Licenciatura en Economía

Trabajo de investigación para obtener el título de Licenciado en Economía

The relationship between private transfers and income in Mexico

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Promoción 2016-2020

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Febrero de 2021

EL COLEGIO DE MÉXICO

CEE Centro de Estudios Económicos

To my parents Mauricio and Berta, for their unyielding support.

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1 Introduction

This work examines the relationship between private transfers and income in Mexico. The main preoccupation of the literature on private transfers is what Cox and Fafchamps (2007) call the "specter of 'crowding-out'", that is, the possibility that donors lower the amount they transfer habitually when their beneficiaries start receiving additional transfers from the government. This crowding out of private transfers by government transfers would effectively diminish the net amount received by the intended population and indirectly benefit some third party. Therefore, this line of research is of great importance to understand the true effect that transfer programs have on the relevant population.

Private transfers are transfers of money or assets from one person to another. The motivation underlying these transfers is a main point of contention in the literature, with important economic consequences. A first model suggests that these transfers are altruistically motivated, that is, that the donor expects nothing in return for their transfer and they care only for the well-being of the recipient. Alternatively, transfers may respond to informal and possibly implicit arrangements where the recipient offers in exchange some sort of service. Finally, it may also be the case that both of these motives are present and become operative at different income levels.

Whether one expects these transfers to be altruistically motivated or not, one should expect these amounts to exhibit some relationship with both the donor and recipient's incomes. The expected direction of this relationship varies according to the motives for the transfer.

Most studies on this phenomenon have failed to find strong effects. But most research has failed to take into account the nonseparability of errors and preferences. What is meant by this is that the individual error u_i will not only affect the level of transfers but also how strongly donors react to changes in their own or the recipient's income. Imagine, if you will, that Emma is a loving person who cares a lot about her brother Jack, who is going through a rough time. In fact, she's significantly more invested in her brother's well-being than some other people in her same situation [1]. Not only will Emma transfer more money to Jack, but she will be more willing to compensate for any loss of income on his part and to share in any windfall she may receive.

Another issue with transfer data is that there are many observations at zero due to a corner solution. This type of data cannot be estimated without bias using OLS. Instead, one must use a "censored model" (Wooldridge, 2010).

I estimate how private inter-household cash transfers in Mexico respond to income at the individual level, using the Altonji-Ichimura estimator. This estimation procedure addresses the non-separability of errors and preferences as well as the existence of corner solutions. I use cross-sectional data from the 2018 Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH)[2].

I find a strong and non-linear relationship between private transfers and income for people with low income, with an average effect of -0.44. This effect is significantly higher in absolute terms than that found in most of the relevant literature, but is consistent with the findings for Mexico specifically. Because my model suffers from omitted-variable bias my results are not precise, but given the expected direction of the bias, they could imply a lower bound (in absolute terms). This has important policy implications for cash transfer programs directed towards Mexico's poor. In particular, these cash transfers would not increase the targeted households' income by their full amount, as some of the linked households appropriate part of the benefit.

This work is organized as follows. Section 2 covers the theoretical underpinnings for the study of transfer behavior. Section 3 presents previous empirical findings for different countries as well as the case of Mexico. Section 4 goes over the methodology behind the estimation. Section 5 examines the data, and section 6 outlines the estimation procedure. Finally, sections 7 and 8 present the results and conclusions, respectively.

[1] That is, someone with the same covariates

[2] National Survey on Household Income and Expenditure

2 Theory

2.1 The altruistic model

The theoretical basis for this work begins with Becker's 1974 model of altruistic transfers, upon which later refinements are introduced. The model begins by introducing an altruistic utility function,

$$U = U(c_d, V(c_r))$$

where the donor's utility depends on their consumption c_d and the recipient's utility $V(c_r)$. The donor can transfer a quantity T to the recipient, and optimizes their utility accordingly. Thus, the optimization problem the donor is faced with is:

$$\begin{aligned} \underset{\mathrm{T}}{max}\ U &= U(c_d, V(c_r)) \\ \text{s.t. } c_d &= I_d - T \\ c_r &= I_r + T \end{aligned}$$

If this level was optimal to begin with, a forced transfer τ from the donor to the donee will have the effect of reducing the private transfer T by the same amount so the optimal level is regained. This would lead to an unchanged utility, as this forced transfer is fully crowded-out by the donor's response. We can break down the overall response from a forced transfer from donor to donee into two distinct relationships:

$$\frac{\delta T}{\delta \tau} = \frac{\delta T}{\delta I_r} - \frac{\delta T}{\delta I_d}$$

Where $\frac{\delta T}{\delta \tau}$ is the overall response to the forced transfer, composed of $\frac{\delta T}{\delta I_r}$, the change in the transfer due to the fall in the recipient's income and $\frac{\delta T}{\delta I_d}$, the change in the transfer due to the equivalent rise in the donor's income. One would expect the first term to be negative, as an altruistically motivated donor seeks to compensate losses to income and withdraw their transfers as the recipient's income increases and their help is no longer needed. The second term should be positive, as an increase in their own income should increase the amount they are willing to transfer. More rigorously, the donor will change the amount transferred until the marginal utility they receive from their own income is equal to the marginal utility they receive from the income of the recipient through $V(\cdot)$.

As argued in Cox and Fafchamps (2007), when testing for evidence consistent with altruistic preferences it is not enough for the sign of $\frac{\delta T}{\delta I_r}$ to be negative. One must also argue that the implied size of $\frac{\delta T}{\delta I_d}$ is plausible. If one were to observe a linear relationship with a derivative $\frac{\delta T}{\delta I_r} = -0.01$, this would imply that $\frac{\delta T}{\delta I_d} = 0.99$, so that 99% of the donor's income on the margin would be transferred to a third party.

However, a small transfer derivative is not in and of itself problematic if the relationship is not linear, and it drops sufficiently fast. While the derivative may be very large on the margin, the overall effect may be less drastic. Note that if $\frac{\delta T}{\delta I_d}$ is changing in I_d, then it implies that $\frac{\delta T}{\delta I_r}$ must also change in I_d if the identity $\frac{\delta T}{\delta I_r} - \frac{\delta T}{\delta I_d} = -1$ is to be maintained[3]. This is also the case for the inverse proposition: if $\frac{\delta T}{\delta I_r}$ is not constant on I_r then $\frac{\delta T}{\delta I_d}$ must also change on I_r.

