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Efficient Delivery of Cash Transfers to the Poor: Improving the Design of a Conditional Cash Transfer Program in Ecuador*

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Abstract

Many governments provide monetary transfers to low-income families. The mechanism through which these subsidies are distributed may contain several inefficiencies that diminish the net-value obtained by the recipients. In this paper, we build and estimate a behavioral dynamic model that allows us to evaluate the efficiency of current and alternative distribution mechanisms. The proposed model is simple and resembles the individual's decision to collect the transfer. To estimate it, we use data from a cash transfer program in Ecuador where recipients incur high transaction costs each time they collect their benefits. Despite its simplicity, our model is able to replicate the observed data remarkably well. We use it to simulate alternative payment mechanisms and show that an adequate design of the delivery of payments can substantially increase the value of cash transfer programs.

Keywords: Cash Transfer Programs, Behavioral Model, Distribution of Payments
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1 Introduction

Conditional Cash Transfer (CCT) programs consist of monetary transfers to low income families that aim to alleviate extreme poverty, while providing households with incentives to increase their consumption of education and health services. These type of programs have become an important part of social assistance in Latin America and have dramatically expanded during the past decade.[1]

Many efforts have been made to measure the effects of such transfers on recipients' well-being. Using controlled social experiments, researchers have found that children of families who receive transfers are healthier, more likely to attend school, and less likely to be part of the labor force (Behrman, Sengupta, and Todd 2005, Schady and Araujo 2006, and Schulz 2004, for example).

While these previous studies provide strong evidence of the overall positive effects that CCT programs have on children's school and health outcomes, less is known about the benefits or costs associated with the current programs' design. For instance, there are many dimensions in which CCT programs differ (rules about eligibility, conditionality, payment schedules, delivery of the payments, etc.), and there may exist important inefficiencies in program implementation. Todd and Wolpin (2006) and Bourguignon, Ferreira, and Leite (2003) use behavioral models to address this question and simulate and evaluate alternative

[1] The first Latin American CCT program started in 1995 in Brazil under the government of the Distrito Federal of Brasilia (Bolsa Escola). The second experience of a CCT program is Mexico's Progresa (now renamed Oportunidades) which began in 1997. Other Latin-American countries that have implemented CCT programs in the past decade include Argentina (Familias por la Inclusion Social), Chile (Chile Solidario), Colombia (Familias en Acción), Costa Rica (Superémonos), Ecuador (Bono de Desarrollo Humano), Honduras (Programa de Asignacion Familiar), Jamaica (Programa de Avance Mediante la Salud y la Educacion), Nicaragua (Red de Protección Social), and Uruguay (Proyecto 300). See Rawlings and Rubio (2003) and Caldés, Coady, and Maluccio (2004) for reviews.

programs in Mexico's *Progresa* and Brasil's *Bolsa Escola*, respectively. Both studies conclude that transfers' conditionality has an important effect on school attendance, and Todd and Wolpin suggest that alternative payment schedules may induce a greater impact on average school attainment.[2]

In this research, we analyze the design of another dimension of CCT programs that, to our knowledge, has not been considered in previous studies. We focus on the mechanism through which governments distribute payments to the beneficiaries. This is an important feature of these programs since there may be high transaction costs involved in the distribution of these transfers, such as transportation, opportunity, and other related costs incurred by both governments and recipients. For this reason, an adequate design of the delivery of payments may drastically increase the value of a CCT program.

To address this issue, we specify and estimate perhaps the most basic version of a behavioral dynamic model that resembles the individual's decision to collect the transfer. Unlike other behavioral models in the literature, ours is simple and easy to solve.[3] However, despite its simplicity, we show that it may be a powerful tool for designing the delivery of payments of a CCT program.

We focus on one particular CCT program in Ecuador: the *Bono de Desarrollo Humano* (BDH). The program consists of cash transfers to a) low-income mothers with children younger than 16 who receive benefit payments of \$15 per month and b) elderly and/or

[2] More importantly, Todd and Wolpin provide evidence that these types of models may be able to replicate the counterfactuals of interest reasonably well by comparing the predictions of their model with those derived from a randomized experiment.

[3] In practice, behavioral models are difficult to implement. In particular, as the state space increases, computing the solution to the model involves advanced numerical methods and approximations (Berkovec and Stern 1989, Keane and Wolpin 1994, 1997 and 2001) that, perhaps, has discouraged many applied researchers to undertake this approach.

disabled low-income individuals who are entitled to \$11.50 per month. As of December 2004, low-income mothers accounted for more than 80% of the total number of beneficiaries. The subsidy is delivered through a payment agency network, composed of 17 financial institutions with approximately 250 payment centers distributed in rural and urban areas of Ecuador. Beneficiaries must travel to one of these agencies and approach the counters/booths to collect their cash. The government provides individuals with the option to cash any -accumulated- subsidy once every one, two, three or four months.

While in most urban areas there is a relative large supply of payment agencies, in many rural areas there is a clear shortage. For instance, in certain rural areas, beneficiaries need to travel for more than two hours to the nearest payment agency. The inefficiency of the program's payment system has been criticized in several government reports which state that, in many cases, the recipients' transportation costs may account for more than 50% of the transfer itself.[4] Partially for this reason, a redesign of the mechanism of the payment's delivery is under consideration.[5] The behavioral model specified in this paper aims to facilitate this task.

The model is simple and intuitive. Every period (month), beneficiaries have the right to receive a lump-sum payment from the government. To receive this payment, households incur a transportation cost that is a function of the travel time from their residence to the closest payment agency. Households are heterogeneous in their location and in their opportunity costs. From each individual's perspective, future opportunity costs are random. Given these assumptions, a household rationally chooses between collecting the transfer in the current

[4] Banco Central del Ecuador, Internal Staff Reports, 2005.

