation between relative leisure and private consumption might give an indication whether partners’ choices are driven by tastes or power. Figure 4 illustrates this correlation.

In fact, the figure shows no correlation between the two variables.

5.2 Control variables

Relative wages. In our theoretical considerations, the relative wage plays a key role for explaining the allocation of time and private consumption between a couple. The model
discussed in section 2 assumes that both partners supply a positive amount of labour to the labour market i.e. $m_A > 0$ and $m_B > 0$. Browning & Gørtz (2007) restrict the sample to partners that are full-time employed. For our empirical application this is not feasible, as it leaves a very small sample size. In the rural setting of developing countries labour markets are often either absent or distorted, which may explain why we have so few observations that report a wage. For coping with this problem we use three measures to proxy relative wages $w_A/w_B$.

First, we do observe non-wage incomes, self-employed incomes, and wages from employment at the individual level. We aggregate these incomes over each partner and take logs. This means we restrict the sample to only those couples that report an individual income for both partners. This wage measure leaves a small number of observations and is theoretically ambiguous as it combines wages and other incomes that generate very different incentives.

Second, we use the sample of people that have a wage to estimate ‘potential wages’ and impute wages for those not having a wage, using standard techniques.

Third, a condition for a person to be indifferent between labour market participation is that her reservation or shadow wage is equal to the offered wage (Gronau 1977). Blundell, Chiappori, Magnac & Meghir (2007) and Lise & Seitz (forthcoming) show that in the collective model the shadow wage condition has to be stipulated, since efficiency requires that not only one person is indifferent towards participation but both partners within a
couple. A key difference between our and Blundell et al.’s (2007) model is that we consider the domestic production of marketable goods and analyse the collective model on leisure and not on labour supply. If households have access to functioning output and factor input markets, farm production decisions are separable from consumption choices (Singh et al. 1986). Separability implies that partners first allocate resources to farm production so as to maximise profits and, given domestic profits, they maximise utility (Bardhan & Udry 1999). If functioning markets are existent, Jacoby (1993) and Skoufias (1994) show that the marginal product of labour in farm production is equal to the market wage. If labour markets are absent or distorted the marginal product of labour in farm production is equal to the shadow wage, which then guides household time-use choices. Incorporating this discussion into the analysis, we estimate the marginal product of male and female labour inputs in farm production to proxy shadow wages.

**Other control variables** Other control variables can be grouped into factors that affect the Pareto weight $z$ and factors that affect preferences, $a$. To proxy the Pareto weight, we include a dummy variable if the community allows women to inherit her husband’s land, since land is a major asset that determines income opportunities in rural households. We also include differences in age and years of schooling between A and B, which we construct on the basis of information on the highest education level completed (we take A minus B’s values for constructing differences). Next, we include a dummy variable if the household contains multiple spouses. In line with the literature, we also include a measure of exogenous income share, which is, in our case, the share of remittances and borrowed income received by the wife to total household remittances and borrowed income. Other control variables include total household income that includes also domestic farm profits. The survey also contains a fertility questionnaire that contains information that may be associated with the status of women within the household. So we include the age at marriage, which impacts on the female education and training level and as such on job opportunities.

To proxy preferences, we include a dummy variable if the couple lives with the family. Because inter-generational influences may impact on preferences, we also include dummy variables if the father and mother have attended an educational system. Also, we include a dummy variable if the religion of the household head is muslim, as we expect this to be associated with a different consumption pattern of certain goods such as, for example, alcohol. We also include a set of dummy variables indicating the tribe of the household head for the same reason. Finally, we include set of dummy variables for the number of male and female pre-school and school-aged children within the household. (We do not construct a measure of differences in the years of education of the parents, as in Beegle, Frankenberg & Thomas (2001), since this would lead to a further reduction in the number of observations.)

It should be noted that it is somewhat arbitrary which variables are identified as preferences, and those as Pareto factors.
We also include a set of year and month dummy variables to capture seasonal and yearly price variations.

6 Results

Before discussing the results of the reduced and structural form estimates, we discuss the shadow and potential wage estimations.

6.1 Shadow wages

For recovering the shadow wages, we have to estimate production functions. The marginal product of labour depends on the functional form assumption of the underlying production function.

We consider three alternative functional form specifications that only differ in the modelling of female and male labour inputs.