Also, note that I make no distinction about the source of the recipient's change in income. One way this could prove to be a problem is if, for any change in income due to an increase in government spending, the donor were to expect that the fiscal burden for this spending would fall on them eventually. That is, if government transfers are thought of as a forced transfer, then one would not be able to separate $\frac{\delta T}{\delta I_r}$ from $\frac{\delta T}{\delta I_d}$, as one would observe $\frac{\delta T}{\delta \tau} = -1$. Other sources of income would still behave as normal. For example, in the case of an increase in a recipient's salary or other non-labor sources of income.

[3]It also may be the case that $\frac{\delta T}{\delta I_r} - \frac{\delta T}{\delta I_d} \neq -1$ in the presence of measurement error by the donor. For instance, if they consistently overestimate the recipient's income by 10%, then $\frac{\delta T}{\delta I_r} > \frac{\delta T}{\delta I_d} - 1$, and this discrepancy would increase with income.

2.2 The exchange model

An alternative explanation of transfer behavior was proposed by Bernheim et al. (1985). Their model is specified in terms of bequeaths from parents to their children. Starting from the same specification as Becker (1974), they further add a term a which represents the "attention" parents receive from their children. Importantly, this represents some sort of care that cannot be obtained through the market. The child's utility function is of the form:

$$U(c_r, a)$$

While the parent's utility function can be written as:

$$U(c_d, a, V(c_r, a))$$

They assume that the child's utility first increases and then decreases with the attention provided a, and that parents tire of attention after their children, if at all. Finally, when allowing for the effect of a through V, the parent's utility declines for a high enough level of a.

From this set of assumptions, they then show that non-strategic behavior results in an equilibrium that is not Pareto efficient, and that Pareto improvements are possible through strategic behavior. The strategy consists of threatening with disinheritance. For this threat to be credible, there must exist another credible allocation of their legacy.

2.3 Mixed motives

Cox (1987) applies the exchange model to inter-vivos transfers[4], and combine it with Becker's model to allow for both altruistic and exchange models at different income levels. The role of attention in the model put forward by Bernheim et al. (1985) is replaced by a wider category of 'services':

[4]Transfers between living people, as opposed to bequests

> "One type of service is help with home production, such as babysitting, running errands, and other forms of housework. These kinds of services, however, would in many cases have clear market substitutes. I am concerned mainly with a more subtle type of service that entails the behavioral constraints associated with attention to parents [...], companionship, and conforming to parental regulations." (Cox, 1987, p. 513)

The other important difference with Bernheim's model is that it's assumed that the child's utility is strictly decreasing in these services s. The parent's maximization problem is constrained by

$$V(c_r, s) \geq V_0(I_r, 0)$$

Where I_r is the child's income. In other words, the optimal solution cannot be worse for the child than their autarkic equilibrium where they only consume out of their own income; otherwise, the child could simply choose not to provide the services and be better off. This equilibrium becomes the child's threat point to which they can retreat if the parent's demands are too great.

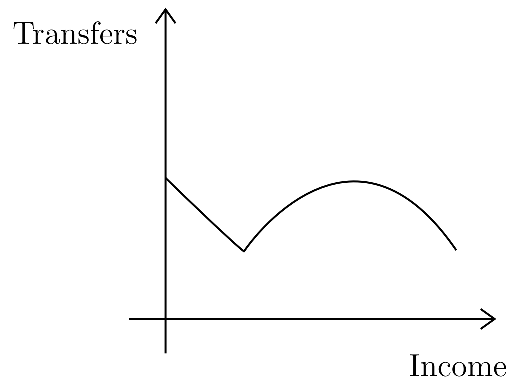
When this restriction is binding, then the solution c_r^*, s^* gives equal utility to the child as the threat point $V_0(I_r, 0)$[5] and the operative motives are exchange-based. To see why suppose

$$V(c_r, s) > V_0(I_r, 0)$$

Which means we are in the altruistic case. This implies that the parent cannot extract more services because the alternative allocation $V_0(I_r, 0)$ is not credible: they would receive no services and a lower utility through $V(\cdot)$. As I_r increases, c_r will not fall as long as $\frac{\delta T}{\delta I_r} < -1$. Therefore, as I_r grows, it will eventually reach the point where $V(c_r, s) = V_0(I_r, 0)$.

[5] Cox (1987) also proposes a strategic extension of the model which makes it so the child is not indifferent between autarky and the exchange solution and but rather prefers the latter one.

Figure 1: A possible relationship between income and transfers for mixed motives[6]



From here on, the threat point $V_0(I_r, 0)$ is credible.

Furthermore, as I_r and therefore the threat point continue to rise, the implicit price of services goes up. This has a price effect, as higher prices elevate the amount of the transfer required for a given level of services, and a quantity effect, as the higher price reduces the demand for such services. One would expect transfers to grow as the price effect dominates and then fall as the quantity effect becomes predominant. Therefore, the behavior as I_r increases is expected to have the pattern shown in figure 1.

In summary, the sign of the relationship between the recipient's income and private transfers is expected to differ according to the underlying transfer motive. Under altruism, we would expect a purely negative relationship, while the exchange model admits both positive and negative effects. Under exchange, a positive relationship would be indicative of a prevalent price effect, while a negative relationship would point towards a more prevalent quantity effect. The precise shape of this relationship would depend on the specific parameters dictating the relative weight of each effect. Finally, under mixed motives, we would expect an initial negative relationship up to an inflection point, after which exchange motives take over.

[6] Recreated from (Cox & Fafchamps, 2007)

3 Previous empirical evidence

Cox and Fafchamps (2007) present an exhaustive literature review on the empirical findings surrounding transfer responsiveness to income. Across these studies, they find a modal transfer derivative of between -0.2 to -0.25.

Cox et al. (2004) theorize that crowding-out may have already taken place in economies where there exists a large public sector. Therefore, they estimate the transfer derivative in a laissez-faire country, Philippines. They find a transfer derivative of -0.4 using a linear spline with a single knot.