[5] Banco Central del Ecuador and Ministerio de Finanzas del Ecuador, 2005.

period or waiting to redeem the accumulated subsidy in the next period. Thus, households that are located closer to payment agencies or that experience lower opportunity costs have stronger incentives to redeem the transfer more often.

We estimate the model using Maximum Likelihood methods and administrative data provided by the Ministry of Social Welfare in Ecuador. The data consists of subsidy-payment data and demographic information from a random sample of approximately 2,500 households (mothers) during 2004.[6] The payment data allows us to identify if a beneficiary decided to collect the transfer in any given month and, if so, the amount received. We also observe several characteristics of the mother, such as her geographical location, level of education, and marital status. In addition, we measure beneficiary accessibility to the payment agencies by estimating the travel distance between the town where the beneficiary resides and the closest town with a payment agency.

The structural estimates have a direct economic interpretation. For example, our results suggest that the time-opportunity cost of beneficiaries is close to \$0.4 per hour. This is a reasonable estimate considering that the minimum hourly wage in Ecuador was \$1 in 2004. More importantly, despite the simplicity of our model, we believe that it is able to replicate the observed data remarkably well. For this reason, we use it to conduct several counterfactual experiments of alternative payment mechanisms.

The first counterfactual we consider consists of increasing the number of periods that households are allowed to accrue their payments (from four to six months). Interestingly, the recipient's welfare gains from such a policy are very small. We compute another counter-

[6] Because behavior of disabled beneficiaries may be significantly different than that of mothers, we restrict our sample to the latter group.

factual that allows us to quantify the household's welfare effects if the government increases the number of payment agencies in rural locations. In particular, we assume that new payment agencies are built such that the home-to-agency travel time of a representative rural household decreases by 60 minutes. We estimate that such policy would increase the value of being enrrolled in the program by about 4%. Finally, the model is used to create a geographically differentiated schedule of payments that compensates rural households for their travel time-opportunity costs.

In the following section, we present the details of the BDH program. Section 3 contains a detailed description of the data sources, including the estimation of several reduced form specifications. Section 4 presents the model and the estimation methods. In Section 5, we include an economic interpretation of our estimates, an assessment of the within-sample fit, and evaluations of alternative payment programs. Finally, the last section concludes.

2 The BDH program

2.1 Overview

The Bono de Desarrollo Humano (BDH) is a conditional cash transfer program (CCT) in Ecuador administered by the Ministry of Social Welfare. The program consists of monthly cash transfers to low income families. The BDH has two types of beneficiaries: a) low-income mothers with children younger than 16, who receive $15 per month in benefits, and b) elderly and/or disabled low-income individuals, who are entitled to $11.50 per month.

The program is the most important social assistance program in Ecuador and is by far the government's largest social expenditure outside of education, with total transfers equal to nearly 8% of Central Government non-debt spending and about one percent of GDP (León, Vos, and Brborich, 2001).[7]

The BDH program started in 2003 by merging two previously existing programs, the Bono Solidario (BS) and the Beca Escolar (BE). The BS was designed as a safety net to compensate poor families for the elimination of gas and electricity subsidies in 1998 and targeted mothers with earnings below US$ 40 dollars per month, people with disabilities, and senior citizens.[8] On the other hand, the Beca Escolar (BS) was a CCT program implemented in the late 1990s. The program consisted of monthly transfers of $5 per child (up to two children per household), which was conditional on the children's enrollment in school and a 90% attendance rate. This program benefited approximately 150,000 households.

The Bono de Desarrollo Humano (BDH) includes all recipients of the BS and the BE, and it aims to increase children's health and school enrollment. For this reason, mothers were required to a) enroll their children (ages 6 to 15) in school and allow them to attend at least 90% of the school days, and, b) bring their children (ages six and under) to health centers for medical check-ups twice a year. However, unlike the other CCT programs in Latin America, the BDH has no mechanisms to verify that these conditions are being met. Consequently, households are not taken off program rosters if mothers fail to comply with

[7] By comparison, in 2004, Central Government Health expenditures was only 5.9% of total non-debt spending and a bit less than one percent of GDP; public education accounts for two-and-a-half percent of GDP.

[8] The BS consisted of a modest unconditional transfer that was non-trivial by Ecuadorian standards. At the time that the program started, mothers received 100,000 sucres per month, and senior citizens and people with disabilities received 50,000 sucres (about 13% and 6.5% of the official monthly minimum wage, respectively). In April of 1999, those amounts were increased by 50%, mostly to account for high inflation. During 2000, the program reached around 1.2 million beneficiary households, representing about 45 percent of Ecuadorian households. Some studies suggest that, by the year 2000, the BS had a positive effect on school enrollment and children's nutritional status. For example, an impact evaluation of the BS, conducted by León, Vos, and Brborich (2001), who used a propensity score matching method, showed a positive impact of around 5 percentage points on school enrollment, although no significant impact was found on poverty indicators. Another study, conducted by León and Younger (2004), who implemented an instrumental variable approach, shows that the program had very minor, yet significant and positive effects on children's nutritional status.

the requirements.[9] Transfers to elderly and disabled individuals remained unconditional.

2.2 Selection of beneficiaries

The eligibility criteria for the 1998 BS was straightforward targeting low-income a) mothers, b) old aged individuals, and c) disabled.[10] At the beginning of the program, potential recipients filled an application form at a local church and were admitted to the program if they complied with the eligibility criterion. Unfortunately, there was no external validation of the data on the application forms, and there is evidence that many non-eligible individuals were admitted early in the program.[11]

Soon after the implementation of the BS, the Ecuadorian government looked for better instruments to verify eligibility. For instance, starting in 2000, the government made efforts to create a more comprehensive poverty proxy-mean index for individuals using targeted surveys. This index, known as the Selben-index,[12] identifies potential beneficiaries of social programs by classifying households according to an unmet basic needs index which is computed using non-linear principal components analysis. This index is scaled from 0 to 100; 0 for the poorest and 100 for the richest.

