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# Intra-household Resource Shares under Poverty Transfers: Evidence from Ecuador*

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**Abstract:** This paper estimates a structural model of household behavior in the presence of cash transfers to recover the amount of resources allocated to men, women, and children. Using data from Ecuador, I find that there are important intra-household inequalities, but the transfer induces a redistribution of resources among household members. I further explore the potential implications of this reallocation of resources in several domains and find that transfers increase the women's control of resources and increase household welfare by reducing poverty, especially for women and children. I also show that when the mother controls the majority of the household resources, it affects the patterns of consumption of the household and how households react to unexpected shocks. These results contribute to understanding better the redistributive effects of income support programs.
**Keywords:** Resource shares, Transfers, Control of resources, Poverty, Consumption.
**JEL Classification:** D13, I38, J22, O12.

**Resumen:** Este trabajo estima un modelo estructural del comportamiento de los hogares en presencia de transferencias monetarias para estimar la cantidad de recursos que se asignan a los hombres, las mujeres y los niños. Utilizando datos de Ecuador, se encuentra que existen importantes desigualdades intrafamiliares, pero que las transferencias inducen una redistribución de recursos entre miembros del hogar. Se exploran las implicaciones de esta reasignación en varios ámbitos y se encuentra que las transferencias aumentan los recursos del hogar controlados por las mujeres y aumentan el bienestar de los hogares al reducir la pobreza, especialmente de las mujeres y niños. También se muestra que cuando la madre controla la mayor parte de los recursos del hogar, esto afecta los patrones de consumo del hogar y la respuesta a choques inesperados. Estos resultados contribuyen a comprender mejor los efectos redistributivos de los programas de trasferencias monetarias.
**Palabras Clave:** Asignación de recursos, Transferencias, Control de recursos, Pobreza, Consumo.

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# 1 Introduction

The main reason many governments in developing countries implement cash transfer (CT) programs is to alleviate poverty by boosting the incomes of the poor. Over the last twenty years, these types of safety net programs have become an increasingly important part of the social policy in many Latin American countries and have expanded to multiple developing countries worldwide.[1]

By influencing the amount of resources available to poor households, these programs are intended to promote desirable social outcomes such as gender empowerment and better childhood nutrition, education, and health. To attain these goals, most countries that have launched CT programs have stipulated that the beneficiary of the transfer has to be the female head or the spouse of the male head of a household. This recurrent feature assumes that women care more about children's well-being. Therefore, an increase in the economic resources controlled by the woman in the household will translate into a higher women's bargaining power, leading to better outcomes for the woman and the woman's children. However, this targeting mechanism poses some questions that remain unanswered and, thus, require further analysis. It is important to understand whether CT programs produce a reallocation of resources within households and the potential implications of this redistribution process. Using data from Ecuador, this paper provides evidence on how resources within the household are apportioned among its members, the role of cash transfers in shifting the intra-household resource allocation, and the implications in terms of women's control of resources, poverty measures, and patterns of consumption.

The analysis is implemented in several steps. First, it is necessary to estimate each household member's resources, which are unobserved in the data. Using a collective household model in the spirit of Dunbar et al. (2013), I structurally estimate the resource shares for the father,

[1]In Latin America, CT programs were launched in 1995 in Brazil, followed by Mexico in 1997. Soon after, many other Latin American and Caribbean countries, such as Argentina, Chile, Colombia, Costa Rica, Ecuador, Honduras, Jamaica, Nicaragua and Uruguay, also implemented these types of social assistance programs. Currently, there are over 40 countries around the world where this type of social policy have been adopted (Fiszbein et al., 2009).

mother, and children.[2] This allows one to examine how the CT affects the share of household resources allocated to each member. To address the potential endogeneity of receiving the CT, I reconstruct the targeting mechanism the Government of Ecuador uses to select the program's beneficiaries. Then, I estimate the structural model using an instrumental variable (IV) approach via generalized method of moments (GMM). I find evidence that the CT generates a redistribution of resources within the household. Specifically, there is an increase in women's and children's share of resources, whereas men experience a decrease in their share of resources.

Subsequently, I explore the potential implication of this redistribution of resources in several domains. I start by looking at women's control of resources. Similar to Tommasi (2019) and Calvi (2020), I use the estimated parameters of the model to create a variable that measures the amount of resources controlled by the woman relative to the man. Results show that the mean distribution of women's control of resources in beneficiary households is 11% higher in relation to non-beneficiary households. Additionally, I show that there exits important heterogeneity in the share of resources of the woman across her life-cycle.

Then, I analyze how the within the household allocation of resources affects the measurement of the well-being of individuals. Widely used indicators of poverty and inequality measure consumption at the household level. However, this procedure does not consider the different factors that could lead to an asymmetric allocation of resources among household members. Using the estimated parameters from the intra-household structural model, I evaluate individual (as opposed to household level) poverty, which is helpful for understanding intra-household inequalities. I find evidence that women are substantially poorer than men. However, the CT reduces poverty rates for women relative to men, implying a reduction in within-household inequality. I also quantify the extent of misclassification of individuals as poor or not when using per-capita measures versus individual poverty measures. I show that women and children face significant probabilities of living in poverty even in households with per-capita expenditure above the poverty threshold.

[2] I estimate resource shares using Engel curves of private assignable goods, which are goods that are consumed exclusively by the mother, father, or children, such as clothes or footwear.

Next, I construct an indicator for whether the woman controls the majority of household resources, which is a proxy for women's bargaining power (Browning et al., 2013; Tommasi, 2019; Calvi, 2020). Using this variable, I analyze the effect of woman's control of resources on household demand for food, health, and education. To examine the response of household spending to the woman's controls resources, I model the demand on each item category as a function of prices, income, and demographics, following specifications from the demand system estimation literature (Deaton and Muellbauer, 1980; Attanasio and Lechene, 2010; Attanasio et al., 2012). However, the variable defining if the woman controls the majority of household resources could be mismeasured due to model misspecification and estimation. To account for this potential problem, I estimate the Mismeasured Robust Local Average Treatment Effect (MR-LATE) following the methodology of Calvi et al. (2018). This methodology allows one to identify and consistently estimate LATE even when the endogenous binary treatment indicator contains measurement errors. Results show that households where mothers control the majority of resources, spend around 5% more on food, 0.6% less on education and do not affect health expenditures. Finally, I complement this analysis by looking at the effect of women's control of resources on the demand for food, education, and health, when households experience unexpected shocks. The evidence suggests that households where the mother controls the majority of resources reduce food expenditures and increase expenditures in health as response to unexpected shocks.

**Related Literature.** This paper contributes to three lines of literature: (i) the literature on poverty transfer programs and household behavior (ii) the literature that studies the relationship between cash transfers and bargaining power, and (iii) the literature on collective intra-household models that allows recovering individual resource shares.

The literature has shown that monetary incentives can affect households' behavior (Bobonis 2009; Attanasio and Lechene 2014; Angelucci and Garlick 2016) and children's school performance, health, and nutrition (Thomas 1990; Duflo 2003; Gertler 2004; Behrman et al. 2005; Paxson and Schady 2010; Duflo 2011; Doepke and Tertilt 2011). Regarding household allocation of consumption, Schady and Rosero (2008), Angelucci and Attanasio (2013) and

Attanasio and Lechene (2014) show that cash transfer programs targeted at mothers are associated with constant or higher shares of household expenditure on food. Following the same line, Tommasi (2019) shows that women's control of resources increases household demand for food. In contrast, using randomization of the gender of the recipient, Benhassine et al. (2015), Akresh et al. (2016), and Haushofer and Shapiro (2016) found no significant differences in program effects on household consumption, production, and investment decisions. These mixed results suggest that a picture related to the mechanisms behind intra-household allocations is still far from clear. To better understand these mechanisms, this paper uses a model of collective household behavior to identify the redistribution and the control of household resources among individual members and to understand the potential effects of poverty policies on these intra-household allocations. This study expands the literature in this area by documenting the impact of women's control of resources on household demand for food, health, and education.

Regarding the second branch of literature, several studies of the effect of CT programs on female decision-making power provide a mixed picture. For example, Adato and Roopnaraine (2010) found no evidence of a direct effect of Mexico's CT on women's decision-making, while Attanasio and Lechene (2010) shows evidence of minor changes in the decision-making of certain intra-household decisions. In the same line, Tommasi (2019) shows that the eligibility to receive the CT induces an increase in the women's decision-making index, whereas Handa et al. (2009) found no evidence of an effect of the CT on women's decision-making power other than the ability to spend their own cash. To measure bargaining power, many studies have relied in a variety of approaches using: self-reported indicators of control and decision power within the household (Reggio, 2011), unearned income (Schultz, 1990; Thomas, 1990), shares of income earned by woman (Hoddinott and Haddad, 1995), assets at marriage (Quisumbing, 1994; Thomas et al., 2002), and education difference (Gitter and Barham, 2008; Schady and Rosero, 2008). In this study, I follow Tommasi (2019) and Calvi (2020) and construct a proxy for women's bargaining power based on individual resource shares. As explained by Tommasi (2019), this is a valuable measure for policy analysis and allows one to document important implications of women's resource control. The present analysis complements this literature by analyzing the implications of women's control of the majority of resources on important dimensions such as household demand and household responses to unexpected shocks.

Regarding the third branch of literature, analyzing behavioral effects of CT programs under the assumption that households act as a single rational unit in which the benefits of a social program are distributed in equal proportion among all family members could be misleading. To address this caveat, this paper benefits from the recent developments in collective intra-household decision models. A relevant point of departure is the collective intra-household decision-making framework proposed by Chiappori (1988), Chiappori (1992) and Apps and Rees (1996). These models have become an important tool for analyzing household allocation decisions since they provide an intuitive and manageable framework to study the distributional impacts of public policies. Several subsequent studies have contributed to making this framework more tractable for empirical purposes (Browning et al. 1994; Chiappori and Ekeland 2006; Blundell et al. 2007; Chiappori and Ekeland 2009; Cherchye et al. 2012; Browning et al. 2013). Attempts to identify resource shares have assumed that single women and men have similar preferences to those of married women and men (Lewbel and Pendakur 2008; Bargain and Donni 2009; Lise and Seitz 2011; Browning et al. 2013). However, Dunbar et al. (2013) proposed a framework that relaxed the assumptions related to similar preferences for different types of households. This approach is applied in this paper to identify all the necessary parameters of the collective intra-houseold model. Finally, the analysis that is perhaps most closely related to this paper is Tommasi (2019). However, and in contrast to my methodology, Tommasi (2019) estimate resource shares directly using a NL-SUR methodology and data from the evaluation of a CT program in Mexico. Obtaining data from randomized evaluations to study the effects of CT programs is complicated, especially in many developing countries. In this paper, I seek to expand the structural approach to estimate resource shares by estimating a collective household model that uses observational data from a national survey and exploits the targeting mechanism used by the governmental authority to classify beneficiaries of the program. This approach will be useful for applications in many contexts where there is no experimental data on the implementation of the program, but there is information in the targeting mechanism for selecting beneficiaries.

**Outline.** In Section 2, I present the most important features of the data used for the analysis. Section 3 presents the model, the identification of the model, and estimation results. Section 4 contains the implications in terms of women's control of resources, poverty measures and patterns of consumption. Lastly, a conclusion is presented in Section 5.

# 2 Data

## 2.1 Cash Transfer Program in Ecuador

Ecuador is a middle-income country in South America with a size slightly smaller than the state of Nevada. According to the World Bank, in 2019, Ecuador had a population of 17.3 million and GDP per capita of 11,878 (in PPP US dollars). The cash transfer program in Ecuador was initially called *Bono Solidario*. It emerged in 1998 as a direct transfer to compensate the poorest households for eliminating subsidies and didn't require any co-responsibility from the program's beneficiaries. After five years, in 2003, the program was restructured in order to consolidate two previous programs in Ecuador: the *Bono Solidario* program and the *Beca Escolar* program (a transfer of 5 USD per child per month, up to two children per household, conditional on children's enrollment in school and a 90% attendance rate). This new cash transfer program was called *Bono de Desarrollo Humano* (BDH). It had an open inscription process that based the identification of beneficiaries by relying on local priests, who were considered to have reliable knowledge of poor people in their local communities. The BDH program followed a human development approach, trying to implement the recommendations of international organizations. This was the first program to use a proxy means test (PMT) to target the poorest families in Ecuador. The main objective of this new program was to improve the effectiveness of the targeting mechanism of this social policy and contribute to human capital formation (Carrillo and Ponce Jarrin, 2009). The change in the program's structure required beneficiary families to enroll their children between the ages of 5 to 18 at school and maintain an attendance rate higher than 75%. Even though the co-responsibility of the program was imposed since the creation of the BDH, the enforcement of these requirements became partially effective only since 2007.

Starting in 2007, a process of reconfiguring the BDH program began within the framework of Ecuador's constitutional and political transformations. The method of identifying the beneficiaries of the BDH has been modified over time, with important changes in 2009 and 2013. Each time the definition of the target population and the mechanism used to carry out the targeting have been modified. It is also worth mentioning that, in contrast to the *Bono Solidario*, which used a self-targeting mechanism, the BDH has always used a PMT to target potential beneficiaries.

Since the present study spans over two years, 2011-2012, the method for defining program beneficiaries is the one established in 2009. The government tracked and monitored potential beneficiaries with a process of registering families located in areas with higher poverty levels according to the 2001 Census. In this new phase, the governmental authorities updated the targeting mechanism by implementing a new database called *Registro Social* (RS) and constructing a new index called *Indice de Bienestar* (RS index). This targeting structure was used from August 2009 until March 2013. This new targeting mechanism also implied another increase in the payment, with a cash transfer fixed to 35 USD per month (16% of the minimum wage) for individuals with families with a score less than or equal to 36.59 points in RS index (Buser, 2015).

## 2.2 Data Description

This study uses the 2011-2012 National Income and Expenditure Survey in Rural and Urban Households (*Encuesta Nacional de Ingresos y Gastos de Hogares Urbanos y Rurales*), that I will denote as ENIGHUR. The ENIGHUR is a household survey that collects information on the amount, distribution, and structure of household income and expenditure, based on its members' demographic and socioeconomic characteristics. This data is convenient for identifying and estimating a collective household model because it allows one to generate private assignable goods for the man, the woman, and the children within a household. Additionally, the ENIGHUR contains enough information to reconstruct the targeting mechanism used by the Government of Ecuador to identify potential beneficiaries of the BDH program and the actual beneficiaries of the BDH program.

To have a homogeneous sample to perform the analysis of interest, I select a sub-sample of the ENIGHUR that satisfies the following restrictions. To ensure comparability across household types, I select only households with both natural parents in my sample and one to at most four children. This restriction implies that households with at least one additional adult member besides the parents are excluded. The intention is to dismiss households with multiple decision-makers. Additionally, to eliminate outliers, I exclude any households in the top or bottom one percent of total household expenditure and restrict the sample to households in which the adults are between 18 and 65 years old.

To avoid issues related to collateral effects of other programs, I drop from the sample households that declared to receive the CT for elderly condition, by disability or for other situations. This means that I only kept the households that report to be non-beneficiaries and mother-type beneficiaries. Then, I select a sample of households whose oldest children are not in secondary-school age (12 years and younger) to be consistent with the reported private assignable goods for the children[3] and to deal with potential sources of endogeneity related to the conditionality of the program. This also excludes adult children that could be playing the role of decision-makers besides the parents. Lastly, households with missing data for any of the household characteristics or relevant expenditures are dropped from the sample. The final sample is composed of 6,242 households.[4]

## 2.3 Descriptive Statistics

Table 1 presents selected descriptive statistics for the sample used for the analysis. All the households in the analysis are composed of a couple and have children.[5] From Table 1, we see that the average man in the sample is 33 years old, whereas the average woman is 30 years old. The age difference within the couples in the sample amounts to 3.7 years. They have

[3] In the survey, households were asked how much they spend on clothing and footwear for girls and boys under 12 years old.

[4] I recognize that this is a limited sample size, preventing me from obtaining externally valid results over the whole population of Ecuador. It does, however, allow me to conform with the assumptions that underpin the structural model used to estimate each household member's resource shares. Furthermore, this sample represents around 77% of the total coupled families with children in the original sample, making the study valuable and relevant.

[5] Additional descriptive statistics differentiating by CT program participation are available in a Appendix A.1.

around 11 years of education, which is less than a high school diploma. In terms of family composition, on average, households have 1.9 children, the mean age of children is around 5 years old, and 49% of children are girls. Related to the CT program, 28% of households are beneficiaries of the program in the sample.