Gibson et al. (2011) use data from four different countries and a nonlinear single knot-spline estimation and find significant but very small transfer derivatives: -0.051 for Urban Indonesia, -0.050 for Rural Indonesia, a positive derivative of 0.061 for Rural Vietnam, -0.042 for Rural China, and -0.083 for Urban Papua New Guinea. They also fail to find evidence for mixed motives from their model specification.

For Mexico, Albarran and Attanasio (2002) find a transfer derivative of -1.69 from a randomized experiment, and Juarez (2009) finds that, upon controlling for the endogeneity of income due to changes in behavior from the introduction of public transfers, a reference individual has a transfer derivative of -1.02. She also finds that the size of the effect decreases in absolute terms with income.

Understanding the overall impact of these effects also requires us to know the involvement rate, that is, the percentage of people that receive any non-zero amount of private transfers. Albarran and Attanasio (2002), found only an 11 percent involvement rate in Mexico, while Juarez (2009) finds a 16 percent involvement rate among urban individuals 60 years old or older and increasing involvement with age.

Despite the low level of involvement, transfer derivatives in Mexico appear to be larger than those found elsewhere. It may be the case that Mexico has gone through an incomplete crowding out process, as a subset of the population continues to be excluded from social security. For instance, as of 2017, 17.3% of Mexico's Population is not affiliated to any healthcare program, either public or private (INEGI, 2017). Further research is needed to ascertain this, however.

Importantly, since 2009 the aid program for the elderly described in Juarez (2009) has been extended to the national level (Arza, 2019). This, along with the decreasing share of people not covered by health services may have caused some additional crowding out in the past few years.

The failure to account for nonseparability between income and preferences means that most of these estimates are biased. My work is therefore most closely related to Altonji et al. (1997), Park (2014), and Kazianga (2006), all of which utilize the Altonji-Ichimura estimator to account for nonseparability.

Altonji et al. (1997) use data from the 1968-1989 Panel Study of Income Dynamics (PSID) which includes data for both parents and children. They control for current and permanent income of the parents, children, and siblings. After correcting for nonseparability using the Altonji-Ichimura estimator, they find a mean effect of the transfer with respect to the child's income equal to -0.088 at the sample means. They also find an effect with respect to the parent's income of 0.035, and therefore conclude that the restriction $\frac{\delta T}{\delta I_r} - \frac{\delta T}{\delta I_d} = -1$ doesn't hold.

Park (2014) also studies inter-generational transfers, specifically "upstream" transfers: that is, transfers from children to parents. He uses the Korean Labor and Income Panel Study. This data set allows the author to include information on both the children and the parent's income. Unlike other studies, he censors transfers at $500 USD. He finds that the effect of the recipient's income (in this case, the parents' income) on transfers is somewhere between 0.097 and 0.149, and the effect of the donor's income to be between -0.83 and -.155, both evaluated at the sample means.

Kazianga (2006) use two rounds from surveys collected in 1994 and 1998 in Burkina Faso, where around 90% of the population lives in rural areas. For those living in rural areas, the author uses rainfall variability to identify transitory and permanent income and control for permanent income. The data do not have matched information for donors and recipients and are analyzed at the household level. Using the Altonj-Ichimura estimator, he finds an effect of -0.051 at the sample means.

4 Methodology

4.1 Altonji-Ichimura Estimator

The Altonji-Ichimura estimator deals with nonseparability of errors and preferences as well as the censored nature of the data. What is meant by nonseparability of errors and preferences is that the individual error u_i affects the size of the marginal effect. A more generous person will not only transfer more money at any given point, but they will be more willing to compensate for any loss of income of the recipient.

The data is censored in the sense that there are many observations for which the observed transfer amount is zero. More precisely, these are corner solutions. But as Wooldridge (2010) explains, corner solutions can be treated as censored variables. Mathematically, following the example from Altonji et al. (1997), suppose the donor has an altruistic utility function of the form:

$$U(c_d, V(c_r), T) = \ln(c_d - T) + w \ln(c_r + T)$$

Where w is some weight assigned to that person's utility, that is, a measure of how much the donor cares for that person. Then the optimal transfer T^*, if positive, is equal to $\frac{c_d w - c_r}{1+w}$. Note that the individual preference w cannot be separated linearly[7]. As Altonji et al. (1997) note, this is generic to the transfer models based on altruism. Failing to account for this property renders the usual estimators biased. The estimator proposed by Altonji et al.

[7] That is, T* cannot be expressed as a sum of some functions $F(c_d, c_r)$ and $G(w)$. If it were, then as either income changes, say $\frac{\delta T^*(c_d, c_r, w)}{\delta c_d}$, then the derivative could be expressed as $\frac{\delta F(c_d, c_r)}{\delta c_d} + \frac{\delta G(w)}{\delta c_d}$. The latter term would be equal to zero, and therefore this change would not be dependent on the preference w. When this is not the case, the response to a change in income will depend on w.

(2012) addresses the issue of nonseparability as well as the censored nature of the data. The Altonij-Ichimura estimator is constructed as follows[8]:

$$\beta_i(x_i) = \nabla\Psi_i(x_i) + \frac{\Psi_i(x_i)}{\mathrm{G}_{\mathrm{M}i}(x_i)}\nabla\mathrm{G}_{\mathrm{M}i}(x_i) \tag{1}$$

Where $\Psi_i(x_i)$ is the conditional mean of the dependent variable y given x_i for $y > 0$ and $\mathrm{G}_{\mathrm{M}i}(x_i)$ is the conditional probability that y is greater than zero. Note that β_i depends on x_i, and therefore the derivative is allowed to change for different values of x. An individuals' received inter-household transfers (transfers$_i$), is modeled in regard to their income (income$_i$) and a vector of socioeconomic controls $\vec{x}_i$.