[9] However, at the beginning of the program in 2003 some television programs were transmitted, at a national level, publicizing the obligation of parents to send children to school in order to receive the transfer. Those informational advertisements may create some level of awareness on the obligation of parents to send their children to school and take them to the health centers in order to benefit from the program (Schady and Araujo 2006).

[10] The Executive Decree Number 129 of the Government of Ecuador established the following eligibility criteria for those receiving the Bono: I) Mothers: a) Need to have at least one child younger than 18 years of age; b) Family income should not exceed 1 million sucres; c) Mothers nor spouses should not have a "fixed" salary income. II) Old Aged: a) Older than 65 years of age; b) Family income should not exceed 1 million sucres; c) Do not have a "fixed" salary income. III) Disabled: a) Between 18 and 65 years of age; b) Disability of at least 70% (according to the Ecuadorian Social Security Institute standards). Notice that, neither eligibility nor the cash transfer itself, depends on the family size or the number of children of the mother.

[11] For example, Parandekar (1999) finds that, in 1999, about 50% of the Bono recipients did not meet the eligibility criteria laid down by the Government.

[12] Selben ("Sistema de Identificación y Selección de Beneficiarios") stands for Beneficiaries' Identification and Selection System.

In 2004, most beneficiaries of the BDH were selected using the Selben criterion. Only those families that score less than 50.65, in the Selben index qualify to receive the benefit (these are families that belong to poverty quintiles 1 and 2). By then, around 90 percent of the beneficiaries of the program had a corresponding Selben index score. The remaining ten percent includes families that have not been given the Selben survey but have received benefits from the program since its initial implementation.

2.3 Payment distribution

Since the BDH began in 1998, payment of the subsidy has been in charge of a network of banks and payment agencies in Ecuador called Banred.[13] The network is composed of 17 financial institutions with about 250 payment agencies distributed in rural and urban areas of Ecuador where recipients may cash their benefits.[14] Each month, the Ministry of Social Welfare delivers the list of persons who can cash the benefit to Banred, who in turn distributes payments through their network of payment agencies. Beneficiaries must physically travel to one of these agencies and approach the counters/booths to collect their cash. Individuals may accrue payments for up to four months.

While in most urban areas there is a relative large supply of payment agencies, in many rural areas there is an evident shortage. To highlight this problem we present in Table 1 the geographical distribution of beneficiaries and payment agencies of the BDH in 2004. As shown in this Table, a large share of beneficiaries resides in two provinces, Pichincha and Guayas, which host the two biggest urban centers in the country. Not surprisingly, in these two provinces, more than 75 percent of the beneficiaries could find an available

[13] http://www.banred.fin.ec/ie/serv6.htm

[14] Banred has a significantly higher total number of bank agencies. However, only a "selected" group of 256 agencies served as payment points in 2004.

payment agency in the same *Parroquia*,[15] where they lived. Their situation contrasts with that of individuals who reside in more rural areas. For example, in Zamora Chinchipe, a rural province in the Amazonian jungle, only 3 percent of the recipients lived in the same Parroquia where a payment point was available.

[Please, insert Table1]

As shown in Table 1, the coverage level of payment agencies in rural areas is low. This raises several important questions. Is it worth it to increase the coverage level of payment agencies in rural areas? How efficient is the current payment system? Can the payment system be improved? In this research, we aim to answer these questions by specifying and estimating a behavioral model that depicts the individual decisions of collecting the transfer. The estimated model will be used to simulate counterfactuals and evaluate the welfare effects of alternative payment mechanisms.

3 Data and reduced form analysis

In this section, we describe the data sources that we have gathered for our empirical analysis. Then, we use simple reduced form models to identify the determinants of the beneficiaries' collection decisions, which later, will guide the empirical specification of the behavioral model.

We have collected data from several sources. Our first source is an administrative payment database managed by Banred. This database records every payment issued to the universe of recipients (1.07 million in December 2004) from January to December 2004. We observe if a beneficiary decided to collect the transfer in any given month and, if so, the amount of the

[15] Ecuador is divided in 22 provinces and each province is composed of several smaller areas called Parroquias. There are about 1,200 Parroquias in Ecuador.

subsidy received.[16] In addition, the database identifies whether the recipient is a mother, an elderly or a disabled individual. Since we focus on the behavior of low-income mothers, we select a random sample of 3,000 mothers from the payment database.

Even though Banred's database has very detailed payment data, it offers very little information about the demographic characteristics of the beneficiaries. However, it includes an individual identifier that may be used to match our sample with the Selben database. As we mentioned in the previous section, the Selben database provides information on many household's demographics such as the geographical location of the recipients (up to the Parroquia level), their education level, marital status, and number of children. Furthermore, certain characteristics of the beneficiaries' housing unit, such as its size and tenure status, are available and provide us with a measure of the household's wealth. In 2004, about 90% of the BHD's recipients had a corresponding Selben index score.[17] Thus, when our payment-sample is matched with the Selben's database, our matched database decreases to 2,523 observations.[18]

Finally, we compute a measure of the beneficiaries' accessibility to the Banred's payment agencies. Ideally, we would like to know the travel time from every beneficiary's residence to the closest payment agency, referred to as the home-to-agency travel time hereafter. Since we cannot obtain such information, we approximate it by estimating the travel distance between the biggest town of the Parroquia where the beneficiary resides and the closest town

[16] For example, we have information whether an individual received $15 in January, $0 in February, $0 in March, $45 in April, etc.

[17] The difference is composed of families that were not given the Selben survey, but have received the program since its initial implementation.