**Table 1:** Descriptive Statistics of Household Characteristics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| **Adult Members Characteristics** | | | | |
| Man Education | 11.10 | 4.25 | 0.00 | 21.00 |
| Woman Education | 11.22 | 4.19 | 0.00 | 21.00 |
| Man Age | 33.16 | 7.62 | 18.00 | 65.00 |
| Woman Age | 29.51 | 6.63 | 18.00 | 62.00 |
| **Household Characteristics** | | | | |
| Number of Children | 1.88 | 0.84 | 1.00 | 4.00 |
| Mean Child Age | 5.26 | 2.91 | 0.00 | 12.00 |
| Share of Girls | 0.49 | 0.40 | 0.00 | 1.00 |
| CT (BDH) (%) | 0.28 | 0.45 | 0.00 | 1.00 |
| Total Non-durable Expenditure | 571.85 | 370.41 | 85.94 | 2566.57 |
| **Expenditures Shares** | | | | |
| Food Share (%) | 0.31 | 0.16 | 0.00 | 0.84 |
| Education Share (%) | 0.02 | 0.04 | 0.00 | 0.58 |
| Health Share (%) | 0.06 | 0.08 | 0.00 | 0.98 |
| **Shares of Assignable Good** | | | | |
| Father Share (%) | 0.03 | 0.02 | 0.00 | 0.21 |
| Mother Share (%) | 0.03 | 0.02 | 0.00 | 0.21 |
| Children Share (%) | 0.04 | 0.03 | 0.00 | 0.28 |

**Notes:** The table shows a set of important characteristics of the households used for the analysis. A woman is a female head of household or spouse and similarly a man is a male head of household or spouse. Mother, Father and Children's assignable goods includes expenditure on individual clothes and footwear.

In Table 1, we also observe expenditure information. Like many consumption expenditure surveys, the ENIGHUR survey asks whether the reported expenditure is monthly, quarterly, semi-annually, or annually depending on the consumption item. The values are then transformed into monthly expenditure. To calculate assignable good expenditures for each household member, I take advantage that expenditures in clothing and footwear are available separately for men, women, and children. Therefore, I aggregate household expenses for clothing and footwear for children, adult women, and adult men, respectively. To obtain the household's total expenditure, I aggregate all non-durable expenditures. We observe from Table 1 that the average household's total non-durable expenditure (including expenditure in food) is 571.85 USD (in 2011 prices). Expenditures in clothing and footwear represent a small portion of the total budget shares (2% and 3%). Finally, household's food, education, and health budget shares are 31%, 2%, 6%, respectively.[6]

# 3 Structural Analysis of Household Behavior

## 3.1 Intra-household Allocation with Children

In this section, I use the collective intra-household model proposed by Dunbar et al. (2013) to quantify how resources are allocated across household members, including children. Consider a household formed by three agents $i \in \{♀, ♂, k\}$. I assume that all households are composed by one female (♀) , one male (♂) and children ($k$), and all men and women live in couple households. Households are heterogenous in several observable characteristics, such as geographic location, number of the children, age of the parents, and other socio-economic variables. The agents within this household may have different preferences but must jointly decide on the purchase of $L$ goods. Let's define $\mathbf{p} = (p_1, \ldots, p_L)$ as the L-vectors of market prices, $\mathbf{x^s} = \left(x_1^s, \ldots, x_L^s\right)$ as the L-vectors of quantities of each good $l$ purchased by a household of size $s$, $\mathbf{c^i} = \left(c_1^i, \ldots c_L^i\right)$ as the L-vectors of quantities of private good equivalents of each good $l$ consumed by member $i$ of the household and $y$ as the household's total expenditure. As in Browning et al. (2013) and Dunbar et al. (2013), I assume economies of scale in consumption through a linear (Barten-type) consumption technology, which takes the form of a matrix denoted by $A$ with $L \times L$ dimension. The advantage of this framework is that it enables the conversion of quantities $\mathbf{x}$ purchased by the household into private good equivalent quantities $\mathbf{c}^i$, so $\mathbf{c} = \mathbf{c}^{♀} + \mathbf{c}^{♂} + \mathbf{c}^k = A^{-1}\mathbf{x}$.[7]

[6] The education expenditure only includes preschool, primary and secondary education, and excludes expenditure in post-secondary education, college and tuition expenses not attributable to any educational level. This procedure allows us to consider expenditures in education related to children between 0 and 12 years old.

[7] This consumption technology provides a general structure to model sharing and jointness of consumption. Let's look at a typical example used in the literature. If good $l$ is a private good (i.e., not jointly consumed),

Each agent $i$, derive utility from consumption of the bundle of $L$ goods, denoted as $U^i\left(\mathbf{c}^i\right)$.[8] Each agent's total utility may depend also on the utility of other household agents, on leisure, and on being a member of a household. For simplicity, I assume that each agent $i$'s utility is weakly separable over the sub-utility functions for goods. So, for instance, member $i$ who gets utility from other family members' well-being as well as her own would have a utility function given by $\overline{U}^i = \overline{U}^i\left[U^1\left(\mathbf{c}^1\right), \ldots, U^I\left(\mathbf{c}^I\right)\right]$. As $\overline{U}^i$ depends upon $\mathbf{c}^{i' \neq i}$ only through the consumption utilities they produce, direct consumption externalities are ruled out. Therefore, $U^i\left(\mathbf{c}^i\right)$ should be interpreted as a sub-utility function over goods, which may be just one component of total utility.[9] Each household maximizes a social welfare function, $\overline{U}$, defined as:

$$\overline{U}\left(U^{♂}, U^{♀}, U^k, p/y\right) = \sum \mu^i\left(p/y\right)\overline{U}^i \tag{1}$$

where the Pareto weights $\mu^i\left(p/y\right)$ depend on prices, individual characteristics and household expenditure. An important assumption of collective models is that, even though agents within the household may have heterogeneity in preferences, they make consumption decisions efficiently. Therefore, efficient allocations can be described as resulting from the following maximization problem:

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then the $l$th row of $A$ would be equal to 1 in the $l$th column and zeros elsewhere. Now, suppose that we look at a married couple without children. They ride their automobile together half of the time, in which case they share the cost of gasoline (50% each). When one family member rides alone, he or she has to assume the payment alone. Then the consumption of gasoline, in private good equivalents, is 1.5 times larger than the purchased quantity of gasoline at the household level. Assuming that the consumption of gasoline does not depend on the consumption of other goods, then the $l$th diagonal element of matrix $A$ will be $\frac{2}{3}$ such that: $x_l = \frac{2}{3}\left(c_l^{♂} + c_l^{♀}\right)$ for $l$ being gasoline. In this example, $\frac{2}{3}$ represents the degree of publicness of good $l$ within the household.

[8] The utility function is assumed to be monotonically increasing, twice continuously differentiable and strictly quasiconcave.

[9] The interpretation of children's utility, $U^k\left(\mathbf{c}^k\right)$ could be either the actual utility function over the bundle of goods $\mathbf{c}^k$ that the kid consumes, or the utility function that parents believe the child has.

$$
\begin{aligned}
\max_{\mathbf{c}^{♀},\mathbf{c}^{♂},\mathbf{c}^{k},\mathbf{x}} \quad & \overline{U}\left(U^{♂},U^{♀},U^{k},p/y\right) \\
\text{subject to :} \quad & \\
& \mathbf{x}=A\left(\mathbf{c}^{♀}+\mathbf{c}^{♂}+s\mathbf{c}^{k}\right) \\
& y=\mathbf{x}'\mathbf{p}
\end{aligned}
\tag{2}
$$

Solving the maximization problem in Equation 2, we can obtain the quantity of private good equivalents, $\mathbf{c}^{i}$ , for each member $i \in \{♀,♂,k\}$. Then, pricing these bundles at within household shadow prices $A'\mathbf{p}$ it is possible to obtain the resource shares $\eta^{i}$, which represents the fraction of the household's total resources that are assigned to each agent within the household.

The Pareto efficient allocation allows us to use duality theory and decentralization welfare theorems to characterize the collective model expressed in Equation 2. The household program can be decomposed into two steps (Chiappori, 1992): the optimal allocation of resources across members and the individual maximization of their own utility function. Conditional on $\eta^{i}$, each household member chooses $\mathbf{c}^{i}$ as the bundle maximizing her own utility function subject to a Lindahl-type shadow budget constraint. By substituting the indirect utility functions $V^{i}\left(A'\mathbf{p},\eta^{i}y\right)$ for $i \in \{♀,♂,k\}$ in Equation 2, the household program simplifies to the choice of optimal resource shares subject to the constraint that total resource shares must sum to one. Note that each member's optimization problem is to maximize her utility subject to a budget constraint characterized by a shadow price vector, which is the same for all household members, and a shadow budget, which is specific to that member. The difference between shadow and market prices reflects the scale economies in consumption from sharing. The optimal household's demand functions for each good $l$ are given by:

$$
c_{l}=A_{l}\left(h_{l}^{♂}\left(A'\mathbf{p},\eta^{♂}y\right)+h_{l}^{♀}\left(A'\mathbf{p},\eta^{♀}y\right)+sh_{l}^{k}\left(A'\mathbf{p},\eta^{k}y\right)\right) \tag{3}
$$

where $h_{l}^{i}$ are individual demand functions, and $\eta^{♂}$, $\eta^{♀}$ and $s\eta^{k}=1-\eta^{♂}-\eta^{♀}$ are the resource shares of the respective agent member $i \in \{♀,♂,k\}$.

### 3.2 Identification and Estimation Strategy

To identify the resource share, it is necessary to have a private assignable good for each agent of the household (see Dunbar et al., 2013). A private assignable good has the characteristic that is consumed exclusively by one member of the household and therefore does not exhibit economies of scale in consumption.[10] Two restriction are imposed by Dunbar et al. (2013) for identification. The first is that $\eta^i$ does not depend on household expenditure $y$, at least at low expenditure levels.[11] The second is that is necessary some restrictions on the shapes of individual Engel curves.[12] Under these conditions, it is possible to simplify the household demand functions given in Equation 3, since the shadow price of a private assignable good is equal to its market price.

For a private assignable good of agent $i$, it is possible to re-express the household demand in Equation 3 as the product of $\eta^i$ and an Engel curve in $i$ individual resources. Then, the household demand functions for private assignable goods have much simpler forms and are given by:

$$W^i(y,\mathbf{p}) = \eta^i(y,\mathbf{p})\, w^i\left(A'\mathbf{p}, \eta^i y\right) \quad (i = ♀, ♂, k) \tag{4}$$

In Equation 4, $W^i$ is the share of total household expenditure spent on each agent $i$ private assignable good, $\eta^i$ is the resource share assigned to agent $i$ and $w^i$ represents the unobserved share of agent $i$'s resources that the individual would spend on his private good when maximizing his own utility function given the shadow price $A'\mathbf{p}$.[13]

Clearly, Equation 4 describes a system of three equations, where $W^i$ and $y$ are observable for

[10] To clarify this definition, a private good is a good that does not have any economies of scale in consumption (e.g., food). In contrast, an assignable good is a private good consumed exclusively by household members of known type $i$ (e.g., clothing and footwear items).

[11] It is not possible to straightforwardly test this assumption. However, in the literature there is some empirical evidence supporting the identification of resource shares based on this assumption (see, for instance, Menon et al., 2012).

[12] In this context, an Engel curve is defined as the functional relationship between a budget share and total expenditure, holding prices constant.

[13] Note that one cannot just use $W^i$ as a measure of $\eta^i$, because different household members may have different tastes for their private assignable good.

each agent $i$, and the objective is to try to identify the resource shares $\eta^i$ for each $i = ♀, ♂, k$. The main complication in identifying these resource shares comes from the inability to observe $\eta^i$ and $w^i$ on the right hand side of Equation 4. Therefore, following Dunbar et al. (2013), it is necessary to impose some preference restrictions. If we restrict functions $w^i$ to have similar shapes (fixed curvatures) either across household members or across household sizes, then resource shares are identified without further restrictions on the shape of the preference function $w^i$. Let's assume that individual preferences are described by utility functions that belong to the PIGLOG class. Then, in Equation 4, the Engel curve for the private assignable good of each household member becomes linear in the logarithm of own expenditure. So, the system of equations can be expressed as:

$$\begin{aligned} W^{♂} &= \alpha^{♂}\eta^{♂} + \beta^{♂}\eta^{♂}\ln\left(\eta^{♂}y\right) \\ W^{♀} &= \alpha^{♀}\eta^{♀} + \beta^{♀}\eta^{♀}\ln\left(\eta^{♀}y\right) \\ W^{k} &= s\alpha^{k}\eta^{k} + s\beta^{k}\eta^{k}\ln\left(\eta^{k}y\right) \end{aligned} \tag{5}$$

where $\alpha^i$ and $\beta^i$ represent linear indexes of underlying preference parameters. As described by Dunbar et al. (2013), for identification it is necessary to impose either similarities of preferences across household agents, called SAP ("Similar Across People") or similarities of preferences across households, called SAT ("Similar Across Types") or combine both. I combine both, SAP and SAT, which implies that $\beta^{♂} = \beta^{♀} = \beta^{k} = \beta$. The data drives the choice to restrict the utility functions among individuals of the same type. On the other hand, Dunbar et al., 2013 suggests that the combination of SAP and SAT strengthen the identification. To limit this simplification, I allow the preference parameters and resource shares to vary with several characteristics in estimation. To account for unobservable heterogeneity, I include additive error terms to the system of equations. It is assumed that errors are correlated across equations and clustered at the primary sampling unit (census sector). The main goal of the model is to determine the impact of receiving a CT on the share of resource of each household member. However, before proceeding with the estimation of the model it is important to address a potential endogeneity problem with the variable of interest, which is CT program participation (receiving the transfer).

### 3.2.1 Addressing the Endogeneity of Receiving the Transfer

To consider the potential endogeneity of participating in the CT program, I reconstruct the targeting mechanism used by the Government of Ecuador to select the program's beneficiaries. The eligibility index is constructed using a restricted methodology together with a survey executed by the Coordinating Ministry of Social Development (MCDS) called "*Registro Social*". With this database, the Technical Secretariat Unit of the MCDS generate a proxy means test index which is expected to be related to the consumption poverty, but with a multidimensional perspective based on Bourguignon and Chakravarty (2003). The RS index is bounded between 0 and 100 and is constructed using Nonlinear Principal Component Analysis (NLPCA) with the combination of 30 variables. These variables can be classified into the following groups: asset possession, dwelling and household characteristics and individual characteristics.

### 3.2.2 Reconstruction of the Eligibility Index

This set of variables allows classifying households according to their eligibility status based on a cutoff (Fabara, 2009). Households that score less or equal than 36.59 points in the RS index were eligible to receive the program. While the RS index is constructed using 30 variables, the database available for this study contains information on 25 of the 30 variables. To replicate the eligibility index, I obtain access to restricted administrative information from the Ecuadorian Government. This information includes the database used by the MCDS to select beneficiaries, the methodology and list of variables used to construct the index and the cutoff value to select beneficiaries. I worked with this database (*Registro Social*) using only the 25 variables available in my ENIGHUR survey data. Using the same statistical procedure (non-linear principal components), I re-estimated the index to obtain the new weights for the restricted set of 25 variables and created an index replica.[14] Then, using these new weights, I can compute the eligibility index using the ENIGHUR survey data.

### 3.2.3 Index-Specific Discontinuity

Since, I am using an index replica, the original cutoff of 36.59 may not be the cutoff where the households are exogenously selected to be beneficiaries of the program. To address this issue, I apply a technique from the structural break literature, following Card et al. (2008) and Ozier (2018). I first restrict attention to a window of scores (5 points) around the actual eligibility cutoff on the eligibility index; I then regress the outcome (receiving the transfer) on indicators for hypothetical discontinuities from 31.59 to 41.59 points and a piecewise linear control for RS eligibility score, one potential discontinuity at a time. Following Ozier (2018) I consider the discontinuity whose regression produces the highest value of R2 to be the "true" cutoff. I perform a similar approach to obtain the point where the probability of receiving the transfer experiences the biggest discontinuity. The R2-maximizing cutoff is 40.66 points rather than 36.59. This is corroborated by the discontinuity in the probability of receiving the transfer. Considering this to be the "true" discontinuity, I use this value for the cutoff in the estimation that follows.[15]

### 3.2.4 GMM Estimation

Now that I have the index replica and the eligibility cutoff in the ENIGHUR survey data, I estimate the model using an instrumental variable (IV) approach via generalized method of moments (GMM). Let $\varepsilon^i$ be an error term for each of each of the equations in the system 5. Let $z$ be a vector of instruments uncorrelated with the error terms, $\varepsilon^i$. These instruments can be any functions of any variables that are conditionally exogenous with respect to $\varepsilon^i$. Then, $E\left[\varepsilon^i z\right] = 0$ implies:

[14] With the available input from the ENIGHUR, I run the CATPCA algorithm attempting to replicate the index as close to the original.