4.2 Fractional Polynomials

It is common practice to manually search through many polynomial specifications of the variable of interest for one that better describes the shape of the data. The fractional polynomial approach formalizes this search procedure for a given set of powers and terms. A fractional polynomial of m terms is defined as follows (Royston & Sauerbrei, 2008):

$$x^{(p_1,p_2,\ldots,p_m)} = \beta_0 + \beta_1 x^{(p_1)} + \beta_2^{(p_2)} + \cdots + \beta_m x^{(p_m)}$$

Where

$$x^{(p)} = \begin{cases} \ln(x) & \text{if } p = 0 \\ x^p & \text{if } p \neq 0 \end{cases}$$

A power may repeat itself. Each time this happens, it is multiplied once by $\ln(x)$. Hence, if $p_1 = p_2 = \cdots = p_m$,

[8] Altonji et al. (2012) also propose extensions to this estimator in order to deal with endogeneity with cross-section and panel data, as well as for discrete regressors. As I will use the most simple estimator that doesn't account for endogeneity, my results imply only a lower bound to the true effect size. Moreover, while I do include discrete regressors these are not the focus of the paper.

$$x^{(p_1,p_2,\ldots,p_m)} = \beta_0 + \beta_1 x^{(p_1)} + \beta_2^{(p_2)} \ln(x) + \cdots + \ln(x)^{m-1} \beta_m x^{(p_m)}$$

5 Data and descriptive statistics

I shall focus on private inter-household cash transfers at the individual level, and only for individuals 12 years old or older. As Kazianga (2006) maintains, most studies in developed countries focus on inter-generational transfers, but within-generation transfers are just as important in developing countries. I use the average normalized quarterly information as this is the average reported on the survey. I examine inter-household transfers due to the nature of the data: the ENIGH doesn't provide information on within-household transfers.

I only include individuals 12 years or older because the income survey is applied only to individuals this age[9]. Income data is reported as a distinct entry for each source of income a person has. If a person doesn't have income from a particular source this source does not have an entry (instead of having an entry equal to zero). Thus if an individual has no reported sources of income I imputed an income equal to zero. As noted by Juarez (2009), income may be endogenous if individuals adjust their behavior due to transfers. For this reason, my estimation was based on non-labor income.

Given the survey's design, it would be desirable to use probability weights when running the estimation, but this process on top of our flexible estimation entails a heavy computational burden when running our bootstrap estimation of standard errors. The unweighted results are not too dissimilar, however.

Transfers received are defined as the sum of cash transfers from other households and remittances[10]. Remittances account for 23.13% of all transfers. Furthermore, 21.37% of recipients of some sort of transfer only receive remittances, while 75.57% receive merely national transfers, and only around 3% receive both types of transfers.

[9]A limited survey is applied to individuals younger than 12 years that includes only scholarships and transfers.

[10]These items are listed separately in the survey

Table 1: Descriptive statistics for individuals 12 years or older in the 2018 ENIGH sample

	Mean	s.d.	Min	Max
Transfers received (quarterly)	509.78	(3,111.02)	0	354,098
Pre-transfer non-labor income (quarterly)	2,393.64	(24,508.81)	0	3,756,522
Pre-tansfer income (quarterly)	12,905.50	(31,984.51)	0	3,756,522
Current Income (quarterly)	13,415.29	(32,027.24)	0	3,756,522
Age	38.42	(18.75)	12	110
Female	0.52			
Rural	0.38			
Married	0.37			
Household head	0.35			
Household composition				
# of children 0-5 yrs old	0.39	(0.68)	0	6
# of children 6-12 yrs old	0.54	(0.79)	0	7
# of teenagers 13-17 yrs old	0.50	(0.73)	0	5
# of adults 18-65 yrs old	2.64	(1.36)	0	11
# of seniors 65+ yrs old	0.28	(0.58)	0	5
Educational attainment				
No elementary school	0.05			
Elementary school	0.15			
Junior high school (unfinished)	0.07			
Junior high school	0.27			
High school (unfinished)	0.07			
High school	0.13			
College degree (unfinished)	0.04			
College degree	0.08			
Graduate education	0.01			
Observations	212394			

Table 2: Proportion of individuals 12 years or older in the ENIGH sample with observations = 0 in the relevant variables

	Proportion
Transfers = 0	0.90
Non-labor pre-transfer income = 0	0.75
Pre-transfer income = 0	0.50
Income = 0	0.22
Observations	212394

In the data, 10.3% of observations receive some monetary transfer (Table 2). When correcting for the survey design, I obtain an involvement rate of 9.27%. Also, 22% of people in our sample receive no income at all (including transfers and non-labor income). Juarez (2009) found that 16% of urban seniors receive some transfer. I find a 21% involvement rate for this same group.

6 Estimation steps

I first run an OLS regression for $T > 0$ such that

$$T_i = \beta_0 + \beta_1 nl\_income_i^{(p_1)} + \beta_2 nl\_income_i^{(p_2)} + \mathbf{z}_i \tag{2}$$

Where T_i is the amount of quarterly monetary transfers received by an individual, both foreign (remittances) and domestic, and *nl_income* is the quarterly pre-transfer non-labor income for that individual. First, note that the way income is defined in the model means one is interested in this amount before any transfers are made. Second, I use non-labor income because labor income is more volatile and if individuals react to changes in transfers by modifying their supply of labor income may suffer from endogeneity. This variable is defined as current income[11] minus cash transfers, remittances, and labor income.

The coefficients (p_1) and (p_2) indicate I am fitting the data using fractional polynomials,

[11] I also exclude in-kind payments and implicit income from house ownership from this definition. My variables are otherwise constructed as they are defined on the ENIGH.

as described in the above section. Finally, $\mathbf{z}_i$ is a vector of socioeconomic characteristics. From this I obtain the marginal effects $\nabla\Psi_i(x_i)$ and the predicted values $\Psi_i(x_i)$.

