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Abstract

This paper exploits the experimental set-up of the cash transfer program PROGRESA in rural Mexico to estimate a collective model of the household in order to investigate how parents allocate household resources. We show that household decisions are compatible with the collective model at the beginning of the program, but reject it later on. This shows that second order effects of cash transfer programs are important and suggests we need richer structural models to thoroughly analyse these policy interventions. We end this paper by proposing such a simple and tractable model of household behaviour, where decision makers may have misaligned preferences as a result of the treatment about the importance of a public good.

JEL Codes: D13, I38, J12, J16, O15

Keywords: collective model, bargaining power, efficiency, PROGRESA, conditional cash transfers.

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1 Introduction

Over the last decades, conditional cash transfer (CCT) programs have occupied a large percentage of governments' annual anti-poverty budgets (Fiszbein and Schady, 2009). PROGRESA, a CCT program implemented in rural Mexico in the late 1990s, is a prime example in which the exogenous cash transfers are targeted to mothers in order to give them a higher share of the household resources. It has been well documented that these large monetary incentives had a substantial effect on households' behavior (see Bobonis (2009), Attanasio and Lechene (2014) and Angelucci and Garlick (2016) for some recent empirical results).

We exploit the experimental set-up of PROGRESA in order to structurally investigate how households respond to the cash transfers in terms of the observed budget allocation of food. Focusing on the budget structure of food is a meaningful exercise as it accounts for around 80% of the expenditures of the targeted (poor) households in our sample. Moreover, Attanasio and Lechene (2014) convincingly show that the changes in the food decisions can not only be explained by the impact of the conditional cash transfer on household income, but are also due to changes in the intra-household decision process. In this paper we want to further investigate the latter.

The starting point of our analysis of the intra-household decision process is the collective model of the household, which was pioneered by Chiappori (1988, 1992) and Apps and Rees (1988) and further extended by Browning et al. (1994), Browning and Chiappori (1998), Blundell et al. (2005) and Chiappori and Ekeland (2006). In recent years this framework has become the main paradigm through which household allocation decisions are studied. There are two main reasons for this, which together make the framework perfectly suitable to study the distributional impacts of public policies. First, the fundamentals of the model, namely individual preferences and the household decision process, can be identified under reasonable conditions (Chiappori and Ekeland, 2009). Second, the model is based on a small set of assumptions, mainly the (Pareto) efficiency of the household allocation process, and yet provides strong testable restrictions.[1]

[1] See Bourguignon et al. (1993); Browning et al. (1994); Browning and Chiappori (1998); Chiappori

We estimate a theoretically consistent demand system on different subsamples and apply a test of Pareto efficiency (i.e. the collective model) developed by Bourguignon et al. (2009) (BBC hereafter).[2] Tests of efficiency based on data collected from randomized experiments are appealing because these programs allow researchers to construct credible *distribution factors*, that is variables that affect the decision process without affecting preferences. In what follows we augment a structural QAIDS model a-la Banks et al. (1997) with two credible distribution factors, and estimate it on household's budget shares of food. The first distribution factor that we use is the treatment indicator, which is exogenous by construction. For the second exogenous distribution factor we follow Attanasio and Lechene (2014) by using data on the network of relatives present in the village. Subsequently, we run the BBC test by focusing on the most responsive demand equations with respect to the chosen distribution factors.

Our estimates show that households satisfy the testable implications of the collective model only in 1998, 6 months after the beginning of the program, but reject them if we use the data 12 months after the first cash transfer. This implies that our results are slightly different from the existing evidence in favor of the collective model (see Bobonis (2009), Attanasio and Lechene (2014) and Angelucci and Garlick (2016)). As we discuss more in detail in Section 4, this is partly explained by our different sample selection and/or our focus on food. Moreover, our more precise conclusion with respect to the importance of heterogeneity across time, is also due the fact that our results are based on the inversion of the most responsive demand equations. This makes our statistical tests much more powerful.

In principle, the rejection of the collective model in the second period leaves open a multitude of possible explanations. First, it could be interpreted as an indication of non-

and Ekeland (2006) for testable implications in a parametric framework and Cherchye and Vermeulen (2008); Cherchye et al. (2009, 2011) for a revealed preference approach.

[2]There is a long tradition on testing the Pareto efficiency hypothesis in a household context. Early papers find efficiency in commodity demand (Bourguignon et al. (1993), Browning et al. (1994), Browning and Chiappori (1998)), labor supply for childless couples (Chiappori et al. (2002), Vermeulen (2005)), demand of childrens' health (Thomas et al., 2002; Duflo, 2003) and female labor supply (Donni, 2007; Donni and Moreau, 2007). However, efficiency has been rejected in household agricultural production (Udry, 1996), labor supply for couples with children (Fortin and Lacroix, 1997) and risk sharing activities (Dercon and Krishnan (2000), Robinson (2012)).

cooperative behavior, which in turn leads to suboptimal decisions. However, Chiappori and Naidoo (2017) show that distribution factors in a noncooperative model should satisfy the same testable implications as the ones we tested (in addition to some extra partial differential equations). This excludes this explanation and in our opinion the same conclusion extends to the so-called semi-cooperative models introduced in d'Aspremont and Dos Santos Ferreira (2014) and Cherchye et al. (2015). Next, an alternative explanation could be the need for extending our static framework to include intertemporal effects. This would allow us for instance to focus on commitment in household decisions, which could in turn lead to an ex-post inefficient decision. As shown in Mazzocco (2007), the significance of our distribution factors indicate that there is only limited commitment. The rejection of the collective model could therefore be interpreted as an indication that the participation constraint for the marriage is binding. That is, the spouses should divorce, which is (currently) not the case for our observed households.

Alternatively, the rejection of the collective model can also be seen as an indication of misaligned preferences due to preference shifts over the period of observation. This interpretation complements the results by Angelucci (2008) and Bobonis et al. (2013), who show that PROGRESA induced a higher level of threats of violence for some targeted households. Due to data limitations we could not explicitly analyze the incidence of violence within the household, but our results confirm once more the fact that there might be second round effects of PROGRESA. Empowering women might threaten their husband's perceived identity, or, more generally, might have created more misaligned preferences between the spouses. This implies that the observed budget allocation of food cannot be solely explained by an induced shift of bargaining power towards the mother.

Motivated by this evidence and by our empirical results, we provide a simple analytical framework to rationalize the results in the context of misalignment in the preferences of the spouses. Albeit simple, our framework can be used as a starting point, both empirically and methodologically, to think more carefully about second round effects of public interventions and household responses following an altering of the decision process inside the household. As such, our paper is also related to the treatment effect literature of CCT programs, which aims at identifying empirical facts on how to obtain the desired policy interventions. One of the focuses of this literature is to establish whether, why and to what extent targeting conditional cash transfers to women is effective (see Yoong et al. (2012) for a systematic review).

The paper is organized as follows. Section 2 describes the general theoretical framework which motivates the empirical analysis. Section 3 discusses the data, the empirical strategy and the methodological issues related to the estimation of a demand system. Section 4 presents the results and their rationalization within an alternative theoretical framework of changes in preferences. Section 5 concludes.

2 Theoretical framework

In this section we discuss the theoretical set-up of individuals' interactions within the household and introduce the test of the collective model that we run in the empirical section. Consider a household comprising two decision makers $i \in \{m, f\}$ and any number of children, where m stands for mother and f for father. Children are not part of the decision making process and enter as a public good within the household. Household member i cares about her own private consumption $\mathbf{c}^i$ and household public goods $\mathbf{k}$. Each member's preferences are assumed to be representable by a continuously differentiable and strictly concave utility function $U^i(\mathbf{c}^i, \mathbf{k})$. The extent to which members m and f care about the children is captured by their preferences for the public good. The resources of the family are derived from total household earnings x, potentially including an endowment entitled to member m. The budget constraint of the family can then be written as follows:

$$\mathbf{p}'\mathbf{c} + \mathbf{P}'\mathbf{k} = x, \tag{1}$$

where $\mathbf{p}$ and $\mathbf{P}$ are the price vectors of private and public goods respectively.