[15] Appendix A.2 provides a detailed description of the methodology used and the results to obtain the actual discontinuity in the index replica.

$$E\left[\left(W^k - s\alpha^k\eta^k - s\beta^k\eta^k \ln\left(\eta^k y\right)\right) z\right] = 0 \tag{6}$$

and

$$E\left[\left(W^i - \alpha^i\eta^i - \beta^i\eta^i \ln\left(\eta^i y\right)\right) z\right] = 0 \tag{7}$$

for $i \in \{♀, ♂\}$. With these moment conditions, I estimate the parameters of the model using GMM. Optimal instruments for these moment conditions (based on the first order conditions for minimizing a quadratic criterion function) would correspond to the derivatives of the error terms $\varepsilon^i$ with respect to the model parameters $\eta$, $\alpha$ and $\beta$.

To improve efficiency, I follow Dunbar et al. (2013) and construct instruments that are close to optimal by suitable transformations of the observed instrument. The estimation procedure is implemented in several steps. First, I estimate Probit predictions of the endogenous variable on the basis of all observed exogenous variables. This is essentially equivalent to the first stage of two stage least squares, when the first stage equations are nonlinear. Then, I obtain initial values of model parameters estimating the model via Nonlinear Seemingly Unrelated Regression (NLSUR) and ignoring the endogeneity of the CT.[16] After that, I evaluate the derivatives of the error terms $\varepsilon^i$ with respect to the model parameters $\eta$, $\alpha$ and $\beta$ at the NLSUR pre-estimates, and plug in Probit predictions of the endogenous variables rather than their true values. Finally, I estimate the model described by the system of Equations 6 and 7 via GMM.

The exogenous variables include: the log of expenditure, all demographic variables, the CT eligibility dummy variable and a flexible functional form of the eligibility index. The endogenous variable is the dummy indicating if a household received the CT. The instrument is very strong in predicting the reception of the CT, conditional on the demographic variables and the log of expenditure. The F-statistic on the excluded instruments in the first stage is over 300. Regarding the exclusion restriction, the instrument is a non-linear function of the

[16] Iterated NLSUR is equivalent to maximum likelihood with multivariate normal errors.

eligibility index and identifying information comes from the non-linearity imposed by the program design.[17] Given this structure, it seems unlikely that an arbitrarily imposed cutoff point in the eligibility index (over which households have no control or information) would be correlated with unobserved characteristics that determine resource shares, especially after controlling for observable characteristics and a flexible functional form of the eligibility index.[18] GMM estimators are iterated until the estimated parameters and error/orthogonality condition covariance matrices converge. I use the sum of clothing and footwear expenditures for each person as the private assignable good.

## 3.3 Estimation of Resource Shares

The estimated coefficients of the effect of the CT on the resource shares of the father $\left(\eta^{♂}\right)$, mother $(\eta^{♀})$ and children $\left(\eta^{k}\right)$ are reported in Table 2. The first four columns present the estimation results of the benchmark specification with dummies for each child.

The results show that the transfer (CT dummy) decreases the father resource share and increases share of resources of the mother and children. In terms of the size of this reallocation of resources, we observe that the positive effect on the mother is larger in magnitude in comparison to the children. Consistent with the literature (see Klein and Barham, 2018 and Tommasi, 2019), these results imply that cash transfers could play an important role in redistributing resources withing the household.

[17] Appendix A.3 shows the relationship between CT program participation and the eligibility index (RS index). We can observe a negative relationship between the RS index and the probability of being treated. In general, as the RS index rises, the likelihood of getting the treatment decreases. Moreover, there is a significant decline at the cutoff point.

[18] In this specification, I Instrument CT program participation with the CT eligibility dummy and a flexible functional form of the eligibility index. In Appendix A.4, I show other specifications. One in which I Instrument CT program participation only with the CT eligibility dummy and I use a flexible functional form of the eligibility index as a control in all the equations. I also estimate another specification in which I Instrument CT program participation only with the CT eligibility dummy.The procedures are similar to the IV approach in regression discontinuity (RD) designs. However, we can not limit the estimation sample to a window close to the cutoff because we experience convergence issues of the GMM estimator. Therefore I use all the sample in the estimation of the collective model. Nevertheless, in Appendix B, I provide a descriptive RD analysis of the effect of CT on women's control of resources around the eligibility cutoff.

**Table 2:** Main Parameters' Estimates

| | By each Child | | | | Linear in Children | | |
|---|---|---|---|---|---|---|---|
| | (1) Father | (2) Mother | (3) Children | (4) Per Child | (5) Father | (6) Mother | (7) Children |
| CT | -0.115** | 0.085** | 0.030 | | -0.130** | 0.081** | 0.049 |
| | (0.052) | (0.036) | (0.057) | | (0.063) | (0.041) | (0.063) |
| One Child | 0.479*** | 0.332*** | 0.189*** | 0.189*** | | | |
| | (0.067) | (0.062) | (0.048) | (0.048) | | | |
| Two Children | 0.466*** | 0.288*** | 0.246*** | 0.123*** | | | |
| | (0.068) | (0.061) | (0.050) | (0.025) | | | |
| Three Children | 0.462*** | 0.243*** | 0.295*** | 0.098*** | | | |
| | (0.071) | (0.060) | (0.055) | (0.018) | | | |
| Four Children | 0.453*** | 0.217*** | 0.330*** | 0.082*** | | | |
| | (0.074) | (0.064) | (0.067) | (0.017) | | | |
| Constant | | | | | 0.521*** | 0.289*** | 0.190*** |
| | | | | | (0.046) | (0.056) | (0.047) |
| Number of Children | | | | | -0.022** | -0.037*** | 0.059*** |
| | | | | | (0.010) | (0.008) | (0.011) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Parameters | 153 | 153 | 153 | 153 | 143 | 143 | 143 |
| N | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 |

**Notes:** The table shows estimates of the resource shares for the father, mother and children. Including controls are: children mean age, share of girls, age of mother and father, education of mother and father, working hours of of mother and father and regional dummies. Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

Results also show that household's composition is important. When the number of children increases, both adults reduce their shares, however, on average the reduction in the share of the mother is bigger in magnitude in comparison to the share of the father. For example, when a household has a second children the father reduced his share by 3% on average, whereas the mother by 13% on average. Table 2 also shows that as the number of children increases, the total share of household resources devoted to children goes up, but the average share devoted to each child declines. A reference household with one child directs 19% of its expenditures to children's consumption. With two children, this share rises to 25%, and four children, to 33%. The amount of resources per child steadily declines from an average of 19% when a household has one child to an average of 8.2% when a household has four children.

When we estimate non-linear models, different specifications may lead to instability of the results. In this type of household models uncertainty about the location of the sharing rule could result in having a large variability of the estimates. A typical specification that may cause instability is the definition of the resource share index with the number of children either entering as dummy variables or linearly. In the context of this study, the choice of the number of children either entering as dummy variables or linearly does not lead to any instability of the estimates. This robustness check is very informative and the results are reported in Columns (5) – (7). As we can observe the estimated parameters in the specification in which children enter linearly are consistent with the result obtained in the initial specification. In Appendix A.4, I provide additional specifications that show that the benchmark specification results are robust.

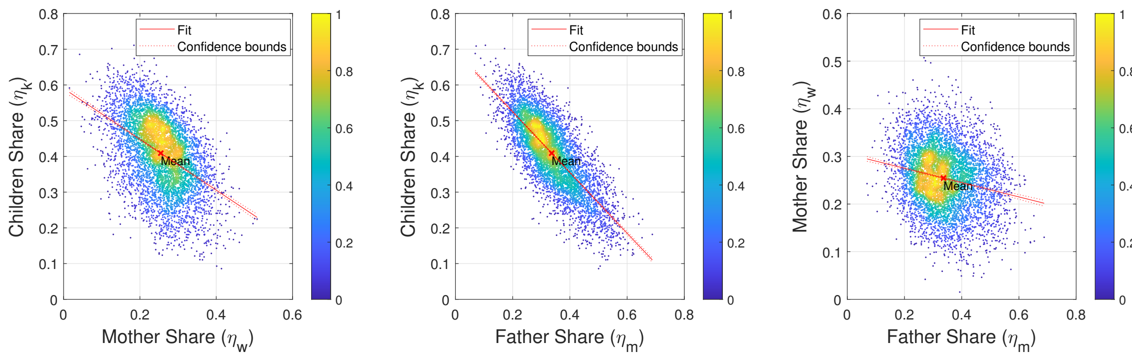
# 4 Implications

## 4.1 Women's Control of Resources

So far, the empirical analysis has been focussing on the levels of resource shares in reference households and the marginal effects of various demographic characteristics. However, given the household characteristics themselves covary with the household structure (size), this does not inform us how resource sharing will change in aggregate across household sizes. Results in Table 2 show that the model provides reliable and stable estimates of the parameters of interest. Using these estimates, I predict the resource shares for women $\left(\hat{\eta}_a^{\female}\right)$, men $\left(\hat{\eta}^{\male}\right)$ and children $\left(\hat{\eta}^k\right)$ in each household. Figure 1 shows a density based scatter plot of the relationship between men, women and children resource shares. We observe that as adult members resource share increases the amount of resources devoted to children decreases. We also observe that there is a negative relation between men and women resource shares, moreover the level of the share of resources of women is lower than the one of men.

**Figure 1:** Relationship between Household Members' Resource Shares

**(a)** Child vs. Mother **(b)** Child vs. Father **(c)** Mother vs. Father




**Notes:** The figure provides information on the relationship between the resource shares of the mother, father and children. The scatter plots are density based and show the means of the shares for each individual within the household.

Then, I compute descriptive statistics, distinguishing beneficiary and non-beneficiary households (Table 3). I show the mean, standard deviation, minima and maxima of the estimated resource shares for each family member.[19] In both types of households, the resource share for women is lower than that for men. In non-beneficiary households, women's resource shares are on average 59.76% of men's whereas in beneficiary households women's resource shares are on average 92% of men's. Resource shares are modeled as linear functions of household characteristics. Therefore, these measures are not necessarily bounded, between 0 and 1. In Table 3, we observe that the minima and maxima of the estimated resource shares do not fall outside the 0-1 range. This is reassuring of the reliability of the model.

Using the predicted resource shares, I compute the amount of resources controlled by the woman relative to the man ($R = \frac{\hat{\eta}_a^{\text{♀}}}{\hat{\eta}_a^{\text{♀}}+\hat{\eta}^{\text{♂}}}$). The summary statistics of this measure, for each type of households, is reported at the bottom of Table 3. Results show that women in non-beneficiary households are estimated to control 40.3% of household resources whereas in beneficiary households they control 51.4%. This indicates that women in beneficiary households experience an increase of 11.1 percentage points of their control of resources relative

[19] Resource shares consider the empirical distributions of the covariates since they are estimated as linear combinations of these variables

to the man. This result is concordant with the findings of Klein and Barham (2018) who show that in Mexico, *PROGRESA* largely increased women's decision making power and with the results of Tommasi (2019) who finds that *PROGRESA* increased women's control of resources, although the effect of the CT in Tommasi (2019) is smaller in magnitude.

**Table 3:** Estimated Resource Shares and Control of Resources

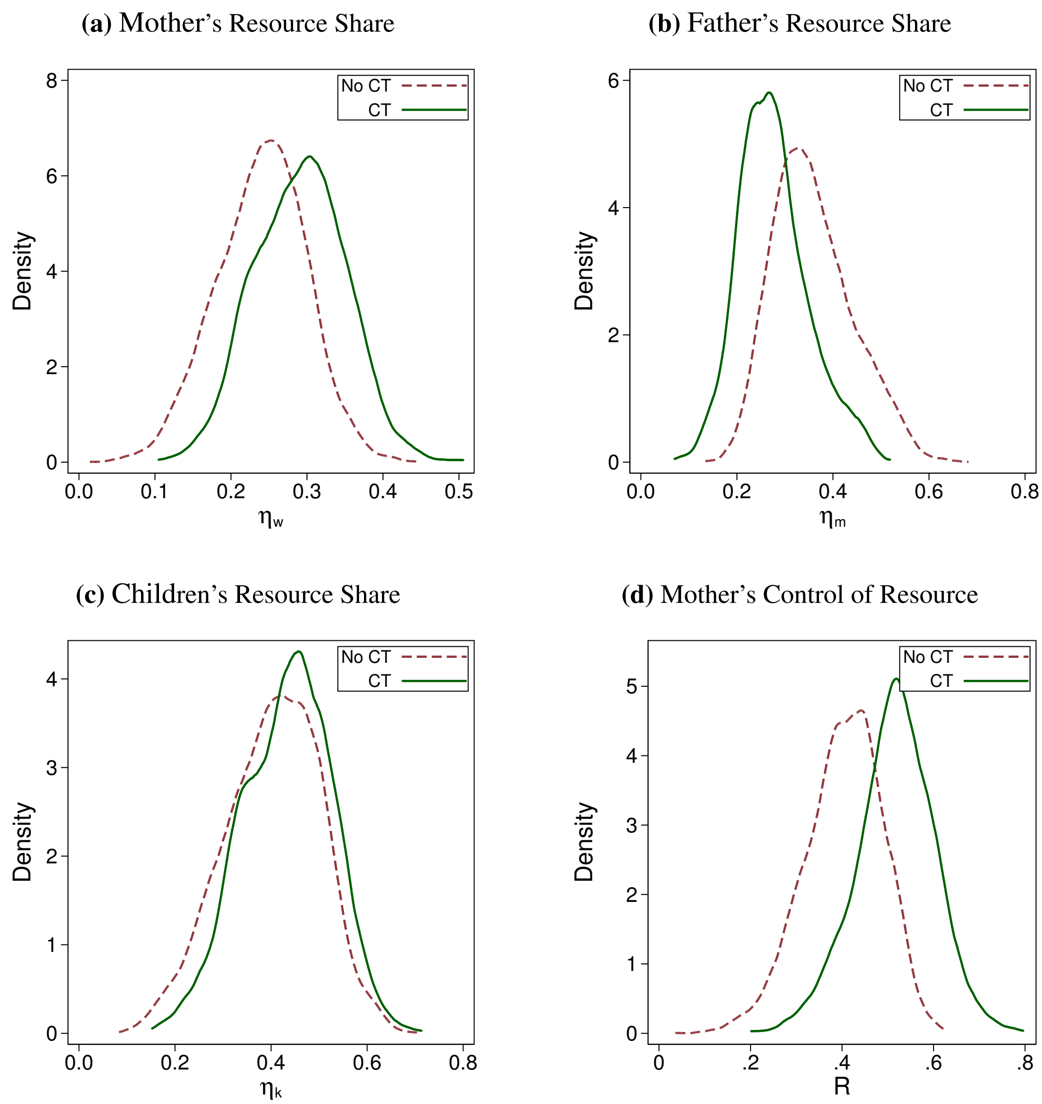
| | No CT (N=4,468) | | | | CT (N=1,774) | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Min | Max |
| Father | 0.360 | 0.083 | 0.134 | 0.688 | 0.278 | 0.073 | 0.069 | 0.522 |
| Mother | 0.240 | 0.059 | 0.015 | 0.449 | 0.292 | 0.060 | 0.106 | 0.507 |
| Children | 0.400 | 0.099 | 0.086 | 0.702 | 0.430 | 0.091 | 0.150 | 0.711 |
| Per Child | 0.259 | 0.107 | 0.059 | 0.609 | 0.231 | 0.101 | 0.075 | 0.586 |
| $R = \frac{\hat{\eta}_a^{\female}}{\hat{\eta}_a^{\female}+\hat{\eta}^{\male}}$ | 0.402 | 0.085 | 0.037 | 0.630 | 0.515 | 0.086 | 0.201 | 0.800 |
| Diff. | | | | [0.113]*** | | | | |
| $R_{ALT} = \frac{\hat{\eta}_a^{\female}+\hat{\eta}^k}{\hat{\eta}_a^{\female}+\hat{\eta}^k+\hat{\eta}^{\male}}$ | 0.640 | 0.083 | 0.312 | 0.866 | 0.722 | 0.073 | 0.478 | 0.931 |
| Diff. | | | | [0.082]*** | | | | |

**Notes:** The table reports the mean, standard deviation, minima and maxima of the estimated resource shares for each family member (mother, father, and children) in beneficiary and non-beneficiary households. Resource shares are modeled as linear functions of household characteristics using the estimated parameters of the model. The bottom of the table shows two measures of the amount of resources controlled by the woman relative to the man.