In particular, we consider a standard Cobb-Douglas production function (CD) of the form:

\[ \log y = \text{const} + \alpha_A \log f_A + \alpha_B \log f_B + \ldots \]

For the collective model we need to proxy the log of the relative wage. This means we have enough information if we recover the ratio of the marginal products i.e. the marginal rate of technical substitution. For the CD this is defined as

\[ \frac{\partial \hat{y}}{\partial f_A} = \frac{\alpha_A}{\alpha_B} \frac{f_B}{f_A} \]

Second, we consider a CD that includes male and female labour inputs as a single Constant Elasticity of Substitution (CES) aggregate:

\[ \log y = \text{const} - \frac{\nu}{\rho} \log [\delta_A f_A^{-\rho} + (1 - \delta_A) f_B^{-\rho}] + \ldots \]

Where \( \nu \) depicts the returns to labour, \( \rho \) is the substitution parameter and \( \delta_A \) is the share parameter that reflects A’s contribution to output. Following Greene (2003, p.129), a linear approximation, using a Taylor series expansion, is given by

\[ \log y = \text{const} + \alpha_A \log f_A + \alpha_B \log f_B + \alpha_{AB} g(f_A, f_B) + \ldots \]

and so is linear in \( \log f_A \), \( \log f_B \) and \( g(f_A, f_B) \equiv [-(\log f_A - \log f_B)^2]/2 \).

Parameter estimates of \( \nu \), \( \delta_A \) and \( \rho \) are uniquely identified from the estimates of \( \alpha_A \), \( \alpha_B \) and \( \alpha_{AB} \).
For the CES the marginal rate of technical substitution is defined as
\[
\frac{\partial \hat{y}/\partial f_A}{\partial \hat{y}/\partial f_B} = \frac{\hat{\delta}_A}{1 - \hat{\delta}_A} \left( \frac{f_B}{f_A} \right)^{1+\hat{\rho}}.
\]

Third, we estimate a simplified version of a Translog production function:
\[
\log y = \text{const} + \alpha^A \log f_A + \alpha^B \log f_B + 1/2 (\alpha^{AB} \log f_A \log f_B + \alpha^{AA} \log^2 f_A + \alpha^{BB} \log^2 f_B) + \ldots
\]

In this case, the marginal rate of technical substitution is given by
\[
\frac{\partial \hat{y}/\partial f_A}{\partial \hat{y}/\partial f_B} = \frac{f_B}{f_A} \left( \hat{\alpha}^A + 1/2 \hat{\alpha}^{AB} \log f_B + \hat{\alpha}^{AA} \log f_A \right).
\]

The CD is strictly nested in both the CES and Translog model. If the parameter \(\alpha^{AB}\) in the CES specification is zero, then the CES reduces to the CD. If the coefficients of the interaction and square terms in the Translog model are jointly zero, then the same happens to the Translog specification.

In terms of data, the KHDS collects information on agriculture outputs in a twelve month period for the first and a six month period for all the subsequent waves. We convert the output information into value measures and aggregate total output value for each household and wave over the crops. We also include the value of harvest kept for seed, lost due to exogenous events, kept in stock and given away in the aggregation.

The data does not include domestic labour inputs in the agricultural questionnaire. This means we have to take the information from the time use questionnaire to proxy male, female and other domestic labour inputs. This is a shortcoming as on-farm labour allocations depend on seasonal fluctuations such as harvesting peak times, but we see no other way to overcome this problem.

We convert all the information into yearly totals. Other inputs include the log of the total crop area in acres, hired labour inputs and a dummy variable whether fertilizer or manure has been applied. We restrict the sample to observations with positive on-farm labour inputs for both men and women, output value and land. To the other labour inputs we add an extra hour to cope with zero inputs. Again, we include a set of year and month dummy variables in all estimations. Table 1 compares the three production function estimations.

We do not find complementarities between male and female labour inputs in the data in the sense that the coefficient on \(g(f_A, f_B)\) in the CES and the interaction term between male and female labour in the Translog specification are not significant.