[18] In addition to the observations that we could not find in the Selben's database, we dropped from our sample 92 observations that reported subsidies of $11.5 per month (the subsidy received by the "elderly" and "disabled") rather than $15 (the transfer received by "mothers").

with a payment agency. This data was computed by the Ecuadorian Ministry of Welfare using software from the Ecuadorian Geographical Military Institute. When computing this variable, it is assumed that all vehicles travel at the legal speed limit and that no other waiting is involved when traveling. Furthermore, if the beneficiary lives in a Parroquia where a payment agency is available, the estimated travel distance is zero. Notice that there may be several sources of measurement error in this variable. For example, in rural areas, roads are not properly maintained, which makes it difficult to travel at the speed limit. On the other hand, there is very little speed-limit enforcement in Ecuador meaning that, despite the roads' conditions, some drivers may be traveling at higher speeds.

In Table 2 we present descriptive statistics of our matched database. On average, beneficiaries collect the subsidy eleven times during 2004. However, while some individuals recieve the subsidy every month, others do it only four times during the year. Individuals, on average, live in a Parroquia that was located 15 minutes away from a payment agency. However, there is significant variation in the beneficiaries' travel times. For example, while some individuals live in the same area where a designated payment agency operates (and have zero travel costs), others spend almost two hours to travel from their residence to the closest Parroquia with a payment point. In our sample, 62 percent of the recipients live in an urban area (as defined by the Ecuadorian 2000 Census) and 90 percent have received at least some type of formal education. Close to three quarters of the mothers in our sample have partners (either married or living together) and, the average mother has 3.5 children. On average, recipients live in small housing units (one room). There are, however, some households who live in very large residences, with up to 13 rooms, and yet are still eligible to receive the subsidy. Only 18 percent of mothers owns their home, which again illustrates the fact that the BDH is targeted towards low income families. Finally, we include the Selben index for every mother in our sample. Recall that this index is between 1 and 100, and those households who score less than 50.65 are eligible to receive the subsidy. The mean index is 40.6, about ten points below the cutoff.

[Please, insert Table 2]

To identify the determinants of the beneficiaries' collection decisions of the subsidy we use a simple linear regression model. The dependent variable is the number of times that mothers collected the $15 subsidy in 2004. The explanatory variables include household's demographics, regional fixed effects, and the distance from the recipient's residence to the closest payment agency. The first column of Table 3 presents a baseline model, and the other three columns explore alternative specifications.

Because the traveling patterns of individuals residing in urban areas significantly differ than those of individuals living in rural areas, we allow the effects of distance to vary in both of these areas. In both urban and rural households, we expect to observe a negative relationship between the home-to-agency travel time and the number of times that the subsidy was collected. As expected, this coefficient is negative and robust across every specification. However, the estimated effect is somewhat small. For instance, a rural household that lives 90 minutes away from a payment agency is expected to cash her payment two times less than an identical counterpart who lives in the same town where the agency is located. In urban areas, the effect is still negative but significantly smaller.

From this point forward, we focus on the most complete specification, which is presented in the fourth column of Table 3. Demographic variables such as age, education, marital status, and number of children have little explanatory power, although there is some evidence that women who have a partner have a higher expected number of subsidy redemptions in a given year. The number of rooms and the tenure of a housing unit are indirect measures of the household's wealth. A negative sign in their corresponding coefficients is expected since the opportunity cost of traveling increases with wealth. As expected, both coefficients are negative and highly significant. Finally, the inclusion of 21 regional fixed effects (province dummy variables) greatly increases the explanatory power of the model. These dummy variables are probably capturing other characteristics of the regions that are likely correlated with the beneficiaries' accessibility to the payment agencies (such as the availability of public transportation, for example).

[Please, insert Table 3]

The previous regression analysis shows that there is an important negative association between the home-to-agency travel time and the number of times that a mother collects the transfer. However, due to measurement error, this coefficient may be biased towards zero. To check if measurement error is an important source of bias we estimate a probit model with unobserved individual heterogeneity.[19] The dependent variable takes the value of one if the family received the transfer in a particular month and zero otherwise.[20] The independent variables include the same variables used in our previous linear regression model and, in some specifications, the random unobserved component. If measurement error in the home-to-agency travel time was an important source of bias, we would expect that the corresponding coefficient would significantly decrease in the latter specifications. The results are shown in Table 4. The first and second columns show the baseline specification, while the third

[19] This model is also known as probit with random effects.

[20] Notice that we have a panel of $12 * 2,523 = 30,276$ observations.

and fourth include the whole set of controls; in addition, in the second and fourth columns we specifically control for unobserved individual heterogeneity (measurement error). The coefficient in the home-to-agency travel time variable is always negative and, as expected, it decreases once we control for unobserved individual heterogeneity. This change is, however, very small suggesting that measurement error is not an important source of bias. All the other coefficients have the expected signs and are robust across all specifications.

[Please, insert Table 4]

The reduced form models shown in this section are useful tools to understand why certain families collect the subsidy more often than others. These models highlight the observed correlations in the data and will serve as a guide for the empirical model's specification.

4 The model

4.1 A stylized theoretical specification

In this section, we specify a theoretical model that resembles the collection decisions of a representative cash transfer beneficiary. We start by assuming that the beneficiary is an infinitely-lived rational agent. Every period t she has the right to receive a lump-sum payment of M monetary units from the government. Payments may be accumulated for up to $\bar{a}$ periods.[21] To redeem this payment, individuals need to travel for d minutes and incur a transportation cost $c(d)$.