I also compute an alternative measure of the amount of resources controlled by the woman. This measure sums the mother and child's resource shares to consider the fact that mothers are eligible to receive the CT conditional on taking care of the children. Using this measure women in non-beneficiary households are estimated to control 64.2% of household resources and in beneficiary households' control 72%. Similarly as the previous measure, this indicates that women in beneficiary households experience an increase of 8 percentage points of her control of resources relative to the man. Therefore, both measure of control of resources are consistent. However, my preferred measure only considers the women's resource share because it provides a clearer comparison and offers a conservative measure.[20]

[20] In Appendix B, I explore the behavior of this effect close to the eligibility cutoff using a simple RD design.

**Figure 2:** Distribution of Resource Shares by CT Status




**(a)** Mother's Resource Share **(b)** Father's Resource Share **(c)** Children's Resource Share **(d)** Mother's Control of Resource

**Notes:** The figure shows the distribution of resource shares for the mother, father and children, as well as the variable measuring the women's control of resources. Panel (a), (b) and (c) provide information on the distribution of resources differentiating between recipients (CT) and not recipients (No CT) of the CT. Panel (d) shows the distribution of women's relative control of resources also differentiating between recipient status.

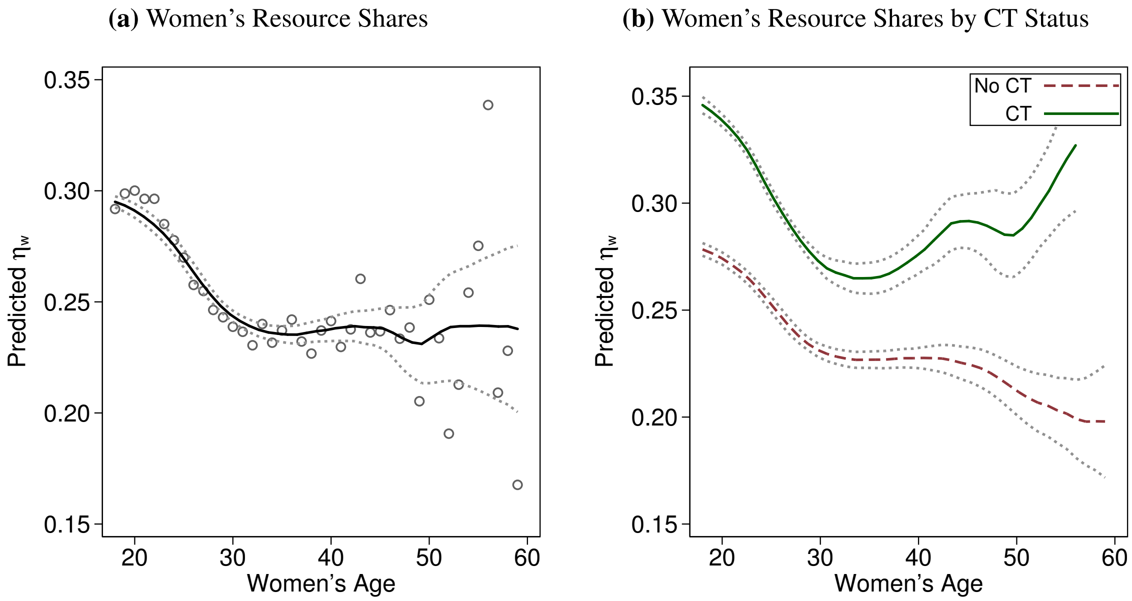
To observe the redistribution of resources within the household caused by the CT, I plot in Figure 2 the empirical distribution of resource shares. Panels (a) – (c) show the resource shares for women, men and children in beneficiary (green continuous line) and non-beneficiary (red dotted line) households. Additionally, in Panel (d) of Figure 2, I plot the distribution of the amount of resources controlled by the woman ($R$).

We observe that the CT induced a redistribution of household resources from the father to both the mother and children. Clearly, the mother is the family member that benefits the most. A possible explanation for this disparity in the redistribution of resources could be that enrollment rates for children between 5 and 12 years old are very high. According to reports of the Ministry of Education of Ecuador, the enrollment rates for children between 5 and 12 years old oscillates between 98% and 99%. Since I use households with young children (up to 12 years old), we can conjecture that the majority of households (beneficiary and non-beneficiary) already allocated resources for child education. Given that school attendance is one of the main conditionalities attached to the program, and households in general have already spent resources for children education, it is logical to think that beneficiary households will allocate the additional resources from the CT to other uses, not necessarily related to the child. Also note that these results do not immediately imply that man in household receiving the CT are poorer. Although there is a within household redistribution of resources there is also an increase in the total resources available for beneficiary household. I will dig deeper in this issue in the next subsection and look at individual poverty rates.

Next, I exploit the cross-sectional variation in women's age to investigate how female control of resources varies across the life-cycle. For each age profile $a \in (18,\ldots,60)$, I compute $\left(\hat{\eta}_a^{\female}\right)$ as the mean predicted resource share for women among all households with women's average age equal to $a$. Figure 3 shows the average predicted women's resource share against women's average age for the entire sample (Panel (a)) and differentiating among beneficiary status of the CT (Panel (b)). The solid lines are the means at each age profile, while the dashed lines display the 95% confidence intervals for the smoothed values.

Women resource shares decrease with age. From 18 to 30 years old we observe a sustain decay in the women's resource share, then it stabilizes between 30 and 60 years old, although there is much more variability. The patterns of women's resource shares seems to differ between women in beneficiary and non-beneficiary households.

**Figure 3:** Predicted Women's and Control of Resources over Age Profiles

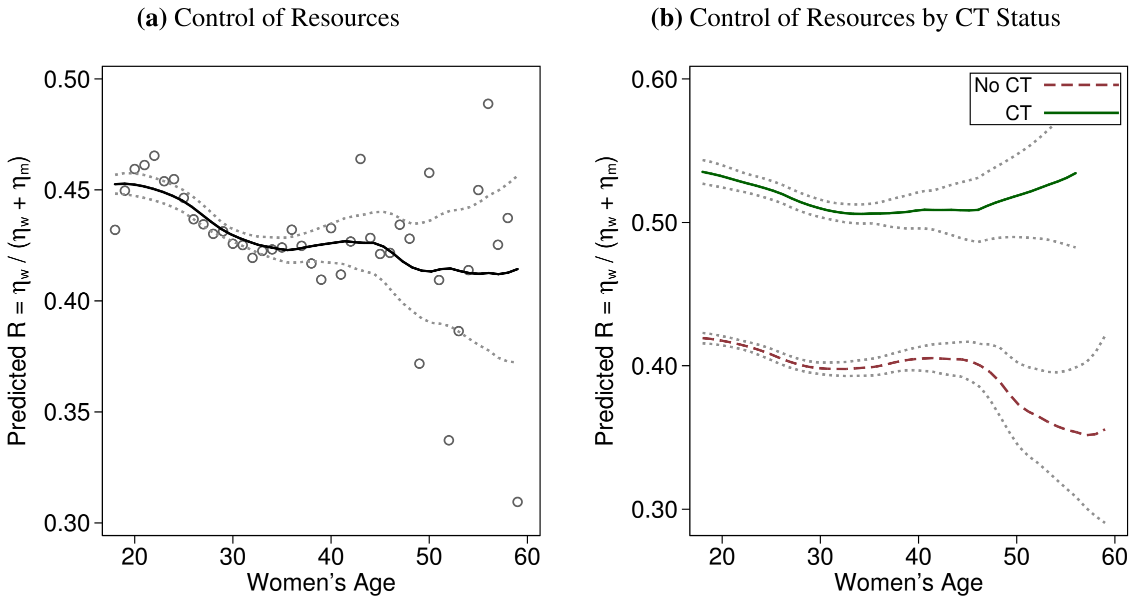



**Notes:** The figure shows the average predicted mothers' resource shares and control of resources among different age profiles. Panel (a) show the mean predicted women's resource share among households with different women's average age. Panel (b) shows the mean predicted bargaining power measured as the resources controlled by the mother relative to the father among households with different women's average age.

The presence of the transfer smooths out the decline in women's share of resource which is consistent with the traditional view of transfers affecting the available resources for the women. At post reproductive ages, the model predicts a divergent pattern of the women's share of resource. Women in beneficiary households experience an increase in their share of resources whereas the contrary occurs for women on non-beneficiary households.

In Figure 4, I analyze the relationship between women's control of resources and women's age. Panel (a) show the overall relationship and Panel (b) portrays this relationship disaggregated by beneficiary and non-beneficiary households. A resource share equal to 0.5 suggest that there is no gender asymmetry in intra-household allocation of resources. Panel (a) show that allocation of resources between adult females and males is not symmetric. Over the women's lifecycle, the control of resource has a decreasing pattern until women reach 45 years old. At post-reproductive ages, women's control of resources experiences a weak increase and then declines steadily. This result is consistent with some recent finding in the literature (see, Tommasi, 2019 and Calvi, 2020).

**Figure 4:** Women's Control of Resource over Age Profiles




**Notes:** The figure shows the average predicted mothers' resource shares and control of resources among different age profiles. Panel (a) show the mean predicted women's resource share among households with different women's average age. Panel (b) shows the mean predicted bargaining power measured as the resources controlled by the mother relative to the father among households with different women's average age.

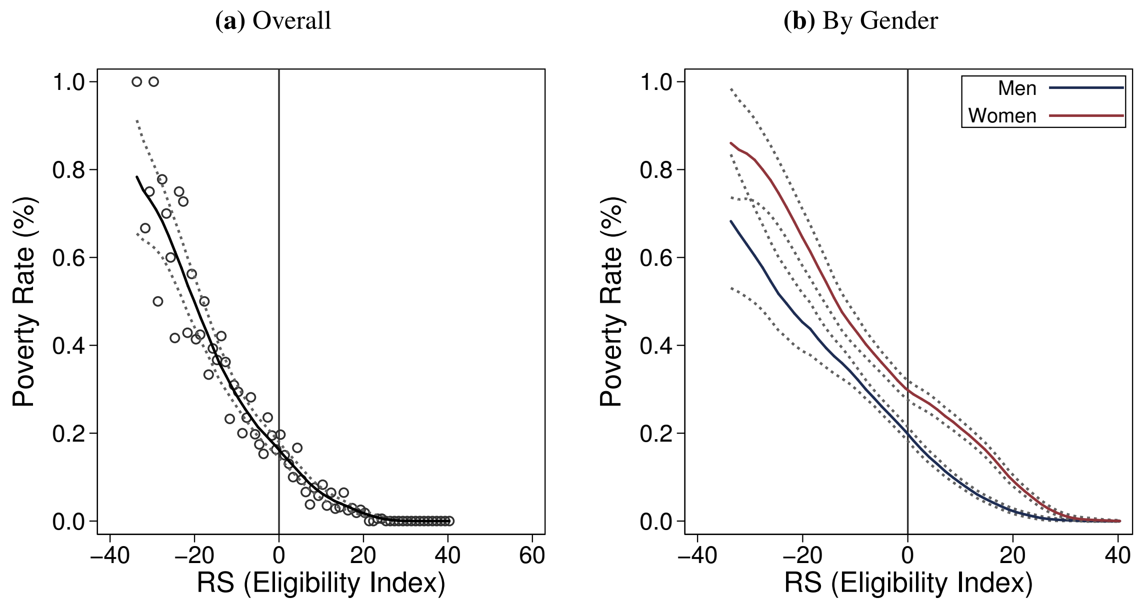
In Panel (b), I disaggregate this measure among beneficiary and non-beneficiary households. This plot shows that in both types of households, women experience a decreasing pattern in terms of their control of resources until they are around 45 years old. However, we observe that the levels differ significantly. Women in beneficiary households have a higher control of resources than their counterparts in non-beneficiary households. At post-reproductive ages this gap starts to diverge, and we observe a decrease in women's control of resources in non-beneficiary households whereas in beneficiary household the women's control of resources rises. A tentative explanation for this pattern is that traditional gender norms defining men as breadwinners and women as caregivers are still prevalent in Ecuador. Childbearing and child-rearing are still mainly women's duties. According to the 2012 Ecuadorian time use survey, women spend on average four times more time (23 hours per week) on unpaid work (domestic and caregiving activities) than men. The fact that women have been performing this type of activities during their adult life could have consequences at post-reproductive ages. From this vantage point, it is possible that women could experience a decrease in their resource share due to their inability to keep performing these functions at older ages and also due to the bad outside options related to entering the labor and marriage market when they are old.

## 4.2 Individual Poverty and Intra-household Inequality

Understanding how household allocate resources under different circumstances is very important to better measure the well-being of individuals. Widely used indicators of poverty and inequality measure consumption at the household level. However, this procedure does not take into consideration the different factors that could lead to an asymmetric allocation of resources among household members. Standard poverty measures assume equal sharing of resources within the household. However, when we go one layer down and take into consideration intra-household inequalities, the poverty assessment can change significantly. This is particularly important in the context of developing countries, where an important part of the population have low levels of household expenditure. Using the estimated parameters from the intra-household structural model, I evaluate individual (as opposed to household level) poverty which is useful to understand the presence of intra-household inequalities. I calculate individual-level expenditures that consider unequal intra-household allocations. I then compare these expenditures with poverty thresholds to calculate individual poverty rates.

Let's start by analyzing the relationship between individual poverty and the eligibility index to qualify as potential beneficiary of the program. Figure 5, shows the mean predicted poverty rate for all the values of the eligibility index. Recall that the index is constructed using a proxy means test which is expected to be related to the consumption poverty, but with a multidimensional perspective. In Panel (a), we observe, as expected, the negative relation between individual poverty the eligibility index. However, Panel (b) shows that along the eligibility index (including the eligibility threshold) there is a substantial difference in terms of individual poverty for men and women. Typically, the eligibility cutoff tries to map the index to a poverty threshold at the household level. This could be inaccurate when there is substantial intra-household inequalities, which could diminish the achievement of the goals of these programs.

**Figure 5:** Individual Poverty over Eligibility Index

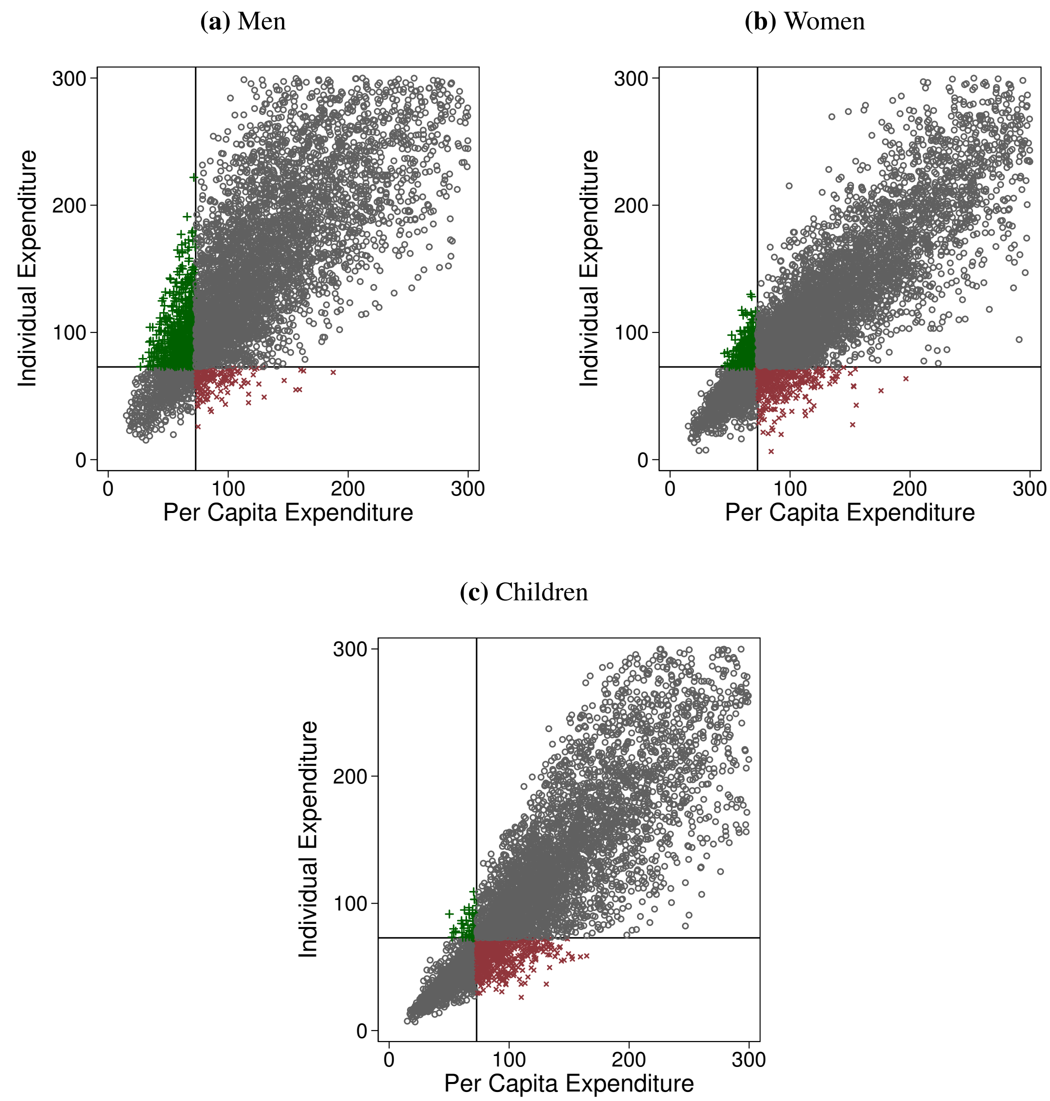



**Notes:** The figure shows the individual consumption that is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. Per-capita consumption is obtained by dividing total annual household expenditure (PPP dollars) by household size. Reference lines correspond to the 1.90 dollar/day poverty line.