The parameter estimate of \(\rho\) is \(-0.78\) and the elasticity of substitution is \(4.72\), which means that female and male labour inputs are highly substitutable. Also, the CES results indicate diminishing returns to female and male labour inputs and that women are less productive than men.
Table 1: Comparison of Production Function Estimations\textsuperscript{*}

<table>
<thead>
<tr>
<th></th>
<th>Cobb-Douglas</th>
<th>CES</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(f_A)$</td>
<td>0.051</td>
<td>0.051</td>
<td>-0.870</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.051)</td>
<td>(0.499)</td>
</tr>
<tr>
<td>$\log(f_B)$</td>
<td>0.087</td>
<td>0.101</td>
<td>-0.996</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.051)</td>
<td>(0.479)</td>
</tr>
<tr>
<td>$g(f_A, f_B)$</td>
<td>-0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\nu$</td>
<td>0.152</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho$</td>
<td>-0.788</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.267)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_A$</td>
<td>0.335</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.261)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\frac{1}{2} \log(f_A) \log(f_B)$</td>
<td>0.126</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\frac{1}{2} \log^2(f_A)$</td>
<td>0.107</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\frac{1}{2} \log^2(f_B)$</td>
<td>0.081</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\frac{\partial y}{\partial f_A} / \frac{\partial y}{\partial f_B}$</td>
<td>0.72</td>
<td>0.49</td>
<td>0.64</td>
</tr>
<tr>
<td>SSR</td>
<td>1663.9</td>
<td>1663.5</td>
<td>1652.3</td>
</tr>
<tr>
<td>$N$</td>
<td>1240</td>
<td>1240</td>
<td>1240</td>
</tr>
</tbody>
</table>

\textsuperscript{*} Robust, couple-corrected standard errors in parenthesis. Other control variables include those discussed in the main text.

The results of the CES and CD are observationally equivalent. There is slight evidence that the interaction and square terms in the Translog specification are relevant which seems driven by non-linearities rather than complementarities. The F-statistic of testing that $g(f_A, f_B) = 0$ is 0.35 and that the interaction and square terms in the Translog are jointly zero is 2.58 with a probability of 55\% and 5.3\%, respectively. In terms of Sum of Squared Residuals (SSR), the Translog model seems to perform somewhat better than CES and CD. However, many of the marginal products derived from the Translog specification are negative.

Considering that the marginal products are highly correlated across the three specifications, the evidence in favour of the Translog is not definite and by opting for the Translog we loose about 16\% of the observations, we choose the CD specification.

### 6.2 Potential wages

In a second step, we impute wages for those partners not having a wage. In line with Blundell et al. (2007) and Lise & Seitz (forthcoming), we estimate wage equations adopting a standard human capital approach. We explain wages as a function of personal characteristics (age, age square, education, gender and parental education), a set of year and month dummy variables and control for community fixed effects.
The data used is taken from the employment and self-employment sections of the activities questionnaire. It contains information on hours worked per week, weeks worked per year and salary by time unit. We generate weekly earnings, and have a so-called ‘division bias’ as wages are constructed by dividing incomes by the number of hours worked (Borjas 1980).

The number of observations is limited and, as we fail to reject that the slope coefficients are equal across gender with a Chow test statistic of 1.44 and probability of 11%, we pool across gender.

A standard problem in explaining wages is that the observation of a personal wage depends on the preceding labour supply decision of the individual. This means that Ordinary Least Squares (OLS) estimates might be biased if the same unobserved characteristics that influence the decision to participate in the labour market determine the wage level; that is, the covariance of the error terms of the two equations, $\sigma_{12}^2$, is different from zero.

Following Verbeek (2004, p.228), the problem can be formalized as follows

$$
\log w^* = x_1' \beta + u_1
$$

$$
h^* = x_2' \beta + u_2
$$

$$
w = w^*, \quad h = 1 \text{ if } h^* > 0
$$

$$
w = ., \quad h = 0 \text{ if } h^* \leq 0,
$$

where $w^*$ is the potential wage which we do not observe if the person does not have a wage and $w$ is the actual wage. The second line models whether the person has a wage as a function of variables in vector $x_2$. The vector comprises the variables in $x_1$ plus factors that affect $h^*$ in an exclusive way. For the latter we include the partner’s demographics, the marginal product of labour in farm production, a dummy indicator whether the mother resides in the same place as the household, there are kids aged below six, the log of the total crop area and non-wage household income. In the analysis below we exclude non-wage household income as it is not significant and reduces the number of observations.

The last two lines summarize the observation rule: if the person does participate, the potential wage equals the actual wage. If she does not participate the actual wage is not observed, as stated in the last line.