Let $u_t(a)$ be the net utility that she obtains when collecting her payment

$$u_t(a) = g\left[aM - c(d)\right] + \varepsilon_t, \tag{1}$$

[21]That is, if the last transfer was recieved a periods ago, the total monetary amount that the beneficiary is eligible to receive in the current period is $j \cdot M$, where $j = \min\{a, \bar{a}\}$.

where $g(.)$ is a non-decreasing function, a is the number of periods since the last transfer was received, and ε_t is a random utility component. At time t, ε_t is revealed to the individual, but future realizations of this component are unknown.[22] In addition, let ε_t be identically and independently distributed (for all t and a) according to the distribution F, which is common knowledge.

Let $V_t(a)$ be the value of having an option to receive an aM payment in period t. If the beneficiary chooses to redeem her payment in the current period, she receives the instant utility $u_t(a)$ and the discounted expected value of the option to receive the transfer next period $\beta E\left[V_{t+1}(1)\right]$. Otherwise, she will have the option to redeem $(a+1)M$ monetary units in the future, and the value of this choice is $\beta E\left[V_{t+1}(a+1)\right]$. Thus, $V_t(a)$ is the highest of these two choices

$$V_t(a) = \max\left\{u_t(a) + \beta E\left[V_{t+1}(1)\right], \beta E\left[V_{t+1}(a+1)\right]\right\}; \qquad a = 1, .., \bar{a} - 1. \tag{2}$$

Because payments may not be accumulated for more than $\bar{a}$ periods, Equation (2) holds only for values of a smaller than $\bar{a}$. If a equals to $\bar{a}$, Equation (2) becomes

$$V_t(a) = \max\left\{u_t(a) + \beta E\left[V_{t+1}(1)\right], \beta E\left[V_{t+1}(a)\right]\right\}; \qquad a = \bar{a}. \tag{3}$$

Let $W_t(a) = E\left[V_t(a)\right]$. It can be shown that, given certain standard conditions, there exists a unique $W^*(a)$ for all $a\epsilon\{1, .., \bar{a}\}$ that solves Equations (2) and (3) which is independent of time.[23] Thus, the solution to our theoretical model consists of an optimal strategy $P_t^*(a)$ where, given the current state a, the function $W^*(a)$, and the information available

[22] Notice that ε_t may be interpreted as the household's time-opportunity costs at time t and that, from the family's point of view, future realizations of these costs are random.

[23] Our model resembles standard search models in the labor literature (Lippman and McCall 1976 provide a survey of such models). A well known result in similar models is that, a unique $W^*(a)$ exists, as long as transportation costs are not too high.

at t, individuals choose to redeem their payment if and only if the utility from collecting the transfer (the left hand side from the maximum operator in Equation 2) is no less than the outside option (the right hand side from the maximum operator in Equation 2).

Notice that, given parametric assumptions, we may solve the model numerically and simulate the recipient's behavior.[24]

4.2 Empirical model

In this section, we incorporate observed and unobserved individual heterogeneity to the stylized theoretical model presented in the previous section and provide specific functional assumptions for $g(.)$, $c(.)$, and F.

We define d_i as the distance between beneficiary i's place of residence and the closest office where she may receive the payment. It is assumed that this distance does not change across time.[25] In addition, let X_i and u_i be a vector of observed and unobserved (from the econometrician's point of view) individual's characteristics, respectively. The observed characteristics include household demographic variables used in the reduced form models. The unobserved individual characterstics capture other features of households that are not available in the data and that may explain their behavior. Examples of such unobserved characteristics include the family's health status and measurement error in the home-to-agency travel time.[26]

[24] We solve the models recursively. That is, given certain functional form assumptions about $g(.)$, $c(.)$, and F, and a set of parameter values, we compute recursively the values of $W_T(a), W_{T-1}(a), W_{T-2}(a), ...$until convergence is achieved for all values of a. Once we have evaluated $\{W^*(a)\}_{a=1}^{\bar{a}}$we may simulate individual's decisions by obtaining realizations from ε_t and applying the optimal rules $P_t^*(a)$.

[25] That is, we assume that neither individuals nor authorized financial institutions move during the time span of our sample (one year).

[26] In the previous section we found that measurement error was not an important source of bias in reduced form models.

We assume a linear specification for both $g(.)$ and $c(.)$. That is,

$$g\left[aM - c\right] = aM - c,$$

and

$$c(d_i, X_i, u_i) = c_0 + c_1 d_i + X_i\gamma + u_i, \tag{4}$$

where γ is a vector of parameters.

Finally, we let both ε_i and u_i be i.i.d. and normally distributed with mean zero and variance σ_u^2 and σ_ε^2, respectively. Notice that, given $\{d_i, X_i, u_i\}$ and a set of parameter values $\theta = \{\beta, c_0, c_1, \gamma, \sigma_\varepsilon^2\}$, we may solve the model and predict the behavior of each individual.

4.3 Estimation

To estimate our model, we use our database and Simulated Maximum Likelihood Estimation (SMLE) methods. In this section, we specify the relevant likelihood function.

Let P_{it} equal one if the individual i redeems her payment in period t and zero otherwise. In addition, let a_{it} be the number of \$$M$ payments that the beneficiary i may redeem at period t. Notice that, for each individual $i = 1, ...N$ in our sample, we observe the variables $\{P_{it}, a_{it}, d_i, X_i\}_{t=1}^{T}$.