According to the formulation of household decisions provided by Chiappori and Mazzocco (2017), the test of efficiency is derived at the *intra-household allocation stage.* At this stage, a household takes as given an arbitrary amount of household-level private goods $\bar{\mathbf{c}}$ and public goods $\bar{\mathbf{k}}$,which are optimally chosen at the *resource allocation stage.* Then the household chooses the allocation of private goods between spouses by solving the following (static) problem:

$$\begin{aligned} U(\bar{\mathbf{k}}, \mu^i(\mathbf{z})) &= \max_{\{\mathbf{c}^m, \mathbf{c}^f\}} \quad \sum_i \mu^i(\mathbf{z}) U^i(\mathbf{c}^i, \bar{\mathbf{k}}) \\ \text{s. t} \quad & \mathbf{c}^m + \mathbf{c}^f = \bar{\mathbf{c}}, \end{aligned} \tag{2}$$

where $\mu^i(\mathbf{z})$ is the Pareto weight summarizing the individual decision power of the two spouses. The resulting demand equation for a generic (private) good j then takes the following form:

$$\theta_j = \xi_j(\bar{\mathbf{c}}, \mu^i(\mathbf{z}); \mathbf{d}, \epsilon), \tag{3}$$

where $\mathbf{d}$ and ϵ are a set of observable and unobservable characteristics of the household. The crucial aspect of this demand function is the presence of the Pareto weight function $\mu^i(\mathbf{z})$ and its functional dependence on distribution factors $\mathbf{z}$. Indeed the manner in which these factors affect demand (3) can be used to test Pareto efficiency, the main underlying assumption of collective models.

BBC derive necessary and sufficient conditions for collective rationality that are valid for any type of good, either private or public. In order to understand the theoretical restriction that we want to test, we have to introduce the concept of *z-conditional demand* functions. Consider the demand for good j resulting from program (2), $\theta_j = \xi_j(\bar{\mathbf{c}}, \mu^i(\mathbf{z}); \mathbf{d}, \epsilon)$, where some of the elements of $\mathbf{z}$ may not be observed but at least one is. In particular, assume that there is at least one good j and one observable distribution factor z_1 such that $\xi_j(\bar{\mathbf{c}}, \mu^i(\mathbf{z}); \mathbf{d}, \epsilon)$ is strictly monotone in z_1. Given strict monotonicity, the demand function for good j can be inverted on this factor: $z_1 = \zeta(\bar{\mathbf{c}}, \mu^i(\mathbf{z}_{-1}), \theta_j; \mathbf{d}, \epsilon)$. We can now define the following:

Definition 1. *The demand function for any good j, private or public, is a z-conditional* *demand if:*

$$\theta_j = \xi_j(\bar{\mathbf{c}}, \mu^i(z_1, \boldsymbol{z}_{-1}); \boldsymbol{d}, \epsilon) = \xi_j[\bar{\mathbf{c}}, \zeta(\bar{\mathbf{c}}, \mu^i(\boldsymbol{z}_{-1}), \theta_l), \mu^i(\boldsymbol{z}_{-1}); \boldsymbol{d}, \epsilon] = \varphi_j(\bar{\mathbf{c}}, \mu^i(\boldsymbol{z}_{-1}), \theta_l; \boldsymbol{d}, \epsilon). \tag{4}$$

In other words, the demand for good j can be written as a function of total expenditure $\bar{\mathbf{c}}$, all distribution factors but the first, $\mathbf{z}_{-1}$, and the quantity demanded for good l. Although conditional demands are often used in demand analysis, it is useful to refer to it as z-demands because it incorporates the idea that distribution factors play a central role in the intra-household allocation stage of collective models. Empirically, the restriction that involves the z-conditional demand says that if there exists a distribution factor such that:

$$\frac{\partial \theta_j}{\partial z_1} \neq 0 \quad, \forall j, \tag{5}$$

the demand for good j is compatible with collective rationality if and only if there exists at least one good l such that:

$$\frac{\partial \varphi_j(\bar{\mathbf{c}}, \mu^i(\mathbf{z}_{-1}), \theta_l; \mathbf{d}, \epsilon)}{\partial z_p} = 0 \quad \forall j \neq l \quad \text{and} \quad p = 2, \ldots, s. \tag{6}$$

The meaning of this testable restriction is the following. If we invert the demand for good l on a distribution factor z_1, which is also significant for any other good $j \neq l$, and we replace this demand into the demand of any other good $j \neq l$, the effect of any second distribution factor z_p is going to be irrelevant. The intuition is that, by definition, distribution factors affect demand only through their effect upon the location of the final outcome on the Pareto frontier. That is, they do not shift the Pareto frontier, because they do not impact the individual preferences nor the budget constraint. Importantly, the effect of the bargaining weight is one-dimensional. Once the location on the Pareto set has been changed by the effect of the first distribution factor, the information brought by any other additional distribution factor is uninformative.[3]

[3]Note that Proposition 2 of BBC provides three equivalent conditions necessary and sufficient for collective rationality. Empirically, the restriction that involves the z-conditional demand is the most powerful because we can employ single equation methods which are more robust than tests of the equality of parameters across equations. This is the reason why in the present paper we employ this restriction.

3 Empirical implementation

We investigate how households respond to monetary incentives using a sample drawn from the surveys collected to evaluate the impact of PROGRESA.[4] This is a conditional cash transfer program implemented in rural Mexico in the late 1990s. The choice of this dataset is motivated by a variety of reasons. First, the monetary incentives were quite large and had a real effect on households' behavior inducing them to change their consumption patterns. Second, the surveys are very detailed and of high quality allowing us to construct vectors of quantity and prices for various important commodities. Third, the available dataset contains two exogenous distribution factors, which allow us to meaningfully test the main hypothesis outlined in the theory part.

The remainder of this section is divided in four sub-sections. First, we provide some background information on the program, we present the evaluation surveys, how prices and quantities are aggregated, and some descriptive statistics of the sample used in our empirical analysis. Second, we discuss the appropriateness of the two distribution factors that we use to test the efficiency of the resource allocation. These are the most important variables for the purpose of our exercise. Third, we discuss the consumption behavior of our sample, that is, household preferences and the observed demand equations, and outline the z-conditional demand system that we are going to estimate. The final subsection deals with the estimation strategy and the methodological issues that have been raised in the literature when one aims to identify the relationship of interest with data coming from a cash transfer programs such as PROGRESA (e.g. Attanasio and Lechene (2002, 2014), Attanasio et al. (2013)). In our context, we are particularly concerned with the endogeneity of both total expenditure and the number of children enrolled in secondary school.

3.1 Program design, sample selection and descriptive statistics

The original PROGRESA program was implemented between April 1998 and December 2000. Later it was extended to include new households both in rural and urban

[4] Specifically, we use exactly the same dataset as in Attanasio and Lechene (2014).

areas. From its start, PROGRESA was subject to rigorous evaluation based on random assignment. 10,000 localities were included in the first expansion phase, and from here 506 were selected in the evaluation sample, 320 of them were randomly chosen to have an early start of the program, whereas the remaining 186 formed the control group. In practice, households in the these latter villages were not included in the program until late 1999, which means that they became eligible for the grant only after this date. "Eligible" households in treatment villages started receiving the cash transfers subject to the appropriate conditionality already in April 1998. Whereas "eligible" households in control villages were still observed during this time, but they started benefiting from the payment (in the same manner) only after November 1999.