The distributional assumptions of the error terms are

$$
\begin{pmatrix}
  u_1 \\
  u_2
\end{pmatrix}
\sim N
\left[
\begin{pmatrix}
  0 \\
  0
\end{pmatrix},
\begin{pmatrix}
  \sigma_1^2 & \sigma_{12}^2 \\
  \sigma_{12}^2 & \sigma_2^2
\end{pmatrix}
\right].
$$

A standard way to correct OLS for potential bias is using Heckman’s two-step estimation procedure.

Table 2 summarizes OLS and selection-corrected wage estimations. The inverse Mill’s ratio is significant at a 10% significance level. However, correcting for sample selection bias deteriorates the estimates. The standard errors get bigger and the signs of the coefficients
turn counterintuitive, despite that the marginal product and mother’s residence impact on participation. Also, we expect a positive sign of the Mill’s ratio itself i.e. a positive correlation between the error terms of the two equations. These results are supported by the fact the $R^2$ of regressing the Mill’s ratio exclusively on the covariates of the wage equation is 0.93. This means our selection identifying variables are not strong enough and our results suffer from serious multicollinearity. So, we choose OLS.

Table 2: Wage Equations*

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Heckman</th>
<th>Selection eqn.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>A or B’s age</td>
<td>0.0720</td>
<td>−0.0169</td>
<td>0.0152</td>
</tr>
<tr>
<td></td>
<td>(0.0245)</td>
<td>(0.0462)</td>
<td>(0.0049)</td>
</tr>
<tr>
<td>A or B’s age2</td>
<td>−0.0008</td>
<td>0.0002</td>
<td>−0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0005)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>A or B’s years of edu.</td>
<td>0.0967</td>
<td>0.0753</td>
<td>0.0035</td>
</tr>
<tr>
<td></td>
<td>(0.0197)</td>
<td>(0.0341)</td>
<td>(0.0038)</td>
</tr>
<tr>
<td>A or B’s father edu.*</td>
<td>0.0917</td>
<td>0.365</td>
<td>−0.0162</td>
</tr>
<tr>
<td></td>
<td>(0.156)</td>
<td>(0.281)</td>
<td>(0.0265)</td>
</tr>
<tr>
<td>Women*</td>
<td>−0.845</td>
<td>−0.307</td>
<td>−0.2230</td>
</tr>
<tr>
<td></td>
<td>(0.138)</td>
<td>(0.441)</td>
<td>(0.0309)</td>
</tr>
<tr>
<td>Partner’s age</td>
<td>0.0007</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Partner’s age2</td>
<td>0.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Partner’s edu.</td>
<td>0.0053</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. kids &lt; 6*</td>
<td>0.0095</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0231)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mother same as hh*</td>
<td>0.0501</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0272)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log of mprod</td>
<td>0.0274</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0057)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log of crop area</td>
<td>−0.0153</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0106)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inverse Mill’s ratio (λ)</td>
<td>−1.0106</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.523)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>McFadden’s adj. $R^2$</td>
<td>0.156</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correctly Classified</td>
<td>83.39%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>906</td>
<td>2480</td>
<td></td>
</tr>
</tbody>
</table>

* Bootstrapped and robust standard errors in parenthesis for Heckman’s two-step and OLS estimates, respectively. Other control variables include those discussed in the main text.

* Marginal effects reported at the mean of the data. (⋆) dy/dx is for discrete change of dummy variable from 0 to 1.
6.3 Reduced and structural form estimates

As discussed above, we expect the error terms of the relative leisure and private consumption equations to be correlated because both equations depend on $\mu$ which contains $\varepsilon_\mu$. An estimator that is able to exploit this correlation is Zellner’s (1962) Seemingly Unrelated Regression (SUR) model. In addition, this estimator has the advantage that cross-equation restrictions are easily implemented and it reduces the sample to couples that report both relative private consumption and leisure.

Before turning to the results, we have to address a problem that results from pooling the data across the couples. In particular, the observations are correlated at the couple level and are, as such, not independent. This means that the standard errors of the OLS estimates are underestimated i.e. the precision of our estimates is overestimated (‘Moulton effect’). This is especially true for coefficients of cluster-invariant regressors (Cameron & Trivedi 2005). We have to address this as the survey is made over short time intervals and the within-variation of many variables is comparatively low. To get an idea about the adjustment dimension, the factor to adjust the variance of the normal OLS estimator is defined as (Cameron & Trivedi 2005, p.836):

$$\nu = [1 + \varrho (M - 1)],$$

where $\varrho$ is the intra-couple correlation and $M$ is the ‘average cluster size’ i.e. the number of observations ($N$) divided by the number of clusters, in our case couples ($C$). For positive relative private consumption $N = 1830$, $C = 645$ and $\varrho = 0.21$. So the standard errors of the relative expenditure equation would have to be multiplied by $\sqrt{1.4} \approx 1.18$. To correct for this, we bootstrap the standard errors over the couples using 400 replications (Cameron & Trivedi 2009).