The vector of socioeconomic characteristics is composed of the individual's age and sex, as well as whether they live in a rural location or not, whether they are married or not, whether they are the household head or not, their level of educational attainment, and a set of variables indicating the number of people in their household by age (table 1). I then run a probit estimation of the form:

$$any\_transfer_i = \beta_0 + \beta_1 nl\_income_i^{(p_1)} + \beta_2 nl\_income_i^{(p_2)} + \mathbf{z}_i \tag{3}$$

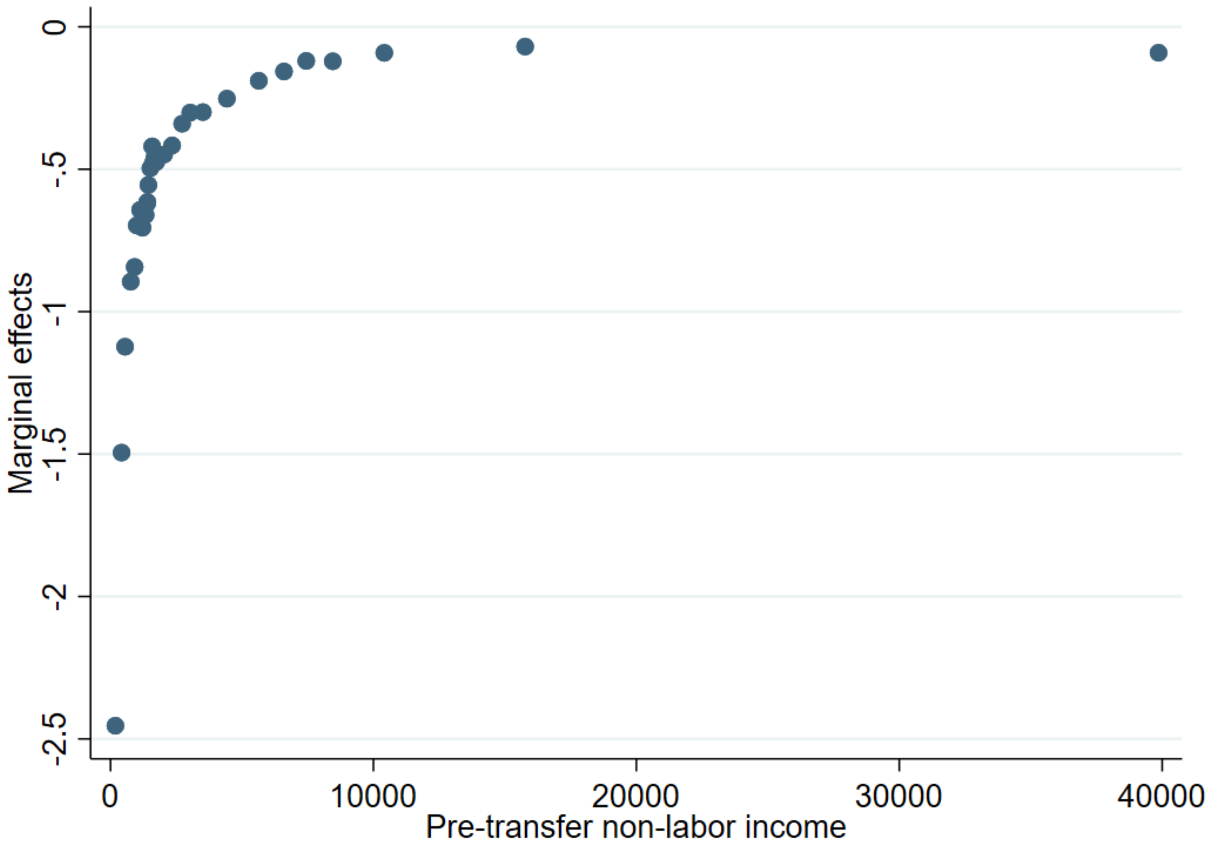
Where $any\_transfer$ indicates whether that person receives any positive non-zero transfer (there are no negative transfers by definition). As in the OLS estimation, I use fractional polynomials to allow more flexibility in the model. [12] Furthermore, Altonji et al. (1997) note that a conditional probability function can always be approximated by the convolution of a particular conditional distribution function $\phi(\cdot)$ and a function $h(Z;\theta_2)$, provided that $h(Z;\theta_2)$ is sufficiently flexible. Therefore one can model this conditional probability using the flexible specification allowed for by fractional polynomials within the probit model. I obtain the predicted values $\mathrm{G}_{\mathrm{M}i}(x_i)$ and calculate the marginal effects to obtain $\nabla\mathrm{G}_{\mathrm{M}i}(x_i)$. At this point I have the necessary data to apply the correction described in equation (1). Given the complicated nature of the estimation, I estimate standard errors using a bootstrap technique.

7 Results

First, I divided the results into 100 bins with a similar number of observations according to their pre-transfer non-labor income. However, because 61% of the observations with

[12] Note I am **not** using net transfers, that is, transfers received minus transfers given. This is the case because we are interested in $\frac{\delta T}{\delta I_r}$, while using net transfers would give us $\frac{\delta T}{\delta I_r} - \frac{\delta T_2}{\delta I_{r2}}$, where T_2 is the transfer given by the donee to yet some other recipient I_{r2}.

Figure 2: Average estimated marginal effects per bin by pre-transfer non-labor income (in pesos, quarterly). Bins > 61



positive transfers have zero pre-transfer non-labor income, the first bin contains most of the observations. This leaves us effectively with 36 bins. Because these bins divide the data into equal parts, they can also be thought of as the corresponding percentiles[13]. I then obtained the mean derivative for each of these bins. Figure 2 presents the mean estimated marginal effects by income level using the Altonji-Ichimura estimator, excluding the very first bin which has a marginal effect orders of magnitude higher (equal to 4932.79).

I ran a bootstrap with 500 replications to obtain standard errors. Because the marginal effect is different for each observation, I obtain a different standard error for each bin average.

[13]With the exception that the first bin includes all the observations equal to zero, which amount to around 61% of observations. Because of this, the numbering starts at bin 61.