The main objectives of the program were to introduce incentives to improve the accumulation of human capital of children and at the same time to alleviate short-term poverty. To be eligible, a household must be sufficiently poor (in the program sense). The transfers were paid to the mother every two months and were largely in the form of scholarships to four grades of primary school, except the first two and the initial three grades of secondary school. These transfers are conditional on certain behavior: first, children must attend at least 85% of classes; second, household members must undergo periodic health checks; third, the transfer recipients must attend nutrition and health classes. The strong involvement of the mother in the program was motivated by the assumption that they have a stronger taste for child well-being and are more responsible at managing households resources. Moreover, a change in relative income of spouses was motivated by the desire to change the position of woman within rural families in Mexico, which was the intended by-product of the intervention.[5]

In the present paper we use two post intervention surveys, October 1998 and May 1999, which were collected 6 months and 12 months, respectively, after the households started

[5]The program was so much a success that later it was expanded to other households in rural areas who were followed throughout the 2000s, as well as households in urban areas. Other countries as well adopted this kind of cash transfers program, both in Latin America, Asia, Africa, and some developed countries as well. PROGRESA has been found to increase education attainment (Schultz (2004), Attanasio et al. (2013)), to decrease short term poverty (Tommasi and Wolf, 2016), and to improve health (Gertler (2004), Behrman and Parker (2011)). Detailed information on the program and its evaluations can be found in Skoufias (2005) and Fiszbein et al. (2009).

receiving the cash transfers. The surveys included detailed information on expenditures at the household level and detailed information on members of the household. In order to have an homogeneous sample on which to test the hypothesis of interest, we select a subsample that satisfies the following restrictions. First, there are only households with both natural parents in our sample and one to at most six children. This means that households with at least one other adult member are excluded and the mother is always the recipient of the cash transfers. Second, households with children aged 17 or above are also excluded from the sample, in order to exclude households with multiple decision makers besides the parents. The resulting sample consists of 5,125 households observed in 1998 and 4,932 households observed in 1999. In Table A.1 of the Appendix, we present the means of various baseline household-level characteristics for eligible households in treatment and control villages. As we can see from this table, households are disadvantaged in a number of important ways. First, the education of head and spouse is quite low, as the average adult has only slightly more than a primary school diploma. Second, families are quite large as the average number of children is 4. Third, 38% of households have an indigenous origin. Finally, only a quarter of localities have a secondary school in the village.

We are interested in studying the household responses to cash transfers in terms of demand for food components, which, in our sample, represents about 80% of non-durable expenditure.[6] The demand for it is modeled assuming separability of these goods from the non-food consumption and labor supply. The PROGRESA data contains very detailed information on both expenditure and consumption for many (narrowly defined) commodities. Following Attanasio and Lechene (2014), we use aggregated data to create budget shares of 5 different commodities: starches; pulses; fruit and vegetables; meat, fish and diary; and other foods. As explained in detail by the authors, for each of the individual commodities that make the 5 commodities that we use, consumption is computed as to include what has been bought as well as quantities obtained from own production, payments in kind and gifts. The quantities are valued in pesos using locality

[6]We focus on demand for food for a variety of reasons. First and foremost, food consumption is the most important commodity in the budget of the expenditure of the households in the sample. Second, prices for the non-food consumption are not observed and hence it is practically impossible to use these goods.

level price information derived from unit values. As reported in Attanasio et al. (2013), the authors take particular care to avoid duplication induced by household production. For instance, if a household has consumed a good that was produced at home, they include the value of this good (valued at average prices in the town) but do not include the value of the raw material that was purchased to make that good.

We compute unit values of the five commodities which allow us to estimate the demand system. These are used to evaluate consumption in kind and to compute price indexes for each of the composite commodities. Unit values are computed for each household dividing the value of the purchase by its quantity. The value of the purchased commodity is computed by using village-level prices for individual commodities, where the village-level price is selected by looking at median unit value of the households that purchased that product in a given locality. More details on the computation of these unit values and how price indexes are constructed can be found in Attanasio et al. (2013). This resulted in considerable variation in prices across villages and time in the data, which in turn allows to get precise parameter estimates of the demand system.

3.2 Distribution factors

For our empirical exercise we need to find at least two variables that affect the allocation of resources but not preferences. These variables are called distribution factors and enter the Pareto weight function of the two agents within the household. Browning et al. (2014) report the most common distribution factors used in the literature. As the authors argue, it is a difficult exercise to find plausible distribution factors because theory does not give guidance as to what constitutes a distribution factor and for each variable it is possible to find a reason why it could also affect preferences or the budget constraint.

In order to conduct a robust analysis, in the present paper we use two of the most credible distribution factors used in the literature: the eligibility to PROGRESA and the relative importance of the husband and wife's family network in the village. Since both these variables have already been used by Attanasio and Lechene (2014), we briefly recapture their discussion in Appendix A.2. Nevertheless, there are two important remarks we want to stress in the main text. First, the choice of the conditioning distribution factor and the conditioning good is crucial for the reliability of the empirical results. Theory indicates that the conditioning distribution factors must be statistically relevant and must affect the conditioning good monotonically. In the empirical analysis we use the network variable as our preferred conditioning distribution factor, which has been shown by Attanasio and Lechene (2014) to satisfy all the requirements of the theory and is statistically significant in our own empirical exercise. Second, part of the discussion in the collective model literature is the nature and validity of the distribution factors used, whether discrete or continuous. We point out that, for the reliability of the results, it is important that the *second* distribution factor (the one on which the demand system is inverted on) is continuous. This is the case in our empirical exercise for our network variable.[7]

3.3 Functional forms

In our empirical application we assume that households have preferences given by the integrable QAIDS demand system of Banks et al. (1997). QAIDS allows flexible prices responses and the quadratic income allows the Engel curves to display a great variety of shapes. The indirect utility function of each household is assumed to be of the following form:

$$V = \left\{ \left[\frac{\ln x - \ln a(\mathbf{p})}{b(\mathbf{p})} \right]^{-1} + \lambda(\mathbf{p}) \right\}^{-1}, \tag{7}$$

where

$$\begin{aligned} \ln a(\mathbf{p}) &= \alpha_0 + \sum_{j=1}^{n} \alpha_j \ln p_j + \frac{1}{2} \sum_{j=1}^{n} \sum_{l=1}^{n} \gamma_{jl} \ln p_j \ln p_l, \\ b(\mathbf{p}) &= \prod_{j=1}^{n} p_j^{\beta_j}, \\ \lambda(\mathbf{p}) &= \sum_{j=1}^{n} \lambda_j \ln p_j. \end{aligned} \tag{8}$$

[7] As for the first distribution factor, which is the treatment indicator in our case, Kapan (2009) discuss the underlying conditions such that a discrete distribution factor can be used to study the impact on bargaining power.

The parameters α_j, β_j, λ_j and γ_{jl} $(\forall j, l)$ are to be estimated. Adding up requires that $\sum_j \alpha_j = 1$, $\sum_j \beta_j = 0$, $\sum_j \lambda_j = 0$ and $\sum_j \gamma_{jl} = 0$ $(\forall l)$. Homogeneity is satisfied if $\sum_l \gamma_{jl} = 0$ $(\forall j)$.[8] Notice that the indirect utility function underlying Deaton and Muellbaur's (1980) Almost Ideal Demand System corresponds to equation (7) where $\lambda_j = 0$ for all goods.