A further problem is that shadow wages are by definition and potential wages by construction endogenous, which means we cannot identify $\rho$ from the estimates and have to set it to a specific value. Following Browning & Gørtz (2007) for these two samples we set $\rho$ to 0.1, and use restriction (18) to impose exogeneity upon the relative wage.

Table (3) summarizes the results of the reduced form estimates. The first two columns report the relative private consumption and leisure system estimation of equation (15) and (16) for the sample with positive individual incomes (‘first sample’), followed by the potential wages (‘second sample’) and the shadow wages (‘third sample’).

Remember, a Pareto weight factor has to be relevant for both equations. For all three specification, we find that the relative wage has a significant positive impact on relative consumption and a negative impact on leisure.

In the unitary model the relative wage does not affect relative consumption and $\delta_w = 0$. So, our results provide evidence consistent with non-unitary household behaviour. In the collective model the negative impact on leisure means that the substitution effect dominates the ‘power effect’. The reverse could only be true if $\delta_w > 1$.

Testing the collective restrictions in (17), we do not find the model supported by the
second and third sample. For the second sample the relevant Pareto weight factors are household income and A’s remittance share. The restrictions in (17) are rejected with a $\chi^2(2)$ if 16.42 probability of 0.03%. For the shadow wage sample, age differences and A’s remittance share are relevant and we reject collective behaviour with a $\chi^2(2)$ of 9.04, probability of 1%.

For individual incomes we get a mixed finding. For this sample we have three Pareto weight factors beyond wages: education of A’s father, household income, and A’s remittance share. If the education of A’s father would be a preference factor, we would expect a negative impact on relative leisure. Our parameter estimates of $\rho = 0.047 (0.011)$ and $\delta_{we} = 0.096 (0.024)$.

For a value of $\rho = 0.047$ we reject collective behaviour. In consequence, we set $\rho$ to 0.1 and re-estimate the model. For household income and education of A’s father we find the test supported with a $\chi^2(2) = 3.39$, probability of 18%. However, this result falls apart once A’s remittance share is added with $\chi^2(3)$ of 10.50, probability of 1.5%. So, we impose the first two restrictions to recover the structural equations derived in (13) and (14) above. The results are summarized in Table 4, column one and two.

---

2 We test the joint significance of the other parental education variables over the two equations and do not find any significance, except for the education of the mother-in-law of the wife. So we exclude the insignificant variables.
Table 3: Relative consumption and leisure system reduced form estimates