The results from the individual poverty analysis show that considering intra-household inequalities is important for evaluating poverty and inequality. Poverty measures are important for governments and international institutions that want to implement policies aimed at improving the welfare of people. However, traditional measure of poverty could misclassify individuals as poor or not.

Using the poverty calculations at the individual level, I measure the extent of this misclassification. I quantify how many individuals are misclassified when we use a measure based on household per-capita consumption versus individual consumption. Figure 6 shows estimated individual consumption against household per-capita consumption for men, women, children. Each plot is partitioned into four quadrants based on whether the estimated individual consumption or per-capita consumption is above or below the poverty line. We observe important miss-classification errors especially for women and children. The quantification of these errors is reported in Table 4.

**Figure 6:** Individual Expenditure vs. Per-Capita Expenditure




**Notes:** The figure shows the individual consumption that is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. Per-capita consumption is obtained by dividing total annual household expenditure (PPP dollars) by household size. Reference lines correspond to the 1.90 dollar/day poverty line.

Results show that 6.63% of women that are reported as non-poor under the traditional measure of poverty (at household level) are actually poor, when we measure poverty at the individual level. The evidence suggests that there are misclassification issues in a range between 11% and 12%, which convey important implications in terms of individuals' well-being.

**Table 4:** Misclassification of Poor People

| | (1) Correct | (2) Poor→No Poor | (3) No Poor→Poor | (4) Incorrect |
|---|---|---|---|---|
| Father | 87.72 | 9.69 | 2.58 | 12.28 |
| Mother | 88.70 | 4.66 | 6.63 | 11.30 |
| Children | 88.47 | 0.85 | 10.69 | 11.53 |

**Notes:** The table reports the percentage misclassified individuals that are considered poor under per-capita measures versus individual measures. The information is disaggregated by mother, father and children and also by the percentage of individuals who are considered poor under per-capita income but are non poor under individual income and the percentage of individuals who are considered non poor under per-capita income but are poor under individual income. Individual-level resources are obtained by multiplying total household expenditure (PPP dollars) by individual resource shares. Poverty head count ratios are constructed by comparing these individual's level expenditures to the poverty line.

Finally, I analyze the behavior of individual poverty by eligibility status and being a beneficiary of the CT. These numbers are reported in Table 5.

**Table 5:** Mean Individual Poverty Rates

| | Poor (%) in Eligible | | | Poor (%) in Non-Eligible | | |
|---|---|---|---|---|---|---|
| | Overall | CT | No CT | Overall | CT | No CT |
| HH | 0.406 | 0.440 | 0.333 | 0.234 | 0.298 | 0.184 |
| Father | 0.267 | 0.341 | 0.111 | 0.132 | 0.253 | 0.041 |
| Mother | 0.354 | 0.281 | 0.507 | 0.261 | 0.155 | 0.342 |
| Children | 0.215 | 0.226 | 0.193 | 0.108 | 0.133 | 0.088 |

**Notes:** The table reports the percentage of poor individuals in beneficiary and non-beneficiary households. This information is disaggregated by households with different compositions in terms of the number of children. Individual-level resources are obtained by multiplying total household expenditure (PPP dollars) by individual resource shares. Poverty head count ratios are constructed by comparing these individual's level expenditures to the poverty line.

Results suggest that in both eligible and non-eligible households, the woman is the member that contributes the majority to explain the poverty level of the household. It is important to note that the cash transfer reduces the prevalence of poverty for women. From Table 5, we observe that for eligible households the transfer reduces women's poverty in 19 percentage points. Similarly, in non-eligible households the transfer mitigates women's poverty in 13 percentage points. It is also observable form Table 5 that for households that do not receive the transfer (eligible and non-eligible) the women are substantially poorer compared to the other household members.[21]

## 4.3 Consumption Patterns

By influencing the amount of resources available to poor households, CT programs are intended to promote desirable social outcomes such as gender empowerment by shifting the control of household resources towards the targeted individual. In the context of Ecuador, the CT is targeted to women which leads one to expect that the allocation of household resources in beneficiary households will be closer with women preferences. To link women's control of resources and the household demand for food, education and health, I need to define an appropriate specification that is concordant with the context of this study and implementable given the available data.

### 4.3.1 Specification of Engel Curves

To perform this estimation, I follow Tommasi (2019) and assume that the discrete value $D = (R > 0.5)$ is a relevant treatment for the demand for each good. The underlying assumption is that an individual within the household controlling the majority of household resources has enough bargaining power to determine most of the expenditure decisions. Then, to analyze the relationship between women's control of resources and patterns of consumption, I estimate Engel curves for food, education and health. Specifically, I estimate:

$$W_{gi} = \alpha + \delta D_i + \gamma P_j + \beta X_i + \theta \ln y_i + \varepsilon_{gi} \tag{8}$$

[21] For comparison, according to the National Institute of Statistics and Census the poverty in Ecuador was around 25.6% and 27.3% in 2011 and 2012, respectively. Of course, these numbers include all types of households in the calculation, and it is reported just for reference purposes as in this study we are considering only coupled households with children.

where $W_{ig}$ is the budget share for good category $g$ in household $i$, $\delta$ is the main parameter of interest and measures the effect of women's control of the majority of resources, vector $P$ is the interaction between the 3 regions and 12 months, $X$ are control variables and $\varepsilon$ is the error term.

### 4.3.2 Estimation Issues

To estimate Equation 8, it is necessary to define whether the relationship between budget and total expenditure is linear or quadratic, how to control for price variation and how to control for endogeneity of total expenditure. Following Attanasio and Lechene (2010) and Tommasi (2019), the preferred specification is a linear relationship with respect to expenditure. I also follow Attanasio et al. (2012) and estimate a separate equation for each good category $g$ allowing for heterogeneous trends across geographical regions. Specifically, to control for price differences, I allow the intercept to shift by region, month, and their interaction. These heterogeneous trends capture regional differences in the evolution of prices. An additional issue with Equation 8 is the presence of division bias because total expenditure appears both, in the left- and right-hand side of the equation. Therefore, to account for the endogeneity of total expenditure, I instrument it with total household income, non-durable expenditure and the average wage in the province where the household is located.

An additional problem in estimating Equation 8 is that the true underlying value of women's control of resources is unobserved. Following Tommasi (2019), I address this identification problem using a Mismeasured Robust LATE (MR-LATE) estimator proposed by Calvi et al. (2018). MR-LATE allows to recover treatment effects when a binary treatment variable is misspecified, misclassified, or estimated with error (Calvi et al., 2018).

To implement the MR-LATE, it is necessary to define two proxies of the true treatment, which are: $D_i^a = 1\left(R_i \geq 0.5 + \kappa^a\right)$ and $D_i^b = 1\left(R_i < 0.5 + \kappa^b\right)$. These proxies depend on chosen constants $\kappa^a$ and $\kappa^b$, and in the framework of this study, $D^a = 1$ if the woman controls the majority of household resources, 0 otherwise, and $D^b = 1$ if the man controls the minority of household resources, 0 otherwise. The measurement error that associates $R^*$ and

$R$, ($R^* = R + \varepsilon$), is unknown and unbounded and consequently the optimal constants $\kappa^i$ are unknown. Therefore, it is possible to bound the LATE. Let $\Omega$ be the percentage of individuals assumed to be misclassified in our sample, and let $\kappa^a$ be the value such that $\Omega/2$ percentage of the sample has $R$ in the interval $[50, \kappa^a]$ and $\kappa^b$ be the value such that $\Omega/2$ percentage of the sample has $R$ in the interval $\left[\kappa^b, 50\right]$. I consider different percentages of $\Omega$. For each element of $\Omega$ there are corresponding values of $\kappa^a$ and $\kappa^b$ that allows one to estimate the MR-LATE. I choose the $\Omega$ that provides the higher F-test of the excluded instrument in the first stage. Since the mismeasured treatment is endogenous, I use the targeting of the CT as an instrumental variable, where $T = 1\,(RS < 36.59)$ if a household is eligible to receive the grant, 0 otherwise. Operationally, the procedure to estimate the MR-LATE has two steps. First, estimate two 2SLS regression of Equation 8. This is performed by using $W^j_{gi}D^j$ as the new dependent variables and $D^j_i$ as the variable of interest, for $j = a, b$. To account for the endogeneity of the mismeasured treatment, this regression use a control function approach, instrumenting $D^j_i$ with $T_i$. Second, compute the MR-LATE parameter as the difference between the estimated coefficients of the two regressions: $\delta_{MR-LATE} = \delta^a - \delta^b$. In this procedure standard errors are bootstrapped.

### 4.3.3 Results

In the first column of Table 6, I report the results of the model without control, column 2 presents the model with controls and the remaining columns show the results of the MR-LATE estimates under different percentages of mis-classification. These estimates allow us to control for potential measurement error by accounting for 2.5%, 5% and 10% of possible misclassified individuals in the sample.The effect of the women's control of resources is positive in all specifications. Results in Table 6 indicate that households where the mother controls the majority of resources have an increase in the demand for food by 2.5–5%, contingent on the specification. These effects are congruent with the recent literature (see Klein and Barham, 2018 and Tommasi, 2019).

**Table 6:** Effect of Women's Control of Resources on Household Demand of Food

| | (1) 2SLS | (2) 2SLS | (3) MR-LATE $\Omega = 2.5\%$ | (4) MR-LATE $\Omega = 5\%$ | (5) MR-LATE $\Omega = 10\%$ |
|---|---|---|---|---|---|
| | | | **Food** | | |
| D | 0.050*** | 0.025*** | 0.024*** | 0.021** | 0.017* |
| | (0.009) | (0.007) | (0.009) | (0.010) | (0.010) |
| $\ln(y)$ | -0.160*** | -0.138*** | -0.136*** | -0.134*** | -0.129*** |
| | (0.004) | (0.006) | (0.017) | (0.017) | (0.018) |
| | | | **Education** | | |
| D | -0.006*** | -0.005*** | -0.005** | -0.004** | -0.004** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\ln(y)$ | 0.027*** | 0.018*** | 0.017*** | 0.017*** | 0.017*** |
| | (0.002) | (0.002) | (0.006) | (0.005) | (0.005) |
| | | | **Health** | | |
| D | -0.012* | -0.004 | -0.004 | -0.003 | -0.001 |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| $\ln(y)$ | 0.001 | -0.011 | -0.013 | -0.013 | -0.012 |
| | (0.006) | (0.009) | (0.008) | (0.008) | (0.009) |
| Controls | × | ✓ | ✓ | ✓ | ✓ |
| N | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 |

**Notes:** The table shows the results of the effects of women's controlling the majority of resources on household demand. Controls include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. The regression also includes the interaction of month and region dummies to control for price variation. Total expenditure is instrumented with total household income and the average wage in the province the household is located. Standard errors are bootstrapped 200 times and clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

As one can see in Table 6, the estimated parameters of the effect of women's control of resources on the demand of education is negative in all specifications, although the magnitude of the effect is very small. Specifically, households where the mother controls the majority of resources have a decrease in the demand for education by 0.5–0.6%. This is reasonable since school attendance in primary school was nearly universal in Ecuador for children less than 12 years old. Moreover, the conditionality imposed by the program is to enroll children in the public school system. Therefore, when the woman has higher bargaining power, she decides to reallocate resources, putting more emphasis on food expenditures since the government already covers education.

Lastly, in Table 6, we can observe the results from the effect of women's control of resources on the demand for health. The result suggests that households where the mother controls the majority of resources do not have a robust effect on the household demand for health.

It is important to mention that in all specifications the Hansen statistic provide confidence that the instrument set is appropriate. The instruments are very strong with F-statistic on the excluded instruments over 200. Also the MR-LATE estimates are somewhat different from the 2SLS indicating that there are a potential mis-classification problem in my sample, however, the result of the robustness checks support the results.

## 4.4 Reaction to Unexpected Shocks

Documenting the existence of heterogeneity in household demand in the face of an unexpected shock depending on whether women have greater bargaining power is fundamental for the design of policies to mitigate the effect of adverse shocks. Women in households admitted to be beneficiaries of a CT program could experience an increase in their intrahousehold bargaining power not just directly, but indirectly, by increasing the perceived legitimacy of their claims related to consumption decisions when the household experiences unexpected difficult situations. To corroborate this hypothesis, I want to measure how women's control of the majority of resources affects the demand for food, education and health when households experience unexpected shocks. I allow adverse shocks reported by the household to shift demand as a covariate in $X_i$ in Equation 8. In this regression, an (unexpected) shock is documented to have occurred if the household faced one of the following situations: economic shocks, health and family shock, crime and legal shock, and natural disaster shock. Since there are a variety shock domains, using each individual domain could overstress the significance of impacts due to chance. Therefore, I construct a composite index that aggregate all these binary indicators.[22]

The main goal is to examine different spending responses by interacting the shock index with the dummy variable $D$, which defines whether a woman controls the majority of resources in Equation 8. I follow the same estimation methodology as in the previous subsection.

**Table 7:** Effect of Women's Control of Resources on Household Responses to Shocks

| | (1) Food 2SLS | (2) Education 2SLS | (3) Health 2SLS |
|---|---|---|---|
| D | 0.034*** | -0.004** | -0.010** |
| | (0.008) | (0.002) | (0.005) |
| D×Shock | -0.045** | -0.002 | 0.029* |
| | (0.023) | (0.004) | (0.017) |
| Shock | -0.009 | -0.001 | 0.043*** |
| | (0.007) | (0.002) | (0.006) |
| $\ln(y)$ | -0.138*** | 0.018*** | -0.012 |
| | (0.006) | (0.002) | (0.009) |
| Controls | ✓ | ✓ | ✓ |
| N | 6,242 | 6,242 | 6,242 |

**Notes:** The table shows the results of the effects of women's controlling the majority of resources on household demand in the presence of unexpected shocks. Controls include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. The regression also includes the interaction of month and region dummies to control for price variation. Total expenditure is instrumented with total household income and the average wage in the province the household is located. Standard errors are bootstrapped 200 times and clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

Results in Table 7 indicate that when there are adverse shocks, households where the mother controls the majority of resources reduce food expenditures and increase expenditures in health. There is not any effect on expenditures in education. A tentative explanation for this finding is that households in developing countries are typically uninsured and they cannot

[22] In Appendix A.5, I explore this effect's heterogeneity by disaggregating the result by each type of shock domain.

execute a consumption smoothing strategy. In this context, in households where the women's control the majority of resources (higher women's bargaining power) the household react by reducing consumption of food and allocating additional resources to the relevant expenditure category (in this case to health since the shocks analyzed are mostly affecting this category) but do not reduce their spending in education. It is important to acknowledge that some households could be more prone, given their characteristics, to suffer specific shocks. Therefore, the result presented in this section should be interpreted as compelling evidence that when the woman controls the majority of resources, it influences how the households react to unexpected shocks.