Applying Roy's identity to equation (7) we obtain the QAIDS budget share equations for each household and commodity j

$$w_j = \frac{\theta_j}{x} = \alpha_0 + \phi'\mathbf{d} + \psi'\mathbf{z} + \sum_{l=1}^{j} \gamma_{il} \ln p_l + \beta_j \ln\left\{\frac{x}{a(\mathbf{p})}\right\} + \frac{\lambda_j}{b(\mathbf{p})}\left[\ln\left\{\frac{x}{a(\mathbf{p})}\right\}\right]^2 + \epsilon_j, \quad (9)$$

where w_j indicates the jth budget share of a household facing a price vector $\mathbf{p}$ and total expenditure level x, whereas $\mathbf{d}$ and $\mathbf{z}$ are vectors of, respectively, individual demographic characteristics and distribution factors. The impact of these variables runs through the coefficients ϕ and ψ, whose estimates constitutes the main purpose of our empirical investigation. In principle both vectors $\mathbf{d}$ and $\mathbf{z}$ could of course affect the demand system in other ways, not necessarily through the intercept only. As a robustness check, we re-estimated the parameters of a general QAIDS model where demographic characteristics and distribution factors were allowed to change the curvature of the demand system in multiple ways. Almost all the additional parameters were not significant, which indicates that it is not restrictive to focus only on changes in the intercept.

In order to estimate the z-conditional demand system (4) for good θ_k, we have to allow that the conditioning good θ_l might be endogenous. This problem can be avoided because the excluded distribution factor on which the demand is inverted becomes a natural instrument for θ_l. Let N, the relative family network, be the excluded distribution factor. The demand function for commodity j $(j = 1, \ldots, n)$ can be inverted on this factor:

$$N = \frac{1}{\psi_N}\theta_l - \frac{\psi'}{\psi_N}\mathbf{z}_{-1} - \frac{1}{\psi_N} f_l(x, \mathbf{p}) - \frac{\phi'}{\psi_N}\mathbf{d} - \frac{1}{\psi_N} u_l,$$

[8]As shown in Browning and Chiappori (1998), Slutsky symmetry no longer needs to hold, so we did not have to impose this. It would be satisfied satisfied if $\gamma_{jl} = \gamma_{lj}$ $(\forall j, l)$.

where now $\mathbf{z}_{-1}$ contains only the remaining distribution factor and, for notational simplicity, $f_l(x, \mathbf{p}) = \sum_{j=1}^{n} \gamma_{lj} \ln p_j + \beta_l \ln\left\{\frac{x}{a(\mathbf{p})}\right\} + \frac{\lambda_l}{b(\mathbf{p})}\left[\ln\left\{\frac{x}{a(\mathbf{p})}\right\}\right]^2$ for each good l. Substituting this equation for N in the demand for all other goods results in the system of z-conditional demand functions:

$$\theta_j = \tilde{\alpha}'\mathbf{z}_{-1} + \tilde{\gamma}\theta_l + \tilde{\beta} f_l(x, \mathbf{p}) + \tilde{\phi}'\mathbf{d} + \tilde{u}_j \tag{10}$$

for all goods $j \neq l$. The test of collective rationality then boils down to a test of the significance of $\tilde{\alpha}$.

3.4 Endogeneity

Since our dataset comes from the evaluation of a cash transfer program, which has some important conditionality attached, the main methodological concern in estimating the demand system (9) is the endogeneity of total expenditure and child school enrollment. A further methodological concern is the non-linearity of the system, which makes the recovery of the parameter estimates more complicated. The latter issue is tackled by estimating the complete system with the iterated Feasible Generalized Non-Linear Least Squares (FGNLS) estimator. The former concern is tackled with a control function approach, as it is commonly applied in demand analysis (e.g. Blundell and Robin (1999)), where the residuals, estimated in the first stage, enter as a polynomial of second order. In the following paragraphs we explain the concern for each of the endogenous variables and how we deal with it.

For the endogeneity of total expenditure, notice that the implicit assumption behind our exercise is the idea that households decide their budget structure under two-stage budgeting: first they decide how much to allocate to food and then how much to allocate to each of the 5 components of food. The residuals in (9) can be interpreted as the household's unobserved tastes that affect each budget share. There are two main arguments in the literature for why total expenditure x should be endogenous. One is that taste shocks that determine total expenditure x may be correlated with the unobserved shocks to a particular food component in the system. The other one is that measurement error in the budget shares may be correlated with measurement error in total expenditure. In the present paper we follow Attanasio and Lechene (2002, 2014) and instrument total expenditure x with the average agricultural wage in the village. This is a strong instrument and the implicit assumption in using it is that any measurement error in village-level income is not correlated with measurement error of household total expenditure, which is a commonly accepted assumption. As the authors explain at length, this is a valid instrument if labor supply is separable from consumption. With respect to this, there is large evidence that PROGRESA did not affect adult labor supply and hence it is not a concern for us (e.g. Skoufias (2005)).

The second endogenous variable in system (9) is the number of children enrolled in school. As it was explained before, eligible households receive a (large) portion of the grant if their children are enrolled and attend school. This conditionality requirement, which is controlled for in the demand equations, might affect consumption behavior if sending children to school imposes additional costs like books, uniforms, etc. Moreover, if children are fed in school, this would further impact the budget share of food. Enrollment in primary school is almost universal in rural Mexico and hence not affected by the grant. In order to allow for endogeneity of children in secondary school, we follow Attanasio and Lechene (2002, 2014) and instrument it with a dummy variable indicating the existence of a secondary school in the village and with the distance from the closest secondary school if no such school is present in the village. The implicit assumption made is that these two instrumental variables affect the schooling decisions of parents but not directly the structure of their expenditure on food.

Finally, before concluding this section, it is worth noticing that the QAIDS budget share equations of the z-conditional demand depicted in equation (10) contains a third endogenous variable: the budget share of the conditioning good. As the conditioning good θ_l is correlated with the unobserved taste shock of the demand for good θ_k, this needs to be instrumented for. The natural instrument to use is already suggested by the theory and by the z-conditional demand test that we run: the distribution factor used to invert the demand of the conditioning good satisfies the common requirements for valid instrumental variables. Hence, in estimating equation (10) we apply the same control function approach as before adding the residuals from the first stage of the conditioning good as well.

4 Results

We divide this section in two parts. First, we present the results of the test of the collective model and show that, contrary to the existing literature, it is not rejected at the beginning of the program (first wave, 6 months after the start of the program) but it is rejected later in time (second wave, 12 months after the start of the program). Second, we provide an alternative simple rationalization that could be used to empirically investigate the rejection of the collective model.

In all specifications we instrument total food expenditure with village-level agricultural wage (and its square), and number of children in secondary school with a dummy if there is a secondary school present in the village and distance to the closest secondary school. We control for a large set of pre-treatment village, household and individual characteristics. Village characteristics include town size and prices. Household characteristics include number of young children, number of children enrolled in primary school, number of children enrolled in secondary school, number of relatives eating in the household and number of household members eating outside the household. Individual characteristics include the level of education of both parents, age of the household head and an indigenous head dummy. All the standard errors are clustered at village level and bootstrapped 200 times.

4.1 Does the collective model rationalize the data?

We first estimate the unconditional (QAIDS) demand system for various interesting (sub)groups in our sample: respectively, the full sample, the sample splitted according to the two years, and subgroups for each year based on different education and age differences between spouses. We report only the results for the tests on the two cross-sections separately, because these are the only ones where there are at least two demand equations with two significant effects of the distribution factors. In all other subgroups that we have defined, the effects of the distribution factors are always too weak to provide reliable estimates of the z-conditional demand test, and hence no clear pattern was found. The full set of regression results are of course available upon request.