<table>
<thead>
<tr>
<th>Preference factors, $\beta_{\gamma}^l/\beta_{\tau}^l$</th>
<th>Individual Incomes $\log(q_m^A/q_m^B)$ $\log(l_A/l_B)$</th>
<th>Potential Wages $\log(q_m^A/q_m^B)$ $\log(l_A/l_B)$</th>
<th>Shadow Wages $\log(q_m^A/q_m^B)$ $\log(l_A/l_B)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. fem. children</td>
<td>(15)</td>
<td>(16)</td>
<td>(15)</td>
</tr>
<tr>
<td>age 0 to 5</td>
<td>0.125</td>
<td>0.0587</td>
<td>0.0578</td>
</tr>
<tr>
<td>(0.0957)</td>
<td>(0.0402)</td>
<td>(0.0721)</td>
<td>(0.0200)</td>
</tr>
<tr>
<td>No. fem. children</td>
<td>0.00208</td>
<td>-0.00287</td>
<td>0.0369</td>
</tr>
<tr>
<td>age 6 to 14</td>
<td>(0.104)</td>
<td>(0.0432)</td>
<td>(0.0655)</td>
</tr>
<tr>
<td>No. male children</td>
<td>0.0365</td>
<td>-0.0563</td>
<td>-0.0611</td>
</tr>
<tr>
<td>age 0 to 5</td>
<td>(0.102)</td>
<td>(0.0484)</td>
<td>(0.0730)</td>
</tr>
<tr>
<td>No. male children</td>
<td>-0.164</td>
<td>0.00950</td>
<td>-0.0846</td>
</tr>
<tr>
<td>age 6 to 14</td>
<td>(0.102)</td>
<td>(0.0496)</td>
<td>(0.0684)</td>
</tr>
<tr>
<td>$z$-factors, $\beta_{\gamma}^l/\beta_{\tau}^l$</td>
<td>$\log(\text{hh income} (Y))$ 0.108</td>
<td>0.0419</td>
<td>0.0356</td>
</tr>
<tr>
<td></td>
<td>(0.0451)</td>
<td>(0.0150)</td>
<td>(0.0231)</td>
</tr>
<tr>
<td>A’s remit. share</td>
<td>0.541</td>
<td>0.277</td>
<td>0.554</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.107)</td>
<td>(0.0980)</td>
</tr>
<tr>
<td>B’s mother edu.</td>
<td>0.318</td>
<td>-0.385</td>
<td>0.145</td>
</tr>
<tr>
<td></td>
<td>(0.209)</td>
<td>(0.135)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>A’s father edu.</td>
<td>0.427</td>
<td>0.132</td>
<td>0.338</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.0606)</td>
<td>(0.0879)</td>
</tr>
<tr>
<td>A’s age – B’s age</td>
<td>-0.00557</td>
<td>0.00143</td>
<td>-0.00602</td>
</tr>
<tr>
<td></td>
<td>(0.00689)</td>
<td>(0.00214)</td>
<td>(0.00420)</td>
</tr>
<tr>
<td>A’s educ. – B’s edu.</td>
<td>-0.0189</td>
<td>0.00435</td>
<td>-0.00778</td>
</tr>
<tr>
<td></td>
<td>(0.0176)</td>
<td>(0.00731)</td>
<td>(0.0119)</td>
</tr>
<tr>
<td>Multiple Spouses</td>
<td>-0.274</td>
<td>0.103</td>
<td>-0.380</td>
</tr>
<tr>
<td></td>
<td>(0.220)</td>
<td>(0.0847)</td>
<td>(0.163)</td>
</tr>
<tr>
<td>Relative wage, $\beta_{\gamma}^w/\beta_{\tau}^w$</td>
<td>$\log(w_A/w_B)$ 0.0958</td>
<td>-0.0423</td>
<td>0.138</td>
</tr>
<tr>
<td></td>
<td>(0.0238)</td>
<td>(0.00999)</td>
<td>(0.0402)</td>
</tr>
<tr>
<td>$N$</td>
<td>595</td>
<td>1726</td>
<td>1141</td>
</tr>
</tbody>
</table>

Couple-corrected, bootstrapped standard errors in parenthesis. All regressions include year and month dummy variables, and the covariates discussed in the main text. The reduced form model jointly estimates equations (15) and (16) using SURE. * Restriction $\beta_{\gamma}^l = 0.1(\beta_{\tau}^l - 1)$ imposed.
### Table 4: Relative consumption and leisure system structural form estimates