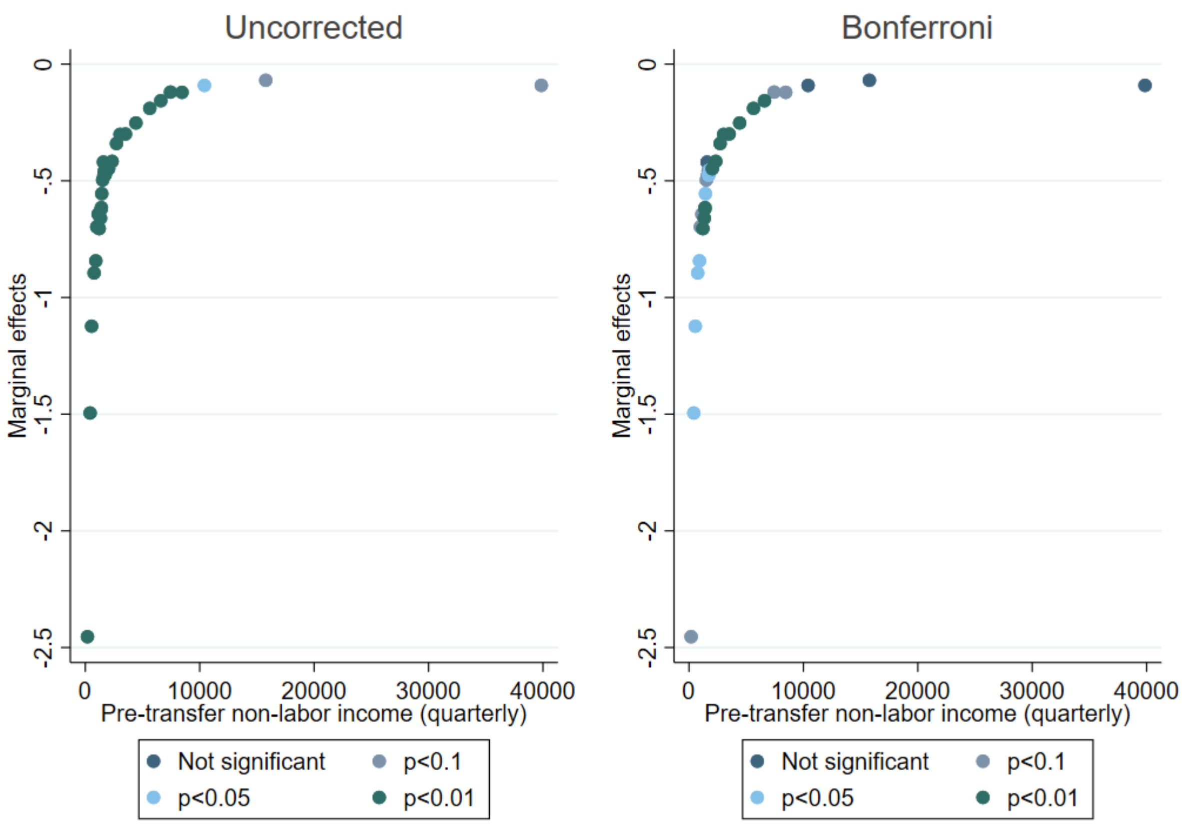
Finally, because I am essentially running 35 different hypothesis tests, it's important to apply Multiple Testing Correction. To this end, I applied the Bonferroni correction. To strike a balance between false positives and false negatives, the analysis that follows will consider only the marginal effects that are significant at the 95% level after applying the Bonferroni Correction.

Table 3: Bins significant at the 95% level after Bonferroni correction. Amounts in pesos (quarterly)

Bin	Avg. pre-transfer non-labor income	Min	Max	Marginal effect	Standard Error	p-value (un-corrected)	p-value (Bon-ferroni)	Avg. current income
63	421.8106	344.26	486.88	-1.49494	0.443293	0.000***	0.016**	7105.7
64	553.8865	489.13	649.18	-1.12306	0.369301	0.001***	0.048**	5978.515
65	769.7459	660.32	880.43	-0.89487	0.284649	0.001***	0.035**	5893.385
66	920.129	885.24	944.26	-0.84306	0.25022	0.000***	0.016**	7437.919
69	1215.188	1173.91	1313.11	-0.70513	0.197945	0.000***	0.008***	8072.71
70	1337.033	1320.65	1392.26	-0.66061	0.182047	0.000***	0.007***	7869.737
72	1394.045	1394.02	1398.91	-0.62022	0.175276	0.000***	0.009***	7174.185
73	1402.58	1401.63	1416.39	-0.61507	0.17372	0.000***	0.009***	8418.36
74	1440.955	1417.12	1467.84	-0.55529	0.170553	0.001***	0.024**	6386.6
84	1712.122	1711.47	1726.22	-0.47557	0.156988	0.001***	0.050**	7130.058
85	1743.651	1730.38	1765.75	-0.47355	0.149571	0.001***	0.032**	6144.405
86	1828.214	1770.49	1908.19	-0.45299	0.137442	0.001***	0.021**	7828.135
87	2040.416	1914.35	2196.18	-0.44833	0.12259	0.000***	0.006***	7404.503
88	2344.333	2201.08	2538.58	-0.41658	0.107008	0.000***	0.002***	8669.094
89	2725.231	2542.61	2931.84	-0.34019	0.090267	0.000***	0.004***	8176.533
90	3035.316	2934.78	3184.23	-0.30103	0.079632	0.000***	0.004***	8561.395
91	3513.633	3186.87	3913.03	-0.29948	0.069405	0.000***	0.000***	9648.19
92	4427.601	3913.04	4989.12	-0.25229	0.053312	0.000***	0.000***	12274.23
93	5640.713	4989.13	6065.21	-0.18959	0.043986	0.000***	0.000***	12991.04
94	6600.279	6089.66	7052.28	-0.15694	0.04085	0.000***	0.003***	13092.45

The resulting marginal effects and their p-values are shown in figure 3. The very high initial marginal effect observed in the first bin was not found to be significant at any level (even for the uncorrected values) and is therefore also excluded from this graph for readability.[14]

Figure 3: Uncorrected and corrected p-values per bin by pre-transfer non-labor income (in pesos, quarterly). Bins > 61



One can see from table 3 that the effect is significant for non-labor income from around 344 up to 7,052 pesos per quarter (around 17 to 350 dollars), or 114 to 2,350 pesos per month (5.6 to 116 USD). Around 16.7% of the population fall within this range (after correcting for sample design). Furthermore, the marginal effects within this range vary from -1.49 up to -0.15.

[14]To see the number of observations per bin, their marginal effect and exact p-values for all bins, refer to Appendix A.

Even though there isn't a perfect relationship between non-labor and total income, I also try to express these results in terms of current income, as this is handier for policy applications. My lowest average value for the significant bins is 5,893 pesos (293 USD) per quarter and the largest is 13,092 pesos (651 USD). This means that we can approximate the relevant significant range for current income to be between 1,964 and 4,364 pesos monthly (97 to 217 USD).