The main parameters of interest are reported in Table 1. The estimated demand system is able to predict very well the observed budget allocation for both control and treatment groups in both periods, as reported in Table A.2 of the Appendix. By taking these demand equations, we investigate whether the collective model is able to rationalize the observed budget allocation. In order to do so, we estimate the z-conditional demands by taking *any* pairwise combination of the most responsive demand equations to the distribution factors. As we can see, these are *starches*, *fruits and vegetables* and *meat, fish and diaries* for the 1998 observation. Whereas for 1999 these are *starches*, *pulses*, *fruits and vegetables* and *other foods*. Hence, this means that in 1998 we first use *fruits and vegetables* as conditioning good, invert it on network and test the collective model on the remaining goods where the treatment variable is significant. Then use *meat, fish and diaries* to invert the system and test the model on the remaining goods. And so on for the remaining goods in 1998 and 1999. Note that, in order to have a high power of the test results, the conditioning good must be responsive to network, that is, the distribution factor on which the system is inverted. Whereas the goods on which the collective model is tested must be responsive, in principle, to both distribution factors. For completeness of the results we report the test of all goods where at least treatment is significant, but one should keep in mind that the most powerful results are on those specifications where *both* demand equations are responsive to *both* distribution factors.

Table 2 shows that in 1998, 6 months after the 1st transfer, the null hypothesis is not rejected for all specifications. In light of the model outlined before, this implies that we find convincing empirical evidence in favor of the collective model. A different story emerges however when we look at the 1999 data, 12 months after the households started receiving the cash transfers. Here not only we reject the null hypothesis in almost all specifications, but the coefficient is always unvaried from the QAIDS estimates. This is a strong rejection of the collective model.[9]

Our results are somewhat different than those of the recent literature (in particular Bobonis (2009), Attanasio and Lechene (2014) and Angelucci and Garlick (2016)). This can be explained by several reasons. First, our sample selection strategy and variables choice is slightly different. Our main, and most informative, results focus on the two waves separately, while all the other papers pool the waves. As our empirical results demonstrate, they fail as such to fully capture the heterogeneity over time. Next, similarly to Attanasio and Lechene (2014), but differently from Bobonis (2009) and Angelucci and Garlick (2016), we use only two waves of data after PROGRESA began to distribute cash transfers and focus only on food consumption. The other authors use three waves and model also non-food consumption. The problem with this implementation is that the surveys do not contain information on prices for non-food commodities and hence it is not possible to implement the QAIDS model as we pointed out above. Finally, again similarly to Attanasio and Lechene (2014), but differently from Bobonis (2009) and Angelucci and Garlick (2016), we use treatment and relative size of husband's and wives family networks as distribution factor.

Besides these differences in the sample selection strategy and the variables choice, a second main difference is our implementation of the test of Pareto efficiency. As explained above, to implement the BBC test, one has to invert the demand equations. To obtain statistically reliable results, it is therefore crucial to have unbiased estimates and to focus on the most responsive demand equations. Therefore, our test is based on the parameters estimated from a full fledged QAIDS model, whereas the other papers are based on a linear version of it, called $\ell-$QAIDS. Although the BBC test does in principle not require neither price variation, nor the estimate of the parameters attached to prices, bypassing a proper estimation of the demand system may lead to biases in the parameter estimates.[10] Next,

[9] Note that the weak instruments problem is not a concern for us. The first stage F-test for both total expenditure and enrollment in secondary school, for both years, are always above 20, which clearly satisfies the Kleibergen and Paap (2006) critical values for strength of instruments under heteroscedasticity.

[10] See, for instance, Pashardes (1993), Buse (1994), Moschini (1995), Buse (1998) and Matsuda (2006) for more discussion on how biased estimates of a demand system may or may not influence the empirical conclusions. The BBC test is an example where the biases are influential.

with respect to inverting the demand functions, some of our sample selections resulted in very small (and often insignificant) estimates of the parameters. As a consequence this makes the BBC test very unreliable, since (after the inversion) it is based on the ratio of two small numbers. This explains why we do not obtain similar conclusions in term of cross-sectional heterogeneity as in Bobonis (2009) and Angelucci and Garlick (2016), but obtain much more robust conclusions for the intertemporal heterogeneity.

Table 1: Unconditional (QAIDS) demand system

Budget shares	starches	pulses	fr. & veg.	m., f. & d.	other foods
Distribution factors:	October 1998, 6 months after the 1st transfer				
Treatment	0.020**	0.004	-0.012**	-0.016**	0.004
	(0.009)	(0.006)	(0.005)	(0.008)	(0.003)
Network	-0.013*	-0.005	0.011***	0.013**	-0.006
	(0.007)	(0.004)	(0.004)	(0.005)	(0.004)
Joint test of (p-value):					
Treatment	0.03				
Network	0.00				
Distribution factors:	June 1999, 12 months after the 1st transfer				
Treatment	-0.049***	-0.021**	0.021***	0.007	0.041***
	(0.008)	(0.009)	(0.005)	(0.006)	(0.003)
Network	0.013**	0.003	-0.000	-0.002	-0.013***
	(0.006)	(0.003)	(0.003)	(0.005)	(0.004)
Joint test of (p-value):					
Treatment	0.00				
Network	0.01				

Notes: We report only the parameter estimates (and standard deviation) of the main distribution factors. The sample size in the two waves is 5,125 and 4,932 observations, respectively. In all specifications we instrument total food expenditure with village-level agricultural wage (and its square), and number of children in secondary school with a dummy if there is a secondary school present in the village and distance to the closest secondary school. We control for a large set of pre-treatment village, household and individual characteristics. Village characteristics include town size and prices. Household characteristics include number of young children, number of children enrolled in primary school, number of children enrolled in secondary school, number of relatives eating in the household and number of household members eating outside the household. Individual characteristics include the level of education of both parents, age of the household head and an indigenous head dummy. All the standard errors are clustered at village level and bootstrapped 200 times. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: z-conditional demand (BBC) test

	October 1998, 6 months after the 1st transfer											
	starches		m., f., & d.		starches		fr. & veg.		m., f., & d.		fr. & veg.	
	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.
Treatment	0.020**	0.011	-0.016**	0.007	0.020**	0.006	-0.012**	-0.002	-0.016**	-0.003	-0.012**	0.010
	(0.009)	(0.013)	(0.008)	(0.010)	(0.009)	(0.010)	(0.005)	(0.006)	(0.008)	(0.010)	(0.005)	(0.006)
Conditioning good		fr. & veg.		fr. & veg.		m., f. & d.		m., f. & d.		starches		starches
p-value Treatment		0.41		0.46		0.51		0.78		0.76		0.11
	June 1999, 12 months after the 1st transfer											
	starches		pulses		fr. & veg.		pulses		fr. & veg.		other foods	
	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.	QAIDS	z-cond.
Treatment	-0.049***	-0.042*	-0.021**	-0.050***	0.021***	0.008**	-0.021**	-0.026	0.021***	0.045*	-0.041***	-0.006
	(0.008)	(0.021)	(0.009)	(0.011)	(0.005)	(0.003)	(0.009)	(0.023)	(0.005)	(0.024)	(0.003)	(0.015)
Conditioning good		other foods		other foods		other foods		starches		starches		starches
p-value Treatment		0.05		0.00		0.01		0.27		0.06		0.70

Notes: We use network as conditioning distribution factor. We report only the parameter estimates (and standard deviation) of the treatment indicator. The sample size in the two waves is 5,125 and 4,932 observations, respectively. All regressions contain the same set of regressors as outlined in Table 1. *** p<0.01, ** p<0.05, * p<0.1.