<table>
<thead>
<tr>
<th>Preference factors, $\gamma'/\rho_{\gamma'}$</th>
<th>Individual Incomes</th>
<th>Potential Incomes</th>
<th>Shadow Wages</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log$(q_{mA}\backslash q_{mB})$</td>
<td>log$(l_A\backslash l_B)$</td>
<td>log$(q_{mA}\backslash q_{mB})$</td>
</tr>
<tr>
<td>No. fem. children</td>
<td>0.124</td>
<td>0.0601</td>
<td>0.0584</td>
</tr>
<tr>
<td>age 0 to 5</td>
<td>(0.0954)</td>
<td>(0.0412)</td>
<td>(0.0721)</td>
</tr>
<tr>
<td>No. fem. children</td>
<td>-0.0130</td>
<td>0.0247</td>
<td>0.0371</td>
</tr>
<tr>
<td>age 6 to 14</td>
<td>(0.104)</td>
<td>(0.0418)</td>
<td>(0.0654)</td>
</tr>
<tr>
<td>No. male children</td>
<td>0.0428</td>
<td>-0.0678</td>
<td>-0.0612</td>
</tr>
<tr>
<td>age 0 to 5</td>
<td>(0.102)</td>
<td>(0.0469)</td>
<td>(0.0730)</td>
</tr>
<tr>
<td>No. male children</td>
<td>-0.166</td>
<td>0.0142</td>
<td>-0.0839</td>
</tr>
<tr>
<td>age 6 to 14</td>
<td>(0.102)</td>
<td>(0.0476)</td>
<td>(0.0684)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>z-factors, $\alpha'/\rho_{\alpha'}$</th>
<th>log hh income ($Y$)</th>
<th>A's remit. share $\theta$</th>
<th>B's mother edu. $\theta$</th>
<th>A's father edu. $\theta$</th>
<th>A's age – B's age $\theta$</th>
<th>A's edu. – B's edu. $\theta$</th>
<th>Multiple Spouses $\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.124</td>
<td>0.0124</td>
<td>0.0357</td>
<td>0.0324</td>
<td>0.00662</td>
<td>0.0341</td>
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<tr>
<td></td>
<td>(0.0443)</td>
<td>(0.00443)</td>
<td>(0.0231)</td>
<td>(0.00673)</td>
<td>(0.0272)</td>
<td>(0.00736)</td>
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<tr>
<td></td>
<td>0.516</td>
<td>0.323</td>
<td>0.571</td>
<td>0.571</td>
<td>0.615</td>
<td>0.615</td>
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<tr>
<td></td>
<td>(0.179)</td>
<td>(0.0994)</td>
<td>(0.0955)</td>
<td>(0.0955)</td>
<td>(0.116)</td>
<td>(0.116)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.689</td>
<td>0.306</td>
<td>-0.385</td>
<td>0.145</td>
<td>-0.365</td>
<td>0.167</td>
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<tr>
<td></td>
<td>(0.211)</td>
<td>(0.123)</td>
<td>(0.140)</td>
<td>(0.0651)</td>
<td>(0.167)</td>
<td>(0.0900)</td>
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<tr>
<td></td>
<td>0.473</td>
<td>0.0473</td>
<td>0.338</td>
<td>0.0376</td>
<td>0.343</td>
<td>-0.0221</td>
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</tr>
<tr>
<td></td>
<td>(0.158)</td>
<td>(0.0158)</td>
<td>(0.0877)</td>
<td>(0.0351)</td>
<td>(0.114)</td>
<td>(0.0397)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.00532</td>
<td>0.00975</td>
<td>-0.00604</td>
<td>0.00166</td>
<td>-0.00879</td>
<td>0.00333</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00689)</td>
<td>(0.00213)</td>
<td>(0.00240)</td>
<td>(0.00123)</td>
<td>(0.00527)</td>
<td>(0.00130)</td>
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</tr>
<tr>
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<td>-0.0187</td>
<td>0.00411</td>
<td>-0.00786</td>
<td>0.00810</td>
<td>-0.00879</td>
<td>0.00218</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0175)</td>
<td>(0.00745)</td>
<td>(0.0110)</td>
<td>(0.00400)</td>
<td>(0.0128)</td>
<td>(0.0491)</td>
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</tr>
<tr>
<td></td>
<td>-0.262</td>
<td>0.0811</td>
<td>-0.379</td>
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<td>0.0799</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.218)</td>
<td>(0.0838)</td>
<td>(0.163)</td>
<td>(0.0502)</td>
<td>(0.189)</td>
<td>(0.0593)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Relative wage, $\delta_w/\rho(\delta_w - 1)$</th>
<th>log$(w_A\backslash w_B)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.121</td>
</tr>
<tr>
<td></td>
<td>-0.0879</td>
</tr>
<tr>
<td></td>
<td>0.138</td>
</tr>
<tr>
<td></td>
<td>-0.0862</td>
</tr>
<tr>
<td></td>
<td>0.162</td>
</tr>
<tr>
<td></td>
<td>-0.0838</td>
</tr>
</tbody>
</table>

| N | 595 | 1726 | 1141 |

*Couple-corrected, bootstrapped standard errors in parenthesis. All regressions include year and month dummy variables, and the covariates discussed in the main text. The structural model is recovered by jointly estimating (13) and (14) and imposing the constraints in 17 and 18.
Although our findings support collective behaviour only in parts, they provide some interesting general results.

For instance, we find that women seem to fare better in richer households both in terms of relative leisure and consumption. An increase in A’s remittance share impacts positively on her private consumption and leisure share. The existence of multiple spouses decreases the first wife’s relative consumption, and education of the father has a positive effect.