Given θ and a particular realization of u_i, the likelihood of observing an individual i receiving a transfer of $a_{it}M$ monetary units in period t is equivalent to the probability that the right hand side of Equation (2) is no less that its left hand side. That is,

$$\begin{aligned}\Pr\left\{P_{it} = 1 | a_{it}, X_i, u_i; \theta\right\} &= \Pr\left\{a_{it}M - c(d_i, X_i, u_i) + \varepsilon_t + \beta W_i^*(1) > \beta W_i^*(a_{it}+1)\right\} \\ &= 1 - \Phi\left\{\beta W_i^*(a_{it}+1) - a_{it}M + c(d_i, X_i, u_i) - \beta W_i^*(1)\right\},\end{aligned}$$

where Φ is a normal cumulative distribution function with mean zero and variance σ_ε^2, and $a_{it} < \bar{a}$. When $a_{it} = \bar{a}$, this probability becomes

$$\Pr\{P_{it} = 1 | a_{it}, X_i, u_i; \theta\} = 1 - \Phi\{\beta W_i^*(a_{it}) - a_{it}M + c(d_i, X_i, u_i) - \beta W_i^*(1)\}.$$

With these definitions, we may compute the conditional likelihood of observing an individual redeeming her payments as

$$L_{it}^1 | a_{it}, X_i, u_i; \theta = \Pi_{j=1}^{\bar{a}} \left(\Pr\{P_{it} = 1 | a_{it}, X_i, u_i; \theta\}\right)^{a_{itj}},$$

where a_{itj} equals one if $a_{it} = j$ and zero otherwise ($j = 1, .., \bar{a}$). On the other hand, the probability that this individual does not redeem her payment is

$$L_{it}^0 | a_{it}, X_i, u_i; \theta = 1 - L_{it}^1 | a_{it}, X_i, u_i; \theta.$$

Thus, the conditional likelihood contribution of observing the behavior of an individual i during T periods is

$$L_i | u_i; \theta = \Pi_{t=1}^{T} \left\{ \left[L_{it}^1 | u_i; \theta\right]^{P_{it}} \left[L_{it}^0 | u_i; \theta\right]^{1-P_{it}} \right\},$$

and the unconditional likelihood function of our sample is

$$L = \Pi_{i=1}^{N} \int (L_i | u_i; \theta) dG(u_i), \tag{5}$$

where G is a normal cumulative distribution function with mean zero and variance σ_u^2.

The integral of the right hand side of Equation (5) will be evaluated using simulation methods. The SMLE parameter estimates are the ones that maximize the log-likelihood of observing this sample.

5 Results

5.1 Estimates and within-sample fit

Because our model's cost function is linear, we are not able to separately identify the mean transportation cost from the mean discount factor. Thus, a normalization is needed. We choose to pick a particular value for the monthly discount factor of low-income mothers and estimate the rest of the parameters of the model. Because these low-income families face important credit constraints, we have assumed a monthly discount rate of 0.98.[27]

In Table 5, we present the SMLE estimates of our structural model. Unlike the parameters of most reduced form models, our estimates have a direct economic interpretation and illustrate how the mothers' home-to-agency transportation costs vary with respect to their own characteristics. For example, the estimated coefficient on distance (0.013) suggests that the opportunity cost of the home-to-agency travel time is close to $0.40 per hour (a little less than one cent per minute).[28] This is a reasonable estimate considering that the Ecuadorian minimum wage in 2004 was close to $1 per hour.

[Please, insert Table 5]

In addition, our results provide evidence that travel costs decrease with age and are somewhat smaller for women who have a partner. Moreover, the coefficients corresponding to the number of rooms and the tenure of a housing unit are both positive and statistically

[27] In 2004, nominal interest rates (including other fees) of consumption credits in Ecuadorian financial institutions averaged 18%. However, most of the low-income households in our sample may not qualify to obtain a loan in the formal financial sector. In the informal sector, they may obtain short term loans that (illegally) charge an average interest rate of 5% per month. For this reason, we think that the corresponding discount factor for this set of households should be relatively low (0.98). The main results of the paper do not change for alternative discount factor assumptions.

[28] Notice that the *distance* variable measures one-way travel time from the individual's residence to the payment agency. Thus, our results suggest that travel time is worth $0.013 for every two minutes, or $0.39 per hour.

significant, meaning that the opportunity cost of traveling increases with wealth. Finally, the coefficient on the Selben index is negative suggesting that travel costs decrease with higher values of this index. This may seem counterintuitive at first since this index is, by construction, positively associated with income and wealth. However, once we control for the household's housing characteristics, home-to-agency distance, and the other demographic variables included in our specification, there may be other factors that are captured by the Selben index that are negatively related to travel costs. For example, families with a high index value in our sample may be more likely to own a vehicle or to know someone who owns one, and this will certainly decrease their cost of traveling.

To examine the within-sample fit, we use the estimated model to simulate the behavior of the households in our sample and compare it with the observed data. For instance, in the first column of Table 6, we compute the predicted share of individuals that receive the subsidy and, in the second column, the actual share observed in our sample. We compute both unconditional and conditional shares. The unconditional share corresponds to the percentage of beneficiaries who decide to cash their benefit in any given month. On the other hand, to estimate the conditional shares, we restrict the sample to those individuals who have received their last payment one, two, three, or four months ago.

[Please, insert Table 6]

Overall, the model fits the observed conditional and unconditional shares of individuals who receive the subsidy very well. For example, there are virtually no differences between the unconditional predicted and actual share of low-income mothers who receive the transfer. This is also true for most conditional shares. The only relevant difference is related to those households who have accrued three months of payments. In our sample, 85% of those families decided to receive the payment in the current month, and our model overpredicts this number by about six percentage points.

In our view, the within-sample fit described above gives us enough confidence in the model to use it to perform counterfactual experiments to explore the benefits and costs of alternative payment mechanisms.

5.2 Policy experiments

One of the primary benefits of estimating a structural model is that it can be used to conduct counterfactual experiments. In this section, we use our estimated model to estimate the economic value of the program and, also, to evaluate alternative payment options.

According to our model, the average economic value of the subsidy is close to \$842 among rural households.[29] Thus, the overall value of the BDH program in Ecuador may be at least \$800 million.[30]

The value of the program, of course, increases with the number of payments that households are allowed to accrue. For instance, the current program, that allows households to accrue up to four months of payments, is about \$5 million more valuable than an identical program with no payment accrual. Increasing the number of periods that households are allowed to accumulate their payments to five or six months, however, does not change the value of the program significantly. This occurs because only a few households with high travel costs are affected by such policy.