# 5 Conclusion

This paper analyzed how intra-household resource allocations and women's control of resources respond to poverty transfers. Using rich household expenditure data and the targeting mechanism of a CT program in Ecuador, I estimated a structural household model using a GMM approach. Specifically, I quantify the effect of the transfer on the share of resources allocated to each household member (father, mother and children). I provide evidence that the CT induces a redistribution of resources within the household, increasing the share of resources allocated to women and children. To further understand the channels through which the redistribution of resources induced by the CT program affects important household decisions, I examine implications in different domains.

**Women's Control of Resources.** Using the model's estimated parameters, I create a measure of the resources controlled by women, which is a proxy for women's bargaining power. The results show that the CT program produced a significant increase in women's control of resources. I also found that women have a decreasing pattern of control of resources until women reach 45 years old. At post-reproductive ages, women's control of resources experiences a weak increase and then declines steadily. However, the levels differ significantly for women in beneficiary and non-beneficiary households.

**Measurement of Poverty and Inequality.** The estimated parameters from the model allowed me to calculate poverty rates that consider the potential disparities in intra-household resource sharing. I evaluated the relative consumption of men, women, and children. I showed that women and children face significant probabilities of living in poverty even in households with per-capita expenditure above the poverty threshold. This generates important misclassification errors. Also, I provide evidence that the policy intervention caused welfare gains in terms of reducing poverty, especially for women and children.

**Consumption Patterns.** Using the estimated proxy for women's bargaining power, I analyzed the effect of women's control of resources on household demand for food, education and health. I found that in households where mothers control the majority of resources, expenditure on food increases, whereas there is a slight decrease in education and no effect on health. Moreover, I further investigated the impact of women's control of resources on demand for food, education and health, when households experience unexpected shocks. I found that households, where mothers have the majority of the control of resources and experience an unexpected shock, decrease the share of food expenditures, increase the share of health expenditures, and do not affect the expenditures on education.

In the last decades, many CT programs have been implemented around the world, and at the same time, poverty measures have improved in quality to try to account for different dimensions of deprivation of resources. Despite these efforts and improvements, there is still work to be done. This paper contributes to the recent literature that emphasizes the correct way of measuring each individual's resources, poverty and inequality(see for instance, Lewbel and Pendakur, 2008; Lise and Seitz, 2011; Dunbar et al., 2013; Browning et al., 2013; Calvi et al., 2018; Tommasi, 2019; Calvi, 2020). This paper also contributes to the discussion on how CT programs influence the intra-household allocation of resources and the women's bargaining power. This study further explores the potential effects of this redistributive process induced by the CT program on various household decision domains. Finally, this paper contributes from an applied perspective by showing that is possible to estimate the effects of anti-poverty programs on intra-household decisions using widely available survey data and information on the targeting mechanism of the program. This procedure could be applied in many different contexts and countries to assess CT programs better. Overall, the evidence provided in this paper contributes to understanding better the direct and indirect effects of these type of welfare policies and contain useful information to improve current CT programs or better design future anti-poverty programs.

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# A Appendix

## A.1 Descriptive Statistics by CT Program Participation

**Table A.1:** Descriptive Statistics of Household Characteristics

| | Beneficiaries[a] (N=1,174) | | Non-beneficiaries[b] (N=4,468) | | Difference (N=6,242) |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | $a-b$ |
| **Adult Members Characteristics** | | | | | |
| Man Education | 8.35 | 4.25 | 12.19 | 3.33 | 3.840*** |
| Woman Education | 8.35 | 4.19 | 12.35 | 3.17 | 4.008*** |
| Man Age | 32.31 | 7.62 | 33.49 | 7.39 | 1.178*** |
| Woman Age | 28.62 | 6.63 | 29.87 | 6.13 | 1.254*** |
| **Household Characteristics** | | | | | |
| Number of Children | 2.19 | 0.84 | 1.78 | 0.92 | -0.406*** |
| Mean Child Age | 5.56 | 2.91 | 5.14 | 2.62 | -0.426*** |
| Share of Girls | 0.66 | 0.24 | 0.69 | 0.24 | 0.027*** |
| Total Non-durable Expenditure | 358.43 | 370.41 | 656.59 | 157.89 | 298.16*** |
| **Expenditures Shares** | | | | | |
| Food Share (%) | 0.39 | 0.16 | 0.28 | 0.15 | -0.118*** |
| Education Share (%) | 0.00 | 0.04 | 0.02 | 0.02 | 0.018*** |
| Health Share (%) | 0.06 | 0.08 | 0.06 | 0.08 | 0.006** |
| **Shares of Assignable Good** | | | | | |
| Father Share (%) | 0.03 | 0.02 | 0.03 | 0.02 | 0.002** |
| Mother Share (%) | 0.03 | 0.02 | 0.03 | 0.02 | 0.002*** |
| Children Share (%) | 0.04 | 0.03 | 0.04 | 0.03 | -0.004*** |

**Notes:** The table shows a set of important characteristics of the households used for the analysis differentiating by CT program participation.*significant to 10%; **significant to 5%; ***significant to 1%.

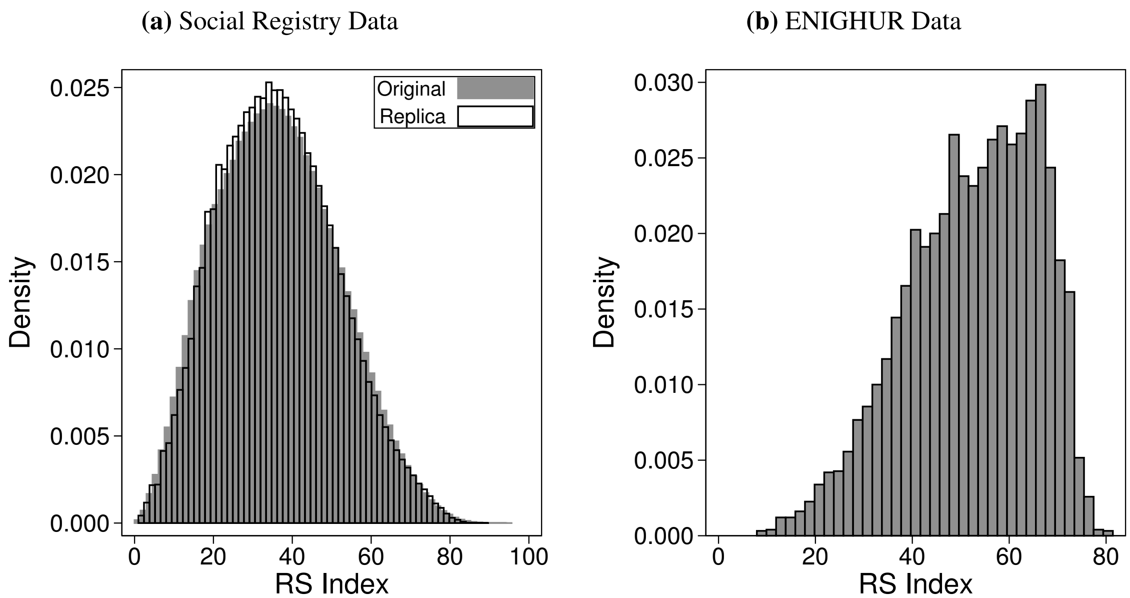
## A.2 Replication of Eligibility Index

To replicate the eligibility index, I collect an administrative data set from the Government of Ecuador and combine it with a detailed consumption expenditure survey of Ecuador that includes the households that receive the transfer, along with other socioeconomic information. The original index is constructed using Nonlinear Principal Component Analysis (NLPCA) with the combination of 30 variables. Using the same statistical procedure, I re-estimated the index to obtain the new weights for the restricted set of 25 variables (available in the ENIGHUR survey) and created an index replica with the Government administrative data set. A regression of the original eligibility index on the index replica shows that the original eligibility index can be computed based on the replica index using the following equation:

$$RS_{original(30)} = 0.976 + 1.180 * RS_{replica(25)} - 0.003 * RS^2_{replica(25)} \tag{9}$$

With the new weights for the restricted set of 25 variables and using the ENIGHUR survey I computed the index replica, while Equation 9 was used to approximate the original index for each family in the ENIGHUR survey.

**Figure A.1:** Original Eligibility Index and Replica



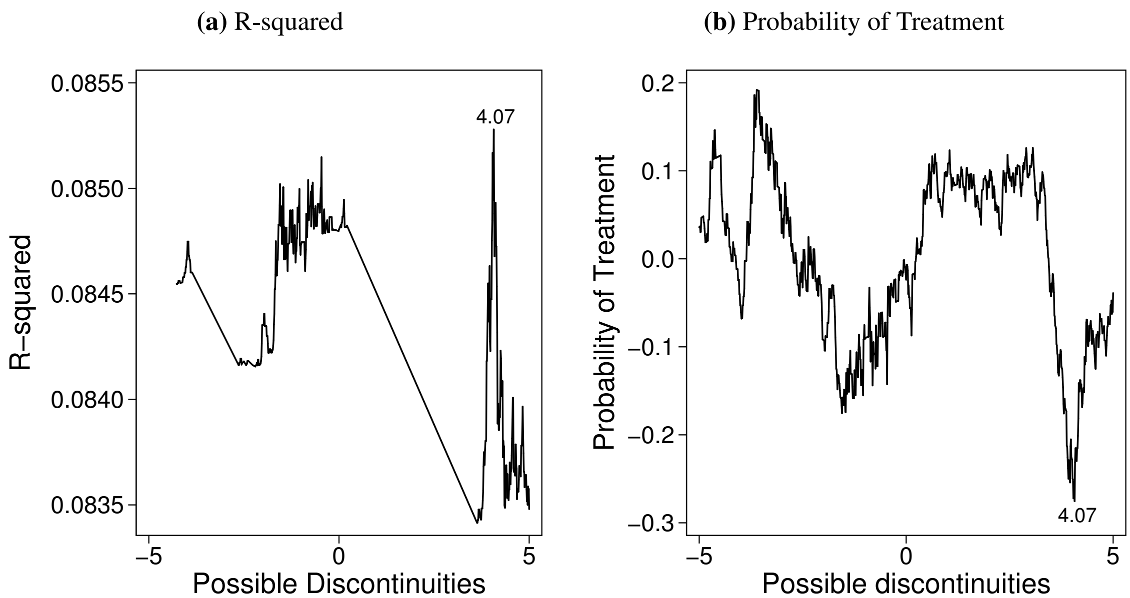

**Notes:** In the left panel I show the distribution of the original index (eligibility tool of the Ecuadorian Government ) and the replicated index for the entire sample using administrative data form Ecuador. In the right panel, I show the replica index using the survey used for the present analysis (ENIGHUR).

In the left panel of Figure A.1 we can see that the original and replica index are very similar. In the right panel of Figure A.1 I show the distribution of the replica index using the consumption expenditure survey (ENIGHUR).

Since I am using an index replica, the original cutoff of 36.59 may not be the cutoff where the households are exogenously selected to be beneficiaries of the program. I use a technique from time series econometrics to identify the structural breaks in patterns of getting the cash transfer. I follow Card et al. (2008) and Ozier (2018) to find the "true" cutoff in the replica index. I first restrict attention to a window of scores (5 points) around the actual eligibility cutoff on the eligibility index. Then, I construct an iterative process that regress the outcome (receiving the transfer) on indicators for hypothetical discontinuities from 31.59 to 41.59 points and a piecewise linear control for RS eligibility score, one potential discontinuity at a time. Following Ozier (2018) I consider the discontinuity whose regression produces the highest value of R2 to be the "true" cutoff. I perform a similar approach to obtain the point where the probability of receiving the transfer experiences the biggest discontinuity using Calonico et al. (2014) regression discontinuity procedure.

In the left panel of Figure A.2 we observe that R2-maximizing cutoff is 40.66 points rather than 36.59. This is corroborated by the discontinuity in the probability of receiving the transfer (right panel of Figure A.2).

**Figure A.2:** Structural Break Search




**Notes:** Estimation based on method used in **?** and **?**. Panel (a) shows the discontinuity whose regression produces the highest value of R2 to be the "true" cutoff.

## A.3 Manipulation Test for the Eligibility Index

Assignment to treatment status (CT) depends on the RS index (RS) in a probabilistic manner. As we are dealing with a fuzzy discontinuity, instead of a deterministic assignment rule, there is a change in the probability of treatment at the cutoff point given by:

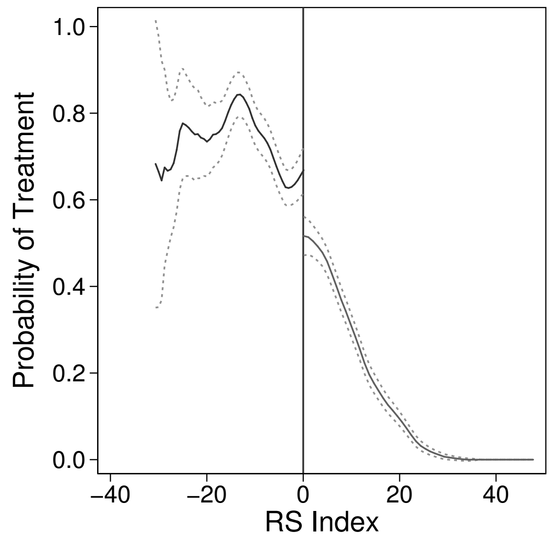
$$P(CT_i = 1 \mid RS_i) = \begin{cases} f_1(RS_i) & if \quad RS_i \leq c \\ f_0(RS_i) & if \quad RS_i > c \end{cases} \tag{10}$$

with $f_1(c) \neq f_0(c)$ and $c = 40.66$. Then, I can create a binary instrumental variable defined as:

$$Z = 1\{RS_i \leq 40.66\} \tag{11}$$

Figure A.3 illustrates the negative relation between the RS index and the probability of being treated. In general, as the RS index rises, the likelihood of getting the treatment decreases. Moreover, there is an important decline at the cutoff point. Households with an RS index of slightly less than the cutoff are about 19 percentage points more likely to be in the treatment group than households with an RS index slightly above this cutoff.

**Figure A.3:** Discontinuity in the Probability of Receiving the CT

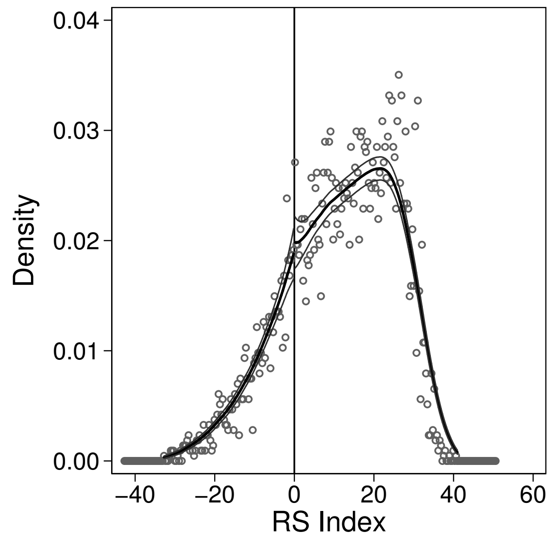



**Notes:** The plot shows the existence of a discontinuity in the probability of treatment. Specifically, there is a decrease of approximately 30% in the probability treatment, at the discontinuity cutoff, given a local polynomial smoothed fit of the RS Index replica score.

As illustrated in Figure A.3, the relationship between the RS index and the probability of getting treated provides exogenous variation in treatment status which may be used to identify the causal effect of the program.

As with many social programs, the CT program in Ecuador is subject to manipulating the beneficiary selection rules. An important condition for identification is the continuity of the conditional expectation of the counterfactual outcomes in the running variable. This continuity assumption may not be credible if individuals can influence the rule that determines assignment to treatment, specifically their position in the RS index relative to the cutoff. In the present study, this should not be a problem as families do not have any control over the calculation of the RS index or information about the scoring procedure. Moreover, the ENINGHUR survey used in this study is not the data employed by the Government to select beneficiary families, so there is no incentive for the household members to misreport information in the ENINGHUR survey. However, one should formally test that there is no manipulation in the running variable, so I test the presence of manipulation related to the running variable. I use the test proposed by McCrary (2008).

**Figure A.4:** McCrary Manipulation Test for the Eligibility Index




**Notes:** The plot is a finely-gridded smoothed histogram showing that there is no apparent difference in density around the threshold. Specifically, the McCray manipulation test is t=-0.860 with a p-value of 0.390. Therefore, there is no statistical or visual evidence of systematic manipulation of the running variable (RS Index). The plot is constructed with a binsize of 0.5 and a bandwidth of 3.