4.2 How can we rationalize these results?

We now want to propose a simple theoretical framework that is able to rationalize the fact that households behave different after having more experience with the features of the PROGRESA program. In particular, it is assumed that, in each period, the household solves the following optimization problem:

$$\begin{aligned} & \max U^f\left(\mathbf{c}^f, k\right) \\ & \text{s.t. } U^m\left(\mathbf{c}^m, k-\bar{k}\left(s\right)\right) \geq 0 \\ & \text{s.t. } \mathbf{p}'\left(\mathbf{c}^m+\mathbf{c}^f\right)+P'k=x. \end{aligned} \tag{11}$$

This problem is similar in spirit to (2), but we have simplified the setting to the case where there is only one public good k (e.g. expenditures on children) and the mother's participation constraint is made explicit. It is summarized by the term $\bar{k}\left(s\right)$, which depends on a preference shifter, denoted by s. We assume $k(0)=0$ and $k'(s)>0$. Furthermore, for all $\mathbf{c}^m$, and s there exists a $\tilde{k}$ such that $U^m\left(\mathbf{0}, \tilde{k}-\bar{k}\left(s\right)\right)=0$.

Notice that, since utility of both household members is assumed to be increasing in all its arguments, that is, for all (private) consumption bundles and values of the preference shifter s, there exists a sufficiently small level of expenditures on the public good such that the participation constraint for the mother is not satisfied. In this case she prefers to obtain her outside option. The value of this outside option is given by the indirect utility from the following problem:

$$\begin{aligned} & \max\ U^m\left(\mathbf{c}^m, 0\right) \\ & \text{s.t. } \mathbf{p}'\left(\mathbf{c}^m+\mathbf{c}^f\right)+P'k=x, \end{aligned} \tag{12}$$

where the mother takes as given $\mathbf{c}^f$, i.e. the father's choice of private consumption.[11] Notice that in case efficient bargaining (cooperation) breaks down, the mother picks $k=\bar{k}(s)$. The interpretation of this framework is the following: the mother can always select some minimal level of expenditures to the public good given by $\bar{k}(s)$, autonomously

[11] The same problem using the father's preferences provides his outside option.

from her husband. Only when the father finds it also profitable to have a higher level of public good expenditures, the household reaches a cooperative (i.e. Pareto efficient) solution.

An important feature of the PROGRESA program is that it consists of a substantial educational component.[12] In particular, mothers receive intensive educational and programmatic meetings, with the aim to empower women on several dimensions (e.g. on the importance of good quality food and speaking up with respect to their rights vis a vis health care providers). Our simple framework is therefore able to capture our empirical results in case we assume that, in the earlier stages of the PROGRESA program, we have $s = 0$. Due to the training, there might subsequently have been a shift in preferences over time, i.e. $s > 0$, which indicates that the mother has a higher preference for expenditures on the public good. This creates a misalignment of preferences for the public good within the household and causes the rejection of the collective model, in which s is fixed over time.

Note that our framework could also be seen to capture the idea that, over time, women get empowered from PROGRESA, both by the cash transfers, which implies a higher bargaining power, but also potentially through a preference shift caused by the educational program. If these women then want to exert their increased bargaining power within the household, this could create tensions with the husband, thereby losing efficiency in terms of household allocations. Indeed, both Angelucci (2008) and Bobonis et al. (2013) have shown that a potential side effect of the PROGRESA program was, for some households, an increased incidence of aggressive behavior from the husbands towards their wives. Moreover, Angelucci (2008) notes that the likelihood to receive more violent threats is related to the size of the cash transfers received by the household, casting doubt on the validity of using the PROGRESA treatment as a valid distribution factor (in terms of the collective household model).

Summarizing, this simple theoretical framework can be seen as a complement to the

[12] These kind of welfare programs have been coined "incentive-based welfare", e.g. Gertler and Boyce (2001). See also Barber and Gertler (2010) for more details concerning the educational component of PROGRESA with respect to health care.

empirical findings of the authors cited above. Though PROGRESA is likely to have an overall positive effect on the welfare of children and the empowering of women in rural Mexico, there might be some second order negative effects, in terms of loss in intra-household efficiency and increased threats of violence, for a portion of targeted households. Our framework can be used as a starting point to reason about these effects within the household.

5 Conclusion

We have structurally analyzed if the collective model can rationalize the demand equations of food for a sample of households affected by the PROGRESA conditional cash transfer program. This CCT program was implemented in rural Mexico in the late 1990s and targeted poor families. The large monetary incentives had a substantial effect on households' behavior inducing them to change their consumption patterns. As shown by Attanasio and Lechene (2014) this change can only be explained by the impact of the conditional cash transfer on the intra-household decision process.

In this paper we have further investigated this impact. Based on the test introduced in Bourguignon et al. (2009) we show that households are consistent with the collective model only in 1998, 6 months after the beginning of the program, but reject it 12 months after the first cash transfer. In other words, the collective model can no longer rationalize the observed behavior in the PROGRESA data in later times of the program. The differences in our results with those of the literature cited above demonstrate the need for using a fully flexible demand system in order to capture the impact of price variation. Moreover, our paper also shows that for obtaining a powerful and reliable application of the BBC test of the collective model, it is crucial to invert the demand system on the most responsive distribution factor.

Our results show that we need new structural models (e.g. including intertemporal features), and corresponding empirical evidence, to analyze second round effects of CCT programs such as PROGRESA. We have presented a simple example of such a structural model that captures the misalignment of the preferences due to the treatment about the importance of public goods. An avenue for further research could use more information from the targeted households (e.g. on threats of violence within the household or the intensity of the educational program within PROGRESA, as proxies for the preference shocks), in order to estimate explicitly their impact on the demand for private and public goods. One of the interesting testable implications of our proposed framework is that, since preferences changes over time, both the standard demand equations of public and private goods are going to have a different shape. Subsequently, this allows to structurally investigate the (un)observed heterogeneity of the impact of the policy intervention on the individual well-being of the recipients.

References

Angelucci, M. (2008): "Love on the Rocks: Domestic Violence and Alcohol Abuse in Rural Mexico," *The B.E. Journal of Economic Analysis and Policy*, 8, 1935–1682.

Angelucci, M. and R. Garlick (2016): "Heterogeneity and aggregation: testing for efficiency in intra-household allocations," *University of Michigan and Duke University working paper.*

Angelucci, M., G. D. Giorgi, M. Rangel, and I. Rasul (2009): "Village Economies and the Structure of Extended Family Networks," *The B.E. Journal of Economic Analysis & Policy*, 9, 44.

Apps, P. and R. Rees (1988): "Taxation and the Household," *Journal of Public Economics*, 35, 199–219.

Attanasio, O. and V. Lechene (2002): "Tests of Income Pooling in Household Decisions," *Review of Economic Dynamics*, 5, 720–748.

Attanasio, O., V. D. Maro, V. Lechene, and D. Phillips (2013): "Welfare consequences of food prices increases: Evidence from rural Mexico," *Journal of Development Economics*, 104, 136 – 151.

Attanasio, O. P. and V. Lechene (2014): "Efficient responses to targeted cash transfers," *Journal of Political Economy*, 122, 178–222.

Banks, J., R. Blundell, and A. Lewbel (1997): "Quadratic Engel Curves And Consumer Demand," *The Review of Economics and Statistics*, 79, 527–539.

Barber, S. L. and P. J. Gertler (2010): "Empowering women: how Mexico's conditional cash transfer programme raised prenatal care quality and birth weight," *Journal of Development Effectiveness*, 2, 51–73.

Behrman, J. and S. Parker (2011): "The impact of the PROGRESA/Oportunidades conditional cash transfer program on health and related outcomes for the aging in Mexico," *PIER Working Paper.*

Blundell, R., P. Chiappori, and C. Meghir (2005): "Collective labor supply with children," *Journal of Political Economy*, 113, 1277–1306.