In the first sample education of A’s father has also a positive impact on leisure and the number of school-aged boys decreases female relative consumption. This might indicate that the women in this sample prefer boys over girls or the existence of cultural norms privileging their consumption over their mothers and sisters. An alternative interpretation could be that teenage boys may not only depend on the benevolence of their parents but that they are themselves decision-makers (see Browning et al. (forthcoming)).

The years since marriage, miscarriages, and community inheritance patterns do not have any significant impact. We exclude years since marriage and miscarriages as these variables are not available for all wives.

Figure 5 illustrates our results for the first sample that most supports the model. Except for the intercept, the Pareto weight is identified from either equation. This means we cannot recover $\mu$ on a metric but have to make an additional assumption. So we normalize the Pareto weight to unity if wages are equal and the father of the spouse has no education. On the vertical axis, the figure illustrates changes in the Pareto weight if on the horizontal axis A’s income varies from being 20% to having 60% more than B.
The parameter estimates are taken from the relative consumption equation. The illustration is based on the parametrization of

$$\mu = \exp(\alpha_0 + \alpha' z + \delta_w \log(w_A/w_B) + \varepsilon_\mu).$$

The upper line highlights the shift in the Pareto weight if A’s father attended an educational establishment. In essence, the figure highlights the elasticity of the Pareto weight with regard to the wage. To put it differently, it illustrates that a one percent increase in her relative wage increases $\mu$ by 0.1 percent.

The equations are only modestly correlated, so that the efficiency gain of using SURE is limited and the $R^2$ are rather low. This means a great fraction of the variation remains unexplained.

Browning & Gørtz (2007) show that if we are willing to make strong assumptions about the correlation of the preference and Pareto weight error terms, then we can decompose the unexplained variation into the proportion due to preference factors (and measurement error) and the Pareto weight.

Assume that the unobserved preference factors and measurement error are uncorrelated from each other and independent of the Pareto factors:

$$E[\varepsilon_\theta \varepsilon_\mu] = E[\varepsilon_\tau \varepsilon_\mu] = E[\varepsilon_\theta \varepsilon_\tau] = 0.$$  

If independence holds, then the correlation between the two error terms is driven by $\varepsilon_\mu$:

$$\text{cov}(\varepsilon_q, \varepsilon_l) = \text{cov}[(\varepsilon_\theta + \varepsilon_\mu), \rho(\varepsilon_\tau + \varepsilon_\mu)] = \rho\sigma^2_\mu \Rightarrow \sigma^2_\mu = \text{cov}(\varepsilon_q, \varepsilon_l)/\rho.$$  

By assumption $\rho = 0.1$, and from the SUR estimation we can retrieve $\sigma_q$ and $\sigma_l$. In addition, SUR provides the correlation coefficient of the error terms which allows deriving the covariance and so identify $\sigma^2_\mu$:

$$\text{cov}(\varepsilon_q, \varepsilon_l) = \sigma_q \ast \sigma_l \ast \text{corr}(\varepsilon_q, \varepsilon_l).$$  

Substituting in our estimates, we get $\sigma^2_\mu/\sigma^2_q = 0.035$ and $\rho^2\sigma^2_\mu/\sigma^2_l = 0.002$.

If we believe these assumptions, then about 3.5% of the latent variation can be attributed to power in the relative expenditure while only 0.2% in the relative leisure equation.

7 Conclusion

This paper analyses the distribution of individual consumption and leisure within rural couples in Tanzania using Browning & Gørtz’s (2007) collective model.

Including shadow wages that are thought to guide decision outcomes when labour markets are absent or distorted, potential wages and individual incomes, we find consistently
that the relative wage has a positive impact on relative consumption and a negative impact on leisure. Although counterintuitive, this is evidence for the collective model or at least non-unitary household behaviour.

Also, our results suggest that women are better off in richer households, both in terms of relative private consumption and leisure. Increasing the remittance share received by the wife has a positive effect on her well-being. In addition, we find that inter-generational influences such as parental education seem to impact on the female position within the household.

While these findings are interesting in their own right, the collective model is only partially supported by the data. In particular, for the shadow and potential wage sample we do not find evidence for the collective model. Restricting the sample to couples with positive individual incomes for both partners allows to recover structural parameters of the model, and we provide partial support for collective behaviour in an application to the rural less-developed world.
References


Cameron, A. & Trivedi, P. (2009), *Microeconometrics using Stata*, StataCorp LP.