Figure A.4 shows no significant discontinuity around the cutoff in the local density function of the households according to their RS eligibility index. This is also formally confirmed by the manipulation test using a local polynomial density estimation. The McCray manipulation test is $t = -0.860$ with a p-value of 0.390. This result suggest that it is not possible to reject the null hypothesis of no statistically significant discontinuity in the density around the threshold.

## A.4 Additional Specifications of the Collective Household Model

**Table A.2:** Robustness of Main Parameters' Estimates

| | Benchmark (IV using eligibility dummy and RS index) | | | | Robustness 2 (IV RD Style) | | | | Robustness 1 (IV using only prob. of receiving) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | Father | Mother | Children | Per Child | Father | Mother | Children | Per Child | Father | Mother | Children | Per Child |
| CT | -0.115** | 0.085** | 0.030 | | -0.144** | 0.093* | 0.050 | | -0.149** | 0.081** | 0.068 | |
| | (0.052) | (0.036) | (0.057) | | (0.070) | (0.057) | (0.064) | | (0.058) | (0.035) | (0.059) | |
| One Child | 0.479*** | 0.332*** | 0.189*** | 0.189*** | 0.576*** | 0.217*** | 0.207*** | 0.207*** | 0.504*** | 0.323*** | 0.173*** | 0.173*** |
| | (0.067) | (0.062) | (0.048) | (0.048) | (0.060) | (0.051) | (0.044) | (0.044) | (0.071) | (0.061) | (0.049) | (0.049) |
| Two Children | 0.466*** | 0.288*** | 0.246*** | 0.123*** | 0.494*** | 0.194*** | 0.312*** | 0.156*** | 0.480*** | 0.272*** | 0.248*** | 0.124*** |
| | (0.068) | (0.061) | (0.050) | (0.025) | (0.062) | (0.053) | (0.047) | (0.023) | (0.070) | (0.059) | (0.052) | (0.026) |
| Three Children | 0.462*** | 0.243*** | 0.295*** | 0.098*** | 0.389*** | 0.162*** | 0.449*** | 0.150*** | 0.470*** | 0.239*** | 0.292*** | 0.097*** |
| | (0.071) | (0.060) | (0.055) | (0.018) | (0.065) | (0.053) | (0.055) | (0.018) | (0.073) | (0.057) | (0.056) | (0.019) |
| Four Children | 0.453*** | 0.217*** | 0.330*** | 0.082*** | 0.289*** | 0.135** | 0.576*** | 0.144*** | 0.451*** | 0.223*** | 0.326*** | 0.081*** |
| | (0.074) | (0.064) | (0.067) | (0.017) | (0.067) | (0.056) | (0.061) | (0.015) | (0.078) | (0.062) | (0.071) | (0.018) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Parameters | 153 | 153 | 153 | 153 | 141 | 141 | 141 | 141 | 135 | 135 | 135 | 135 |
| N | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 | 6,242 |

**Notes:** The table shows estimates of the resource shares for the father, mother and children. In the benchmark model, I Instrument CT program participation with the CT eligibility dummy and a flexible functional form of the eligibility index. In the first robustness check, I Instrument CT program participation only with the CT eligibility dummy and I use a flexible functional form of the eligibility index as a control in all the equations, like in a parametric RD specification. In the second robustness check, I Instrument CT program participation only with the CT eligibility dummy. Including controls are: children mean age, share of girls, age of mother and father, education of mother and father, working hours of of mother and father and regional dummies . Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

## A.5 Household Responses to Shocks

**Table A.3:** Effect of Women's Control of Resources on Household Responses to Shocks

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Shocks | | | Health and Family Shock | | | Crime and Legal Shock | | | Natural Disaster Shock | | |
| | Food | Education | Health | Food | Education | Health | Food | Education | Health | Food | Education | Health |
| D | 0.022* | -0.005** | -0.007 | 0.034*** | -0.005*** | -0.007 | 0.027*** | -0.004*** | -0.006 | 0.024*** | -0.004*** | -0.003 |
| | (0.012) | (0.002) | (0.007) | (0.008) | (0.002) | (0.005) | (0.007) | (0.002) | (0.005) | (0.007) | (0.002) | (0.005) |
| D×Shock | 0.006 | 0.000 | 0.005 | -0.060** | 0.002 | 0.010 | -0.042 | -0.002 | 0.040 | 0.057 | -0.007 | -0.159** |
| | (0.018) | (0.003) | (0.009) | (0.026) | (0.005) | (0.020) | (0.046) | (0.008) | (0.028) | (0.086) | (0.017) | (0.073) |
| Shock | 0.004 | -0.002 | -0.004 | -0.007 | -0.003 | 0.067*** | -0.005 | -0.000 | -0.012* | -0.010 | -0.002 | 0.074** |
| | (0.005) | (0.002) | (0.003) | (0.008) | (0.002) | (0.008) | (0.011) | (0.004) | (0.007) | (0.025) | (0.009) | (0.034) |
| $\ln(y)$ | -0.136*** | 0.018*** | -0.012 | -0.138*** | 0.018*** | -0.012 | -0.138*** | 0.017*** | -0.006 | -0.139*** | 0.017*** | -0.007 |
| | (0.006) | (0.002) | (0.009) | (0.006) | (0.002) | (0.009) | (0.006) | (0.002) | (0.009) | (0.006) | (0.002) | (0.009) |
| N | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 | 6242 |

**Notes:** The table shows the results of the effects of women's controlling the majority of resources on household demand in the presence of unexpected shocks. This table shows the heterogeneity of the effects over the different types of shocks. Controls include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. The regression also includes the interaction of month and region dummies to control for price variation. Total expenditure is instrumented with total household income and the average wage in the province the household is located. Standard errors are bootstrapped 200 times and clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

## A.6 Perception of the Standard of Living

To complement the analysis on poverty and inequality, this Appendix presents how perceptions of living standards are associated with women's control of resources.

In this context, it is interesting to test if intra-household bargaining is likely to affect household perceptions related to living standards. This implies that relative women's intra-household bargaining power are an important variable that have to be considered when trying to understand household perceptions. To this aim, I construct an index that aggregates 4 dimensions of perception of the standard of living. In the survey, respondents were asked to report if they believe they live well, perceptions of the current economic situation of the household with respect to the solvency of its expenses, perception of the change of the status of standards of living with respect to a year ago and if they believe their household is poor. I follow a similar estimation procedure as in Subsection 4.3 and the results are presented in Table A.4.

**Table A.4:** Effect of Women's Control of Resources on Living Conditions Perception

| | (1) Living Conditions Perception Index 2SLS | (2) Living Conditions Perception Index MR-LATE $\Omega = 2.5\%$ | (3) Living Conditions Perception Index MR-LATE $\Omega = 5\%$ | (4) Living Conditions Perception Index MR-LATE $\Omega = 10\%$ |
|---|---|---|---|---|
| D | -0.120** | -0.113** | -0.104* | -0.097* |
| | (0.048) | (0.055) | (0.054) | (0.054) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| N | 6,242 | 6,242 | 6,242 | 6,242 |

**Notes:** The table shows the results of the effects of women's controlling the majority of resources on the perception of household living conditions. Controls include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. Standard errors are bootstrapped 200 times and clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

According to the findings, women's controls of the majority of resources is negatively related to the perception of standard of living. Results indicate that households where the mother controls the majority of resources experience a decrease in the perception of living conditions index in 0.12 standard deviations (around 2.6 percentage points in the index). A tentative explanation for this pattern is that households where the mother has a higher bargaining power are poorer, or an increase in woman say, increase the legitimacy of their claims which translates into a higher degree of household awareness related to its living conditions.

# B Appendix

## B.1 An RD Analysis of Mother's Control of Resources

To further confirm a causal link between the cash transfer and women's control over household resources, I check whether the estimated measure of women's control of resources is impacted by being a beneficiary of the policy. Since the mother's control of resources is an estimated object, this RD analysis only provides a description of the behavior of this variable close to the eligibility threshold. Given that I have information on the RS index (running variable), the exogenous threshold of program assignment (40.66 points), the treatment indicator of receiving the CT and information on the outcomes of interest, the fuzzy regression discontinuity (RD) design allows me to isolate a local average treatment effect (LATE) of the CT, by associating a jump in mean outcome with a jump in the probability of treatment, when the running variable crosses the threshold (Thistlethwaite and Campbell, 1960; Imbens and Lemieux, 2008). Program participation, or the first stage equation, is treated as a function of an instrument ($Z$), the RS index ($R$) and the vector of individual and household characteristics ($X$). This first stage equation can be expressed as:

$$CT_i = \gamma Z_i + f(RS_i) + \mathbf{X}_i'\delta + \mu_i \tag{12}$$

As we will see below the assignment rule is correlated with the probability of treatment, consequently as the instrument $Z$ is based on the assignment rule it is likely to be highly correlated to program participation. Additionally, it is necessary to assume that any unobserved characteristics that determine mothers's control of resources are not correlated with the instrument, i.e., we assume, $E[Z_i\varepsilon_i \mid X_i, R_i] = 0$. If this assumption holds then consistent estimates of the CT program can be obtained by estimating:

$$R_i = \alpha \hat{CT}_i + f(RS_i) + \mathbf{X}_i'\beta + \varepsilon_i \tag{13}$$

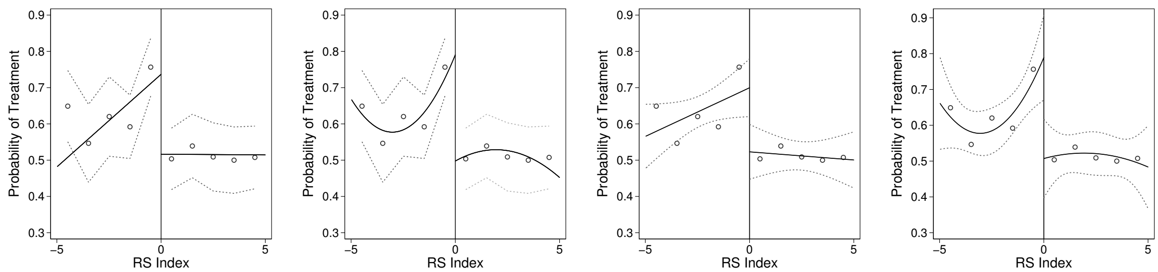
where $\hat{CT}$ is obtained from Equation 12.

### B.1.1 First Stage Discontinuity

Figures A.5 and A.6 complement Figure A.3 with additional plots showing the discontinuity in the probability of treatment using data-driven choices of the number of the evenly spaced bins (see Calonico et al., 2014, 2015, 2019). These plots exhibit a similar pattern as Figure A.3, and reveal the existence of a discontinuity in the probability of treatment that oscillates between 25 and 30 percent.

**Figure A.5:** Discontinuity in the Probability of Receiving the CT (5 Pts. Window)

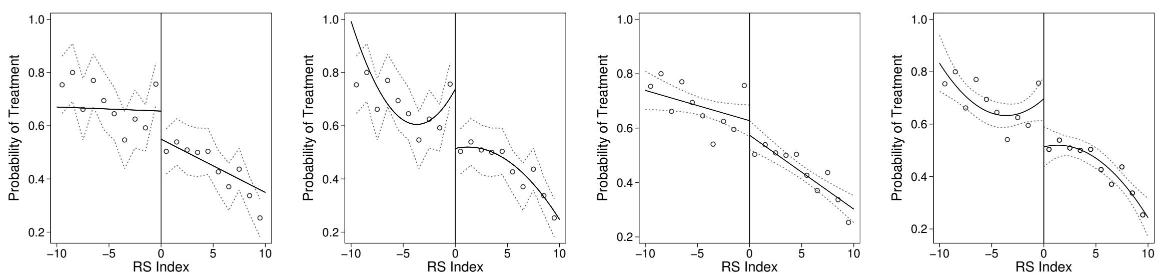
**(a)** Linear **(b)** Quadratic **(c)** Linear **(d)** Quadratic




**Notes:** All the plotrs show the discontinuity in probability of participating in CT program. Panels (a) and (b) use the methodology of Calonico et al. (2014) and Calonico et al. (2015). This method allows us to plot and report CIs for local means within each bind. Panels (c) and (d) show standard CIs for a linear and quadratic least squares fit.

**Figure A.6:** Discontinuity in the Probability of Receiving the CT (10 Pts. Window)

**(a)** Linear **(b)** Quadratic **(c)** Linear **(d)** Quadratic




**Notes:** All the plotrs show the discontinuity in probability of participating in CT program. Panels (a) and (b) use the methodology of Calonico et al. (2014) and Calonico et al. (2015). This method allows us to plot and report CIs for local means within each bind. Panels (c) and (d) show standard CIs for a linear and quadratic least squares fit.

**Table A.5:** First Stage Discontinuity Estimates (Parametric)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All | | 5 Pts. Window | |
| | CT | CT | CT | CT |
| Below cutoff point (T) | 0.185*** | 0.190*** | 0.277*** | 0.267*** |
| | (0.025) | (0.025) | (0.081) | (0.079) |
| N | 6,242 | 6,242 | 1,103 | 1,103 |
| Controls | × | ✓ | × | ✓ |
| F-statistic | 53.58 | 59.75 | 11.77 | 11.36 |

**Notes:** The table shows the results of the effect of the CT on the mother's control of resources (R). Controls, when indicated, include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

**Table A.6:** Participating in CT Program (Data Driven Bandwidth)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | CT | CT | CT | CT | CT | CT |
| **MSE-optimal bandwidth** | | | | | | |
| Below cutoff point (T) | 0.276*** | 0.249*** | 0.303*** | 0.267*** | 0.298*** | 0.272*** |
| | (0.073) | (0.069) | (0.075) | (0.072) | (0.076) | (0.074) |
| N | 869 | 950 | 1629 | 1752 | 2664 | 2743 |
| Controls | × | ✓ | × | ✓ | × | ✓ |
| Function | Linear | Linear | Quadratic | Quadratic | Cubic | Cubic |
| **CER-optimal bandwidth** | | | | | | |
| Below cutoff point (T) | 0.302*** | 0.270*** | 0.303*** | 0.284*** | 0.318*** | 0.309*** |
| | (0.081) | (0.077) | (0.086) | (0.082) | (0.087) | (0.084) |
| N | 616 | 674 | 1052 | 1124 | 1750 | 1794 |
| Controls | × | ✓ | × | ✓ | × | ✓ |
| Function | Linear | Linear | Quadratic | Quadratic | Cubic | Cubic |

**Notes:** The table shows the results of the effect of the eligibility status on the actual treatment. Each cell is the result of a regression. CER refers to the optimal coverage error probability bandwidth proposed by Calonico et al., 2014 and MSE refers to the mean squared error optimal bandwidth proposed by Imbens and Kalyanaraman (2012). Controls, when indicated, include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

### B.1.2 RD Validity

In Table A.7, I carry out validity tests of the smoothness assumption using observables. The father and mother's education, the father and mother's age, the children's mean age, the share of girls, and living in a rural area vary smoothly at the boundary, with differences that are neither large enough to be important nor statistically significant. Since the averages of the covariates around the cutoff are very similar, signaling as good as random local assignment of the CT. Therefore, we can expect households with index scores below and above the cutoff to be similar in all observed and unobserved confounders.

**Table A.7:** RD Validity: Local Quadratic Regressions of Covariates on RS Index Scores

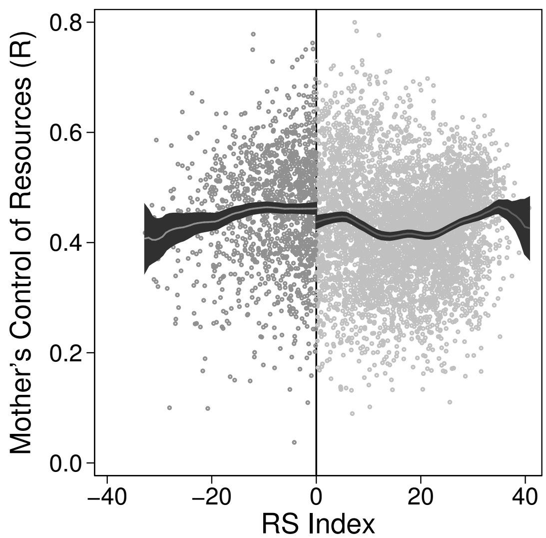
| | (1) Father Education | (2) Mother Education | (3) Father Age | (4) Mother Age | (5) Mean Child Age | (6) Share of Girls | (7) Rural Area |
|---|---|---|---|---|---|---|---|
| | | | **MSE-optimal bandwidth** | | | | |
| Below cutoff point (T) | 0.251 | -0.008 | -1.184 | -0.620 | 0.004 | -0.028 | -0.041 |
| | (0.189) | (0.196) | (1.027) | (0.933) | (0.135) | (0.041) | (0.079) |
| N | 2405 | 2681 | 2204 | 2334 | 2278 | 1892 | 2375 |
| | | | **CER-optimal bandwidth** | | | | |
| Below cutoff point (T) | 0.164 | -0.025 | -1.306 | -0.902 | -0.043 | -0.025 | 0.006 |
| | (0.218) | (0.226) | (1.159) | (1.056) | (0.150) | (0.046) | (0.090) |
| N | 1526 | 1742 | 1408 | 1476 | 1450 | 1212 | 1506 |

**Notes:** Each cell is the result of a regression. CER refers to the optimal coverage error probability bandwidth proposed by Calonico et al., 2014 and MSE refers to the mean squared error optimal bandwidth proposed by Imbens and Kalyanaraman (2012). Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

### B.1.3 Intention-to-treat (ITT)

In Figure A.7, I show the effect of the instrument in the outcome (mother's control of resources), i.e. the intention-to-treat (ITT).