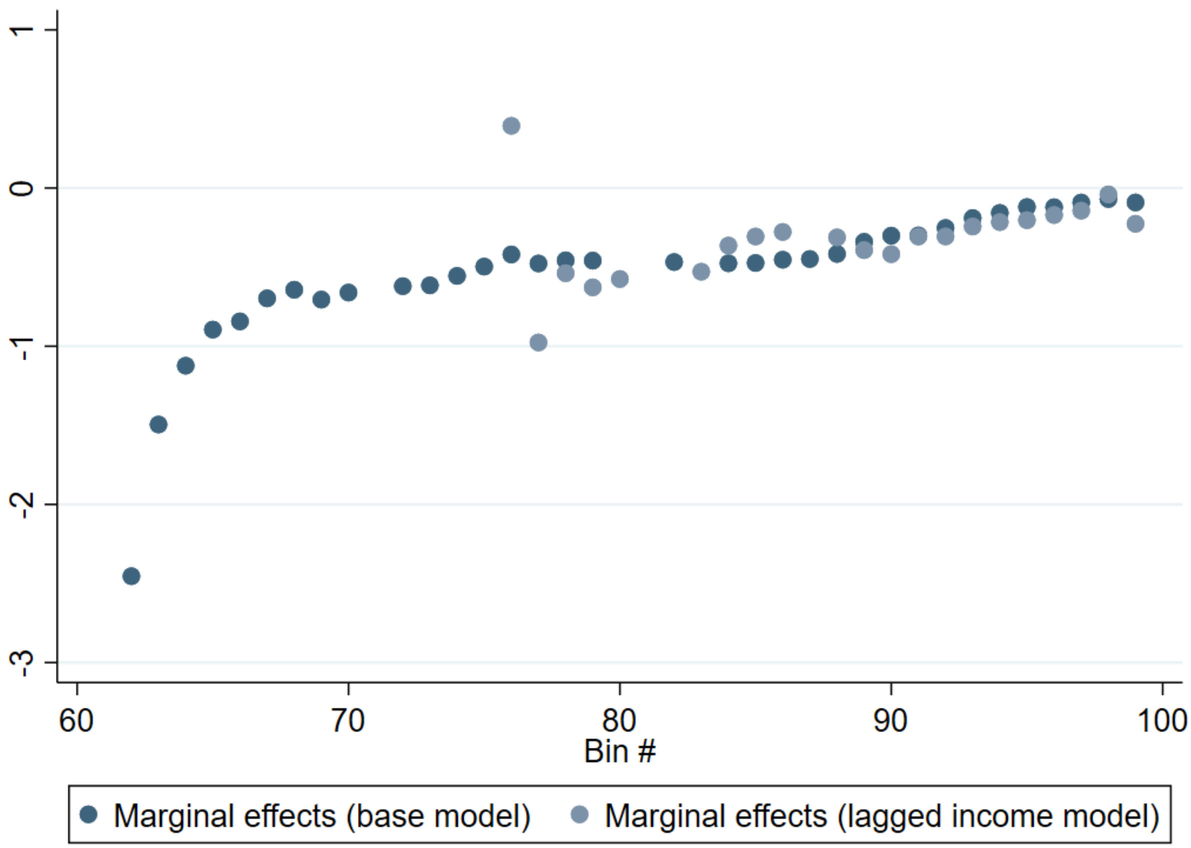
The average pre-transfer non-labor income for this range is 1,953.53, which corresponds to the bin with an average effect of -0.44. This value is higher in absolute terms than most estimates found in the literature, but lower than those found in (Albarran & Attanasio, 2002) and (Juarez, 2009). This is slightly puzzling because they do not employ the Altonji-Ichimura estimator and may therefore be underestimating the effect in absolute terms. One possibility is that the effect is more pronounced because these studies specifically analyze the response to government programs. As I outlined in section 2.1, the source of these transfers may be important. Moreover, transfers from government programs may be more "visible" (that is, more strongly signaled) than other types of transfers, and therefore be less prone to measurement error on the part of the donor.

7.1 Robustness

As I mentioned previously, I focus on non-labor income to overcome possible endogeneity issues. Nevertheless, it's still possible for non-labor income to suffer from endogeneity. Therefore, I estimate the model once more using the average transfer received in the fifth and sixth months before the interview and the average pre-transfer non-labor income received in the first and second months before the interview. In this manner, recipients are less likely to adjust their behavior in response to the transferred amount. My results are very similar when using lagged income, as shown in figure 4.

The bins for the lagged observations start at 76, as there are more observations with zero

Figure 4: Average estimated marginal effects per bin by pre-transfer non-labor income (in pesos, quarterly). Comparison of base model and model with lagged income. Bins > 61



income[15]. Because the 76th bin includes all these observations with zero income, it's not directly comparable to the 76th bin of the main regression. Otherwise, the only inconsistency between the models can be observed at the 77th bin. The estimate for this bin was not found to be significant, however.

My results may also be biased due to the omission of the donor's income and characteristics from the estimation. As noted by Basu (2020), when running a multiple regression one cannot assume the direction of the omitted variable bias in the same manner as in a univariate regression. Omitted variable bias in a multiple regression context for the k-th regressor given m omitted variables is defined as follows:

$$\text{bias}(\beta_k) = \sum_{m=1}^{M} \gamma_m \delta_{mk}$$

Where γ is the coefficient for the omitted variable m had it been included in the regression, and δ_{mk} is the coefficient of the linear projection of m onto the full set of included regressors. From this expression one can readily see that in order to have an unambiguous sign, one has to be able to characterize the direction of all pairs $\gamma_m \delta_{mk}$ for all m omitted variables. In our case, these omitted variables are the donor's income and the socioeconomic characteristics of the donor.

However, even if there is a strong relationship between the characteristics of the donor and the recipient, it seems unlikely that the donor's characteristics have a direct impact on the recipient's income. Therefore I shall assume that $\delta_{mk} = 0$ for all omitted variables other than the donor's income.