Blundell, R. and J. Robin (1999): "Estimation in Large and Disaggregated Demand Systems: An Estimator for Conditionally Linear Systems," *Journal of Applied Econometrics*, 14, 209–232.

Bobonis, G. J. (2009): "Is the allocation of resources within the household efficient? New evidence from a randomized experiment," *Journal of political Economy*, 117, 453–503.

Bobonis, G. J., M. Gonzlez-Brenes, and R. Castro (2013): "Public Transfers and Domestic Violence: The Roles of Private Information and Spousal Control," *American Economic Journal: Economic Policy*, 5, 179–205.

Bourguignon, F., M. Browning, and P.-A. Chiappori (2009): "Efficient intra-household allocations and distribution factors: implications and identification," *The Review of Economic Studies*, 76, 503–528.

Bourguignon, F., M. Browning, P.-A. Chiappori, and V. Lechene (1993): "Intra-Household Allocation of Consumption: A Model and some Evidence from French Data," *Annales d'Economie et de Statistique*, 29, 137–156.

Browning, M., F. Bourguignon, P.-A. Chiappori, and V. Lechene (1994): "Income and outcomes: A structural model of intrahousehold allocation," *Journal of Political Economy*, 102, 1067–1096.

Browning, M. and P. Chiappori (1998): "Efficient intra-household allocations: A general characterization and empirical tests," *Econometrica*, 66, 1241–1278.

Browning, M., P.-A. Chiappori, and Y. Weiss (2014): *Economics of the Family*, Cambridge University Press.

Buse, A. (1994): "Evaluating the Linearized Almost Ideal Demand System," *American Journal of Agricultural Economics*, 76, 781–793.

——— (1998): "Testing Homogeneity in the Linearized Almost Ideal Demand System," *American Journal of Agricultural Economics*, 80, 208–220.

Cherchye, L., S. Cosaert, T. Demuynck, and B. De Rock (2015): "Noncooperative Household Consumption with Caring," *ECARES working paper 2015-46*.

Cherchye, L., B. De Rock, and F. Vermeulen (2011): "The Revealed Preference Approach to Collective Consumption Behaviour: Testing and Sharing Rule Recovery," *Review of Economic Studies*, 78, 176–198.

Cherchye, L., B. D. Rock, and F. Vermeulen (2009): "Opening the Black Box of Intrahousehold Decision Making: Theory and Nonparametric Empirical Tests of General Collective Consumption Models," *Journal of Political Economy*, 117, 1074–1104.

Cherchye, L. and F. Vermeulen (2008): "Nonparametric Analysis of Household Labor Supply: Goodness of Fit and Power of the Unitary and the Collective Model," *The Review of Economics and Statistics*, 90, 267–274.

Chiappori, P. (1988): "Rational household labor supply," *Econometrica: Journal of the Econometric Society*, 56, 63–90.

——— (1992): "Collective labor supply and welfare," *Journal of Political Economy*, 100, 437–467.

Chiappori, P., B. Fortin, and G. Lacroix (2002): "Marriage Market, Divorce Legislation, and Household Labor Supply," *Journal of Political Economy*, 110, 37–72.

Chiappori, P. a. and I. Ekeland (2006): "The micro economics of group behavior: General characterization," *Journal of Economic Theory*, 130, 1–26.

Chiappori, P.-A. and I. Ekeland (2009): "The Microeconomics of Efficient Group Behavior: Identification1," *Econometrica*, 77, 763–799.

Chiappori, P.-A. and M. Mazzocco (2017): "Static and Intertemporal Household Decisions," *Journal of Economic Literature*, 55.

Chiappori, P.-A. and J. Naidoo (2017): "The Engel Curves of Noncooperative Households," *Boston College Department of Economics.*

d'Aspremont, C. and R. Dos Santos Ferreira (2014): "Household behavior and individual autonomy: an extended Lindahl mechanism," *Economic Theory*, 55, 643–664.

Dercon, S. and P. Krishnan (2000): "In Sickness and in Health: Risk Sharing within Households in Rural Ethiopia," *Journal of Political Economy*, 108, 688–727.

Donni, O. (2007): "Collective female labour supply: theory and application," *The Economic Journal*, 117, 94–119.

Donni, O. and N. Moreau (2007): "Collective Labor Supply: A Single-Equation Model and Some Evidence from French Data," *The Journal of Human Resources*, 42, 214–246.

Duflo, E. (2003): "Grandmothers and Granddaughters: OldAge Pensions and Intrahousehold Allocation in South Africa," *The World Bank Economic Review*, 17, 1–25.

Fiszbein, A. and N. R. Schady (2009): *Conditional cash transfers: reducing present and future poverty*, World Bank Publications.

Fiszbein, A., N. R. Schady, and F. H. Ferreira (2009): *Conditional cash transfers: reducing present and future poverty*, World Bank Publications.

Fortin, B. and G. Lacroix (1997): "A test of neoclassical and collective models of household labour supply," *Economic Journal*, 107, 933–955.

Gertler, P. (2004): "Do Conditional Cash Transfers Improve Child Health? Evidence from PROGRESA's Control Randomized Experiment," *American Economic Review*, 94, 336–341.

Gertler, P. J. and S. Boyce (2001): "An Experiment in Incentive-Based Welfare: The Impact of Progresa on Health in Mexico," *University of California, Berkeley.*

Kapan, T. (2009): "Property Division Laws: The Effects on Labor Supply and Household Bargaining," *Columbia University Department of Economics.*

Kleibergen, F. and R. Paap (2006): "Generalized reduced rank tests using the singular value decomposition," *Journal of Econometrics*, 133, 97 – 126.

Matsuda, T. (2006): "Linear approximations to the quadratic almost ideal demand system," *Empirical Economics*, 31, 663–675.

Mazzocco, M. (2007): "Household Intertemporal Behaviour: A Collective Characterization and a Test of Commitment," *The Review of Economic Studies*, 74, 857–895.

Moschini, G. (1995): "Units of Measurement and the Stone Index in Demand System Estimation," *American Journal of Agricultural Economics*, 77, 63–68.

Pashardes, P. (1993): "Bias in Estimating the Almost Ideal Demand System with the Stone Index Approximation," *The Economic Journal*, 103, 908–915.

Robinson, J. (2012): "Limited Insurance within the Household: Evidence from a Field Experiment in Kenya," *American Economic Journal: Applied Economics*, 4, 140–64.

Schultz, T. P. (2004): "School subsidies for the poor: evaluating the Mexican Progresa poverty program," *Journal of Development Economics*, 74, 199 – 250.

Skoufias, E. (2005): "PROGRESA and Its Impacts on the Welfare of Rural Households in Mexico," *Research Report 139 International Food Policy Research Institute, Washington DC.*

Thomas, D., D. Contreras, and E. Frankenberg (2002): " Distribution of power within the household and child health," *RAND, Santa Monica, California.*

Tommasi, D. and A. Wolf (2016): "Overcoming Weak Identification in the Estimation of Household Resource Shares," *ECARES working paper 2016-12.*

Vermeulen, F. (2005): "And the winner is... An empirical evaluation of unitary and collective labour supply models," *Empirical Economics*, 30, 711–734.

Yoong, J., L. Rabinovich, and S. Diepeveen (2012): "The impact of economic resource transfers to women versus men," *Technical Report. London: EPPI-Centre*.

Appendix

The structure of this appendix is as follows. Section A.1 reports the summary statistics of our sample of households in the treatment and control villages. Section A.2 discusses more in detail the validity of our two distribution factors. Finally, Section A.3 shows that our model fits the data very well.