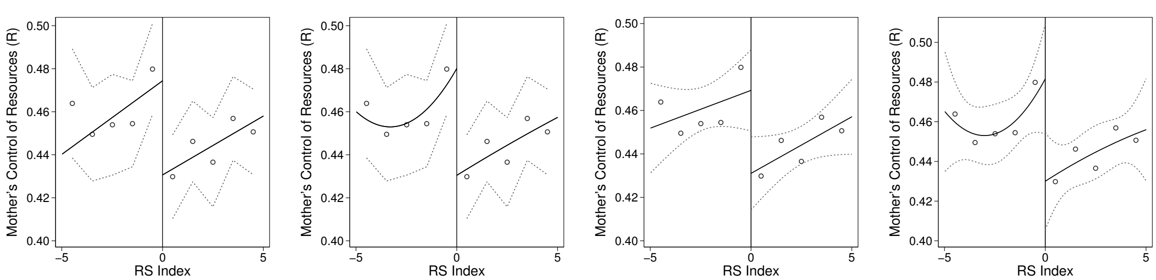
**Figure A.7:** Intention-to-treat (ITT)




**Notes:** The plot shows the existence of a discontinuity in the probability of treatment. Specifically, there is a decrease of approximately 30% in the probability treatment, at the discontinuity cutoff, given a local polynomial smoothed fit of the RS Index replica score.

**Figure A.8:** Intention-to-treat (5 Pts. Window)

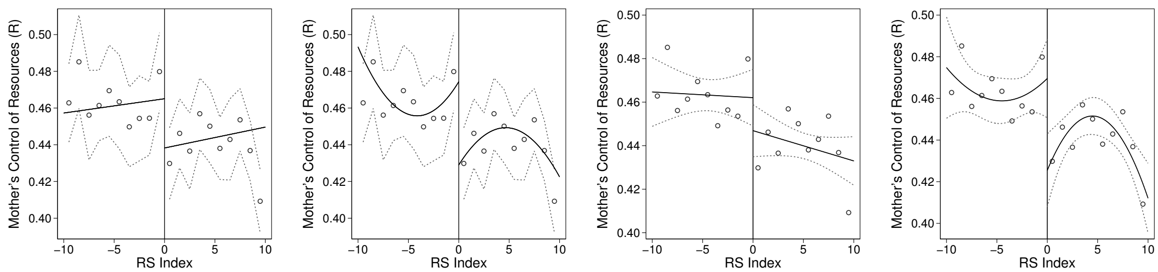
**(a)** Linear **(b)** Quadratic **(c)** Linear **(d)** Quadratic




**Notes:** All the plots show the ITT of the CT on Mother's control of resources. Panels (a) and (b) use the methodology of Calonico et al. (2014) and Calonico et al. (2015). This method allows us to plot and report CIs for local means within each bind. Panels (c) and (d) show standard CIs for a linear and quadratic least squares fit.

**Figure A.9:** Intention-to-treat (10 Pts. Window)

**(a)** Linear **(b)** Quadratic **(c)** Linear **(d)** Quadratic




**Notes:** All the plots show the ITT of the CT on Mother's control of resources. Panels (a) and (b) use the methodology of Calonico et al. (2014) and Calonico et al. (2015). This method allows us to plot and report CIs for local means within each bind. Panels (c) and (d) show standard CIs for a linear and quadratic least squares fit.

The effect of the instrument in the outcome, showed a significant coefficient for all the specifications.

**Table A.8:** Intention-to-treat (ITT)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | R | R | R | R | R | R |
| | | | **MSE-optimal bandwidth** | | | |
| Below cutoff point (T) | 0.046*** | 0.053*** | 0.050*** | 0.055*** | 0.052*** | 0.055*** |
| | (0.015) | (0.015) | (0.017) | (0.017) | (0.018) | (0.017) |
| N | 1321 | 1081 | 2026 | 1858 | 2953 | 2952 |
| Controls | × | ✓ | × | ✓ | × | ✓ |
| Function | Linear | Linear | Quadratic | Quadratic | Cubic | Cubic |
| | | | **CER-optimal bandwidth** | | | |
| Below cutoff point (T) | 0.049*** | 0.053*** | 0.052*** | 0.055*** | 0.054*** | 0.059*** |
| | (0.017) | (0.017) | (0.020) | (0.019) | (0.021) | (0.019) |
| N | 881 | 742 | 1298 | 1199 | 1963 | 1963 |
| Controls | × | ✓ | × | ✓ | × | ✓ |
| Function | Linear | Linear | Quadratic | Quadratic | Cubic | Cubic |

**Notes:** The table shows the results of the effect of the eligibility status on the mother's control of resources (R). Each cell is the result of a regression. CER refers to the optimal coverage error probability bandwidth proposed by Calonico et al., 2014 and MSE refers to the mean squared error optimal bandwidth proposed by Imbens and Kalyanaraman (2012). Controls, when indicated, include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

### B.1.4 Fuzzy RD Results

The ratio of these ITT (outcome discontinuity) to the first stage (treatment discontinuity), is the effect of the CT for the compliers within the chosen bandwidth. All of these ratio estimates was found to be significantly different from 0 which lead to reject the null hypothesis of no effect.

**Table A.9:** IV Estimates (LATE)

| | (1) | (2) |
|---|---|---|
| | R | R |
| CT | 0.241*** | 0.179*** |
| | (0.029) | (0.020) |
| N | 6242 | 6242 |
| Controls | × | ✓ |

**Notes:** The table shows the results of the effect of the CT on the mother's control of resources (R). Controls, when indicated, include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

The findings from the non-parametric procedure based on the work by Calonico et al. (2015) and Calonico et al. (2019), account for estimates very similar to those from the IV method. Using a similar specifications, but relying on data driven bandwidths, the local polynomial robust estimates showed a statistically significant effect of the CT over mother's control of resources.

**Table A.10:** Fuzzy Regression Discontinuity Estimates (LATE)

| | (1) R | (2) R | (3) R | (4) R | (5) R | (6) R |
|---|---|---|---|---|---|---|
| | | | **MSE-optimal bandwidth** | | | |
| CT | 0.192*** | 0.245*** | 0.171*** | 0.215*** | 0.176*** | 0.206*** |
| | (0.061) | (0.071) | (0.057) | (0.054) | (0.057) | (0.049) |
| N | 1134 | 1793 | 1715 | 2044 | 2756 | 2880 |
| Controls | × | ✓ | × | ✓ | × | ✓ |
| Function | Linear | Linear | Quadratic | Quadratic | Cubic | Cubic |
| | | | **CER-optimal bandwidth** | | | |
| CT | 0.180*** | 0.233*** | 0.167*** | 0.203*** | 0.168*** | 0.194*** |
| | (0.058) | (0.051) | (0.060) | (0.047) | (0.055) | (0.045) |
| N | 783 | 1218 | 1106 | 1313 | 1807 | 1894 |
| Controls | × | ✓ | × | ✓ | × | ✓ |
| Function | Linear | Linear | Quadratic | Quadratic | Cubic | Cubic |

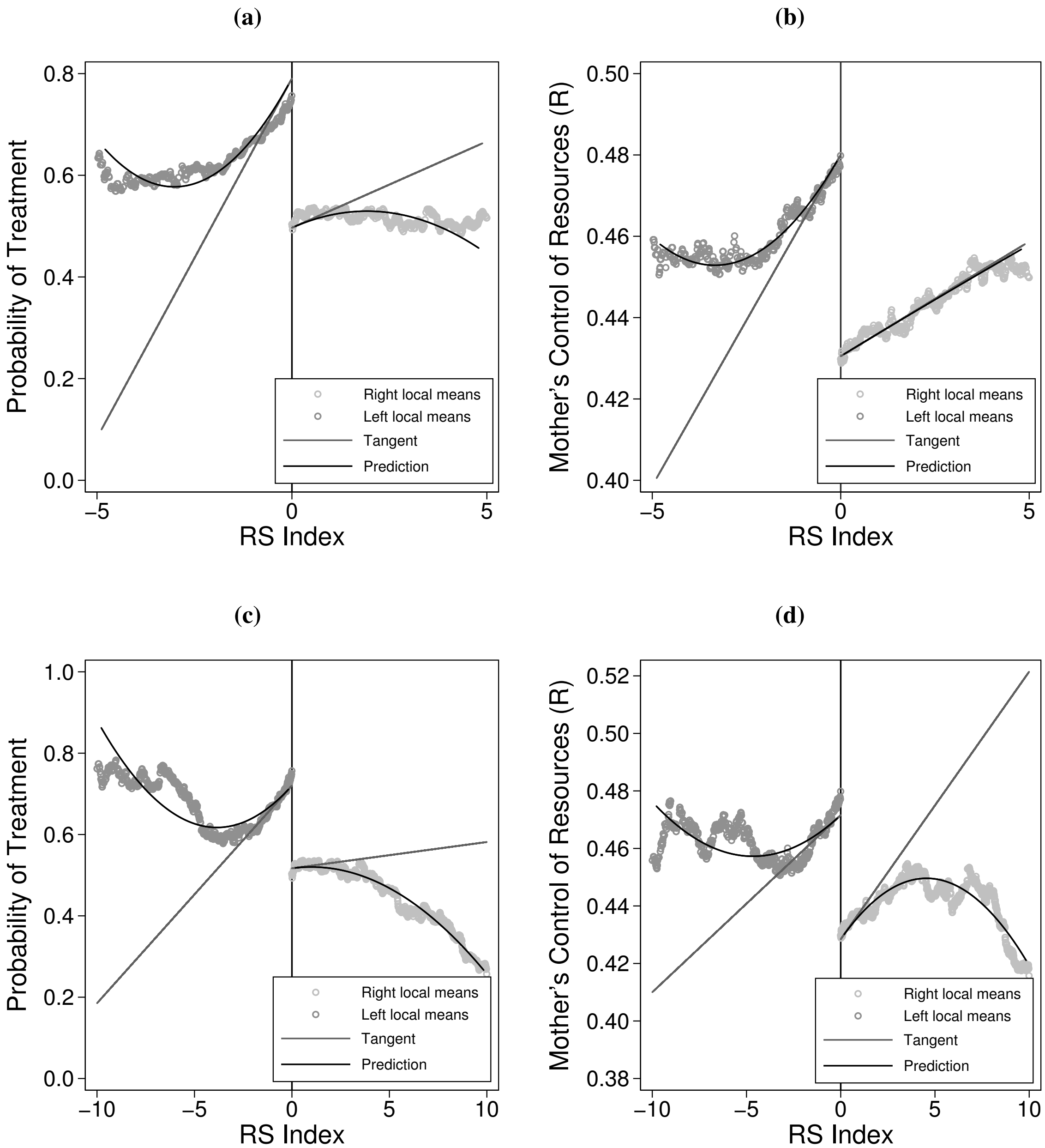
**Notes:** The table shows the results of the effect of the CT on the mother's control of resources (R). Each cell is the result of a regression. CER refers to the optimal coverage error probability bandwidth proposed by Calonico et al., 2014 and MSE refers to the mean squared error optimal bandwidth proposed by Imbens and Kalyanaraman (2012). Controls, when indicated, include: number of children, children mean age, share of girls, age of mother and father, education of mother and father. Standard errors clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

The regression discontinuity estimates show that woman's control over family resources increases considerably when the woman live in a beneficiary household, which supports a causal interpretation of the main findings.

### B.1.5 Testing Stability of RD Results

The estimated treatment effect of the CT on the mother's control of resources applies to households having an RS index close to the cutoff. In this context, it is important to analyze the stability of RD estimates, that is, to examine whether households with other values of the RS index would have expected treatment effects of similar sign and magnitude. Following Dong and Lewbel (2015), I estimate the complier probability derivative (CPD) and the treatment effect derivative (TED). TED is the derivative of the RD treatment effect with respect to the running variable. Just as TED measures the stability of the treatment effect, the CPD measures the stability of the population of compliers in fuzzy designs. If ceteris paribus, a slight change in the RS index away from the cutoff would significantly change the average effect of treatment, then one would have serious doubts about the general usefulness and external validity of the estimates since other contexts are likely to differ from the given one in even more meaningful ways than a marginal change in the RS index. In contrast, having TED near-zero provides some evidence supporting the stability of RD estimates.

**Figure A.10:** Testing Stability of Regression Discontinuity




**Notes:** The left-hand side plots show the fuzzy RD discontinuity in the probability and tangents lines at the threshold. The right-hand side plots show the fuzzy RD discontinuity in the outcome and tangents lines at the threshold. I use a triangular kernel and all estimates are based on local quadratic regressions.

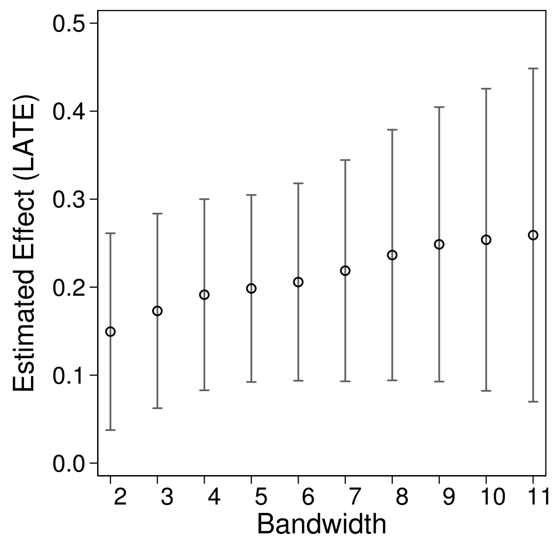
The estimates of CPD in Table A.6 range from -0.107 to -0.097, and only the MSE CPD is statistically significant. The normalized eligibility index ranges from -32.75 to 40.74. These estimates suggest that, given a 10-point increase in the elegibility index score, the percent of households who are compliers would decrease between 10 and 11 percentage points. Given these results, the set of compliers looks somewhat unstable. The estimates of TED in Table A.6 are rather small and not statistically significant. The magnitude of the TED here means there is a good chance that the magnitude of the treatment effect could be quite similar at somewhat lower or higher values of the threshold. Together these results indicate that although the set of compliers is not very stable, the conclusion that the CT affects the mother's control of resources does appear stable.

**Table A.11:** TED and CPD of Fuzzy RD Treatment Effects of CT on Mother's Control of Resources

| | (1)<br>CER | (2)<br>MSE |
|---|---|---|
| CPD | -0.107 | -0.097** |
| | (0.096) | (0.048) |
| LATE | 0.169*** | 0.181*** |
| | (0.057) | (0.046) |
| TED | -0.025 | -0.046 |
| | (0.064) | (0.036) |
| Bandwidth | 4.885 | 7.756 |
| N | 1,106 | 1,715 |

**Notes:** All estimates are based on local quadratic regressions; CER refers to the optimal coverage error probability bandwidth proposed by Calonico et al., 2014 and MSE refers to the mean squared error optimal bandwidth proposed by Imbens and Kalyanaraman (2012). I use a triangular kernel; bandwidth and sample size N refer to those of the outcome equation. Standard errors are bootstrapped 200 times and clustered at the primary sampling unit (census sector) level. *significant to 10%; **significant to 5%; ***significant to 1%.

**Figure A.11:** Fuzzy RD LATE Point Estimations and Confidence Intervals over a Range of Bandwidths




**Notes:** The plot shows the fuzzy RD LATE point estimates and confidence intervals of the effect of the CT on mother's control of resources over a range of bandwidths.