Because we expect $\frac{\delta T}{\delta I_d}$ to be positive when operating with altruistic motives, the direction of the bias depends on the relationship between donor and recipient income. This relationship is probably positive; while we expect the recipient's income to be lower than the donor's, as the donor's income increases so should the recipient's. In that case, our estimated effects

[15] This is to be expected, as some people's income may be more variable over time, and therefore may receive no income on the selected months.

are most likely biased upwards towards zero, and therefore represent a "lower" bound in absolute terms.

8 Conclusion

To the best of my knowledge, this work is the first to use the Altonji-Ichimura estimation for the case of Mexico. The introduction of fractional polynomials also allows for a much more flexible specification than previous work done with this technique.

Upon correcting for nonseparability using the Altonji-Ichimura estimator, I find significant and noteworthy effects for low incomes. These effects also appear to be non-linear and decreasing in absolute value[16]. These effects are significant at the 95% level for people earning between 1,964 and 4,364 pesos per month (approximately 97-217 USD). The effect for the average individual within this range is -0.44, a much stronger effect than those found in most of the relevant literature. Due to possible endogeneity issues, my estimated effects represent a lower bound for the effect in absolute terms. My findings are consistent with Albarran and Attanasio (2002) and Juarez (2009) in that they suggest a high transfer derivative for those in the lower end of the income distribution of Mexico. Therefore, the crowding-out of private transfers is a real concern that must be addressed when designing cash transfer programs to help Mexico's poor.

In order to advance our understanding of transfer derivatives, it's important to generalize the use of the Altonji-Ichimura estimator. Most published results do not make use of this method and therefore underestimate the true effect. It is also possible that high transfer derivatives are idiosyncratic to Mexico, as previous results without this method also point to strong effects.

Moreover, while a lot of work has been done to determine the existence of crowding out, there has still been little to no effort to investigate where transfers are crowded out to.

[16]Theoretically, this is not unexpected. While not explicitly modeled, it's quite reasonable to assume that an altruistic individual has diminishing returns to those with whom he is altruistically linked.

This is mainly because data that relates donors with recipients is hard to come by. Further research is needed in this direction to fully understand the crowding out of private transfers.

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Appendix A - Marginal effects and p-values by bin

Bin	N	Pre-transfer non-labor income	Min	Max	Marginal effect	Standard Error	p-value (uncorrected)	p-value (Bonferroni)	Current income
61	13610	0.149637	0	48.91	4932.793	825.43	1	36	9605.156
62	220	186.2303	49.18	344.26	-2.45363	0.818311	0.002***	0.055*	7240.685
63	213	421.8106	344.26	486.88	-1.49494	0.443293	0.000***	0.016**	7105.7
64	227	553.8865	489.13	649.18	-1.12306	0.369301	0.001***	0.048**	5978.515
65	213	769.7459	660.32	880.43	-0.89487	0.284649	0.001***	0.035**	5893.385
66	198	920.129	885.24	944.26	-0.84306	0.25022	0.000***	0.016**	7437.919
67	233	997.8206	944.75	1074.03	-0.69736	0.232499	0.002***	0.055*	6378.955
68	208	1126.512	1076.08	1173.9	-0.64295	0.222251	0.002***	0.076*	5525.587
69	186	1215.188	1173.91	1313.11	-0.70513	0.197945	0.000***	0.008***	8072.71
70	226	1337.033	1320.65	1392.26	-0.66061	0.182047	0.000***	0.007***	7869.737
72	397	1394.045	1394.02	1398.91	-0.62022	0.175276	0.000***	0.009***	7174.185
73	275	1402.58	1401.63	1416.39	-0.61507	0.17372	0.000***	0.009***	8418.36
74	260	1440.955	1417.12	1467.84	-0.55529	0.170553	0.001***	0.024**	6386.6
75	215	1516.863	1475.4	1565.21	-0.49646	0.166159	0.002***	0.057*	6106.855
76	63	1586.104	1566.29	1614.12	-0.41982	0.157839	0.004***	0.152	4792.246
77	379	1621.289	1614.13	1640.88	-0.47683	0.162485	0.002***	0.067*	5967.923
78	192	1679.004	1643.47	1696.3	-0.45702	0.159139	0.002***	0.081*	5878.615
79	74	1696.72	1696.72	1696.72	-0.45873	0.157635	0.002***	0.072*	6873.321
82	697	1702.264	1702.17	1710.97	-0.46768	0.157669	0.002***	0.061*	6065.664
84	505	1712.122	1711.47	1726.22	-0.47557	0.156988	0.001***	0.050**	7130.058
85	287	1743.651	1730.38	1765.75	-0.47355	0.149571	0.001***	0.032**	6144.405
86	222	1828.214	1770.49	1908.19	-0.45299	0.137442	0.001***	0.021**	7828.135
87	205	2040.416	1914.35	2196.18	-0.44833	0.12259	0.000***	0.006***	7404.503
88	232	2344.333	2201.08	2538.58	-0.41658	0.107008	0.000***	0.002***	8669.094
89	183	2725.231	2542.61	2931.84	-0.34019	0.090267	0.000***	0.004***	8176.533
90	258	3035.316	2934.78	3184.23	-0.30103	0.079632	0.000***	0.004***	8561.395
91	216	3513.633	3186.87	3913.03	-0.29948	0.069405	0.000***	0.000***	9648.19
92	223	4427.601	3913.04	4989.12	-0.25229	0.053312	0.000***	0.000***	12274.23
93	220	5640.713	4989.13	6065.21	-0.18959	0.043986	0.000***	0.000***	12991.04
94	211	6600.279	6089.66	7052.28	-0.15694	0.04085	0.000***	0.003***	13092.45
95	228	7446.068	7081.96	7904.34	-0.11983	0.040348	0.002***	0.060*	13203.7
96	218	8454.439	7906.07	9038.141	-0.12113	0.041204	0.002***	0.066*	14454.98
97	221	10413.08	9039.12	11845.56	-0.09131	0.04131	0.014**	0.508	17458.9
98	218	15771.74	11857.01	20850.49	-0.06929	0.042393	0.052*	1.867	23698.92
99	222	39861.61	20883.97	151756.9	-0.09115	0.059318	0.063*	2.268	52904.18