We compute another counterfactual that allows us to quantify the household's welfare

[29] According to our model, the average economic value of the program can be computed as $\bar{W}^*(1)$. This corresponds to the minimum cash amount that recipients would be willing to accept to give up the program.

[30] Because urban households are on average closer to payment agencies than their rural counterparts, we expect that the economic value of the subsidy is higher among these households. Since there are a little more than 1 million of recipients, the overall value of the program should be at least \$800 million.

gains if the government raises the number of payment agencies in rural locations. In particular, we assume that new payment agencies are built such that the home-to-agency travel time of a representative rural household decreases by 60 minutes. In Table 7, we show that such policy increases the value of being enrrolled in the program by about 4%. To assess the efficiency of such policy, the Ecuadorian authorities should evaluate both the magnitude of the total benefits (4% increase per household) and the total costs (operating costs of such agencies) involved in such operation.

[Please, insert Table 7]

Finally, the model may also be used to create a differentiated schedule of payments that compensates rural households for their travel time-opportunity costs. That is, the payments could be geographically differentiated so that the total value of the program is the same for every household.[31] We present estimates of this counterfactual experiment in Table 8. This results suggest that rural households located in the Amazon and in the Highlands should receive between \$0.25 and \$0.50 higher monthly transfers than their urban counterparts to compensate them for their travel costs.

[Please, insert Table 8]

6 Conclusions

In this paper we have specified and estimated a simple behavioral model that resembles the household's collection decisions of a CCT program in Ecuador. Despite its simplicity, the

[31] To construct this experiment, we first compute the value of the BDH program for a representative family that has the option to receive \$15 per month. The representative family has the mean characteristics of our sample of rural households, except for the home-to-agency travel time. This variable has been set to zero, since we are interested in computing the value of the program for a family that lives in an area with a payment agency. Then, we find the transfer that the average household in each Province should receive to match the value of the program of the former representative family.

model replicates the observed data well and may be a powerful tool for designing the delivery of payments of such a program. In addition, the counterfactual experiments suggest that an adequate design of the delivery of payments can substantially increase the value of CCT programs.

In our model, transportation costs are the main source of households' transaction costs. We recognize that there may be other sources of transaction costs that influence the collection's decisions of households. For example, the opportunity cost from waiting in line at the payment agencies and other illegal fees that may be charged at the time of collecting the transfer may also affect the value of the program. We emphasize that, with the appropriate data, the model specified in this paper may be a useful benchmark to analyze household's behavior under these circumstances as well.

References

[1] Behrman, J., P. Sengupta, and P. Todd, "Progressing through Progresa: An impact Assessment of a School Subsidy in Mexico", Economic Development and Cultural Change, 2005, 54(1), 237-75.

[2] Berkovec, J. and S. Stern, "Job Exit Behavior of Older Men", Econometrica, 1991, 59(1), 189-210.

[3] Bourguignon, F., F. Ferreira, and P. Leite, "Conditional Cash Transfer, Schooling, and Child Labor: Micro-Simulating Brazil's Bolsa Escola Program." The World Bank Economic Review, 2003, 17(2): 229-254.

[4] Caldés N., D. Coady, and J. Maluccio, "The Cost of Poverty Alleviation Transfer Programs: A Comparative Analysis of Three Programs in Latin America." IFPRI, 2004, Washington.

[5] Keane, M. and K. Wolpin, "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence", Review of Economics and Statistics, 1994, 76(4), 648-672.

[6] Keane, M. and K. Wolpin, "Career Decisions of Young Men", Journal of Political Economy, 1997, 105(3), 473-522.

[7] Keane, M. and K. Wolpin. "The Effect of Parental Transfers and Borrowing Constraints on Educational Attainment", International Economic Review, 2001, 42(4), 1051-1101.

[8] León M. and S. Younger, "Transfer Payments, Mother's Income, and Child Health in Ecuador", Journal of Development Studies, Forthcoming.

[9] León, M., R. Vos, and W. Brborich, "Son efectivos los programas de transferencias monetarias para combatir la pobreza? Evaluación de impacto del Bono Solidario en el Ecuador." Unpublished manuscript, Sistema Integrado de Indicadores Sociales del Ecuador, Quito, Ecuador, 2001.

[10] Lippman, S., and J. McCall, "The Economics of Job Search: A Survey." Parts I and II. Economic Inquiry, 1976, (14), 155-189 and 347-368.

[11] Parandekar, S., "Protecting the Poor in Ecuador: Priorities and Options for the Bono Solidario", in World Bank, 1999.

[12] Rawlings, L. and G. Rubio, "Evaluating the Impact of Conditional Cash Transfer Programs: Lesson from Latin America.", Policy Research Working Paper. No. 3119, 2003, 1-25.

[13] Schady N., and C. Araujo, "Cash Transfers, Conditions, School Enrollment, and Child Work: Evidence from a Randomized Experiment in Ecuador", Policy Research Working Paper. No. 3930, 2006, 1-31.

[14] Schultz, T., "School Subsidies for the Poor: Evaluating the Mexican Progresa Poverty Program", Journal of Development Economics, 2004, (74), 199-250.