A.1 Summary statistics

Table A.1: Summary statistics: Treatment vs Control

Variables	Observations	Control	Observations	Treatment	Difference
Town size	2,360	41.7	3,951	39.7	1.97***
N children in primary school	2,322	1.3	3,893	1.4	-0.050
Household size	2,366	5.6	3,960	5.6	-0.050
N of children	2,366	3.6	3,960	3.6	-0.050
N of young children	2,366	2.2	3,960	2.3	-0.030
N of older children	2,366	1.3	3,960	1.3	-0.010
Education of the spouse	2,366	2.2	3,960	2.2	0.020
Education of the head	2,366	2.3	3,960	2.3	-0.010
Head is indigenous	2,366	0.4	3,960	0.4	-0.010
Age of head	2,365	37.7	3,949	37.4	0.260
ln(price of starches)	2,366	1.3	3,960	1.3	-0.02***
ln(price of pulses)	2,366	2.4	3,960	2.4	0.01**
ln(price of fruit and vegetables)	2,366	1.9	3,960	1.9	0.01***
ln(price of meat, fish and diary)	2,366	2.7	3,960	2.7	-0.01***
ln(price of other foods)	2,366	2.4	3,960	2.4	0.02***
Secondary school	2,347	0.3	3,960	0.3	0.000
Network	2,002	0.4	3,252	0.4	0.010
Education	2,366	1.0	3,960	1.0	0.010
Expenditure on food	2,366	749.0	3,960	800.7	-51.73***

Notes: Mean values and difference between eligible households in control and treatment villages. The data refer to the 1998 wave. *** p<0.01, ** p<0.05, * p<0.1.

A.2 Distribution factors: details

In what follows we describe and motivate each of the two distribution factors used in this paper. The first distribution factor used is the eligibility to PROGRESA. This is a dummy variable taking value 1 if the household belongs to a treated village and 0 otherwise. Since the grant is targeted to the mother, receiving the transfers constitutes an exogenous increase in the share of the household income that she controls. This share of income is not an argument of preferences, and conditional on total resources available, it does not affect the budget constraint. Given the random assignment of the program, the treatment variable constitutes an ideal distribution factor, which explains why it has been used in the recent literature to test the collective model.

Two remarks on the treatment dummy are in order. First, the grant affects not only the distribution of resources within the household but also the total resources available. This implies that we need an appropriate specification of the demand system to control for total resources available after the treatment. Conditional on all the resources, including also those coming from the program, receiving the PROGRESA transfer should make no difference to the allocation of household resources among different commodities. If instead, after conditioning, the grant has a residual effect on allocation, it must be because it has shifted the Engel curves as a consequence of a shift in Pareto weights. Second, the PROGRESA grant is a conditional cash transfer, where the most stringent conditionality is the child school enrollment. In the case of the Mexican context, the conditionality is not stringent for families who have to enroll their children to primary school, as primary school enrollment is almost universal. It is however stringent in the case of families with children going to secondary school. A correct specification of the demand system needs to account for this as well.[13]

The second distribution factor used is the relative importance of the husband and wife's family network in the village. This information was collected by Angelucci et al. (2009) and used as a distribution factor to test the collective model by Attanasio and Lechene (2014). The main idea behind the use of the network information is the fact that a stronger presence of family members in the village affects the individual value of their outside option. Indeed, as the authors argue, it is possible that the relative weights of husband and wife in the allocation of resources depend, within the context of poor

[13] In principle, there is a third remark that should be made. If the PROGRESA grant affected labor supply, then it would not be a valid distribution factor. However, it has been shown that the grant did not have any effect on labor supply of adult members and hence it is likely that this does not constitute a problem in our specific case (Skoufias (2005)).

marginalized rural households, on the relative strength and influence of the two extended families in the village. The relative importance of the spouse's networks is constructed by Angelucci et al. (2009) as follows. The authors exploit the fact that the PROGRESA evaluation surveys are a census of each village and the convention of Spanish last names to map the network of relatives within each community. Indeed, in Spanish-speaking countries, individuals get two surnames, the first one from the father and the second one from the mother. Using the PROGRESA surveys it is possible to know the number of relatives, for each adult, that are present in the village. The relative importance of husband and wife's networks is then constructed in two ways: the size and wealth of the networks.[14]

At this point, one may be worried that, in the presence of altruism, if an adult member cares about their siblings, presumably their siblings care about them. Hence one could argue that if this adult has a relatively large family network, social norms may induce him or her to behave in a way that is closer to the preferences of the network. In other words, the number of siblings might affect preferences rather than bargaining. However, under the assumption that both adult members live under the same set of social norms, the construction of the distribution factor as a ratio of the two adults' network, would net away this concern. Next, concerning the effect on budget, the main reason why one could argue that the number of siblings in the village might have a direct effect on the demand for food is, if in rural Mexico it is common practice that siblings share meals. Although this fact would not invalidate that relative family network does not affect the budget, if we do not account for the direct effect of the number of siblings on the demand for food, we might obtain biased estimates. Our empirical implementation avoids this potential bias because we indeed control for the number of relatives who share meals with the household as a determinant of expenditure shares.

[14]More formally, for each individual $i = m, f$, they construct the relative size of the networks as the ratio of $n_i/n_m + n_f$, where n_i is either the number of relatives in the village or the value of their wealth for each individual i. Wealth is proxied by (food) consumption of individual's relatives.

A.3 Fit of the data

Table A.2: Actual and Predicated effect of PROGRESA, full sample

		1998						
		Actual			**Predicted**			**Predicted - Actual**
		C	**T**	**D*100**	**C**	**T**	**D*100**	**D*100**
starches	*mean*	0.40	0.40	-0.20	0.41	0.40	-0.65	-0.45
	sd	0.15	0.14	0.20	0.03	0.03	0.05	0.20
pulses	*mean*	0.13	0.12	-0.91	0.13	0.12	-0.72	0.20
	sd	0.08	0.08	0.11	0.02	0.03	0.04	0.12
fr. & veg.	*mean*	0.13	0.14	0.48	0.12	0.13	0.69	0.20
	sd	0.09	0.08	0.12	0.02	0.02	0.03	0.12
m., f., & d.	*mean*	0.16	0.17	1.15	0.16	0.17	1.17	0.02
	sd	0.13	0.12	0.18	0.05	0.05	0.06	0.19
other foods	*mean*	0.18	0.17	-0.52	0.18	0.18	-0.49	0.02
	sd	0.10	0.09	0.13	0.04	0.04	0.05	0.14
		1999						
		Actual			**Predicted**			**Predicted - Actual**
		C	**T**	**D*100**	**C**	**T**	**D*100**	**D*100**
starches	*mean*	0.43	0.41	-1.91	0.42	0.41	-1.26	0.65
	sd	0.15	0.15	0.21	0.04	0.04	0.05	0.22
pulses	*mean*	0.11	0.10	-0.92	0.11	0.10	-1.14	-0.22
	sd	0.07	0.07	0.10	0.02	0.02	0.03	0.11
fr. & veg.	*mean*	0.10	0.11	1.07	0.11	0.12	0.88	-0.19
	sd	0.07	0.07	0.10	0.02	0.02	0.02	0.10
m., f., & d.	*mean*	0.16	0.19	2.32	0.17	0.19	2.11	-0.21
	sd	0.13	0.13	0.18	0.05	0.05	0.07	0.19
other foods	*mean*	0.19	0.18	-0.56	0.18	0.18	-0.60	-0.04
	sd	0.10	0.10	0.14	0.04	0.04	0.06	0.15

Notes: Predicted impacts computed using the QAIDS model. C, T and D stand for Control and Treatment groups and Difference between the two.