[15] Todd, P. and K. Wolpin, "Using Experimental Data to Validate a Dynamic Behavioral Model of Child Schooling: Assessing the Impact of a School Subsidy Program in Mexico", American Economic Review, 2006, 96(5)

Table 1: Geographical distribution of beneficiaries and payment agencies of the Bono de Desarrollo Humano in 2004

		Agencies from Banred		
Province	**Number of Beneficiaries**	**Total number of payment agencies**[a]	**Share of *Parroquias* (a smaller geographic region) with a payment agency**[b]	**Share of beneficiaries that reside in a *Parroquia* with a payment agency**
Azuay	47,486	15	0.04	0.28
Bolivar	25,418	2	0.06	0.31
Cañar	18,381	8	0.06	0.28
Carchi	13,589	5	0.11	0.42
Chimborazo	48,758	4	0.06	0.31
Cotopaxi	38,261	7	0.09	0.30
El Oro	49,221	20	0.14	0.73
Esmeraldas	38,967	7	0.06	0.48
Francisco De Orellana	8,875	2	0.06	0.42
Galapagos	340	2	0.25	0.71
Guayas	271,156	46	0.39	0.75
Imbabura	36,476	8	0.08	0.47
Loja	46,428	9	0.08	0.37
Los Rios	66,533	20	0.17	0.64
Manabi	148,581	19	0.12	0.52
Morona Santiago	9,500	2	0.03	0.20
Napo	7,922	2	0.05	0.38
Pastaza	5,011	5	0.05	0.41
Pichincha	123,500	55	0.41	0.79
Sucumbios	13,244	4	0.03	0.33
Tungurahua	41,601	9	0.08	0.36
Zamora Chinchipe	9,222	2	0.06	0.03
Other	1,571	3	0.25	0.51
Total	1,070,041	256	0.13	0.56

Notes:

The information displayed on this table was tabulated using the universe of the payment data collected by BANRED.

We thank Miguel Acosta from the Banco Central del Ecuador for sharing this information with us.

[a] We have included agencies with at least 20 transactions per month.

[b] According to the Ecuadorian 2000 Census, there are 1149 *Parroquias* in Ecuador.

Table 2: Descriptive Statistics

Number of observations: 2523

Variables	Mean	Std. Dev.	Min.	Max.
Number of payments : Number of times that the subsidy was collected from January to December 2004	11.04	1.53	4	12
Distance : Travel time (minutes) from center of the Parroquia where beneficiaries reside to the closest point where they can collect the transfer	15.20	19.95	0	118.18
Urban : Takes the value of one if beneficiary resides in an Urban Area (as defined by the Ecuadorian 2000 Census)	0.62	0.49	0	1
No education : One if beneficiary has not received any type of formal education	0.09	0.29	0	1
Age : Age (in years) of beneficiary	32.36	8.13	14	61
Family partner : Equals to one if beneficiary has a partner living at home	0.75	0.44	0	1
Children : Number of living children	3.51	2.16	0	13
Rooms : Number of rooms in housing unit	1.05	0.86	0	5
Tenure : Equals to one if individual owns the housing unit where she resides	0.18	0.38	0	1
Selben index : Selben proxy-means index	40.62	6.36	12.88	50.64

Table 3: Linear Regressions
Dependent variable: Number of times that the subsidy was collected in 2004

Number of observations: 2,523
White - Robust Standard errors in parenthesis

Independent Variables	Model (1)	(2)	(3)	(4)
Constant	11.079 ***	11.353 ***	10.494 ***	11.282 ***
	(0.073)	(0.424)	(0.493)	(0.510)
Distance	-0.021 ***	-0.020 ***	-0.019 ***	-0.019 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Urban	0.245 ***	0.241 ***	0.031	-0.024
	(0.084)	(0.085)	(0.088)	(0.091)
Urban x Distance	0.017 ***	0.017 ***	0.017 ***	0.017 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Age		-0.023	-0.014	-0.030
		(0.026)	(0.026)	(0.026)
Age^2		0.001	0.000	0.001
		(0.000)	(0.000)	(0.000)
No education		-0.137	0.000	0.030
		(0.113)	(0.118)	(0.121)
Has a partner		0.078	0.121 *	0.108 *
		(0.067)	(0.067)	(0.065)
Number of children		-0.041 **	0.007	0.009
		(0.019)	(0.021)	(0.021)
Number of rooms in housing unit			-0.173 ***	-0.095 **
			(0.038)	(0.040)
Housing unit tenure (One if owns)			-0.459 ***	-0.297 ***
			(0.101)	(0.112)
Selben index			0.022 ***	0.014 **
			(0.006)	(0.006)
Region Fixed Effects (21)	No	No	No	Yes
R-squared	0.085	0.089	0.113	0.170

Note: Coefficients of the dummy variables for areas are not reported
*   : Statistically significant at the 10% level
** : Statistically significant at the 5% level
*** : Statistically significant at the 1% level

Table 4: Probit Regressions
Dependent variable equals to one if subsidy is collected in any period (month)

Number of observations: 30,276
White - Robust Standard errors in parenthesis

Independent Variables	Model (1)	(2)	(3)	(4)
Constant	1.394 ***	1.739 ***	1.516 ***	1.712 ***
	(0.021)	(0.045)	(0.204)	(0.365)
Distance	-0.008 ***	-0.009 ***	-0.007 ***	-0.008 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Urban	0.191 ***	0.238 ***	0.042	0.046
	(0.029)	(0.055)	(0.032)	(0.058)
Urban x Distance	0.005 ***	0.007 ***	0.006 ***	0.007 ***
	(0.001)	(0.002)	(0.001)	(0.002)
Age			-0.015	-0.008
			(0.011)	(0.019)
Age^2			0.0003 *	0.0002
			(0.000)	(0.000)
No education			0.002	-0.040
			(0.041)	(0.073)
Has a partner			0.070 ***	0.097 **
			(0.026)	(0.047)
Number of children			0.004	0.004
			(0.008)	(0.013)
Number of rooms in housing unit			-0.058 ***	-0.083 ***
			(0.014)	(0.026)
Tenure			-0.136 ***	-0.170 ***
			(0.033)	(0.061)
Selben index			0.007 ***	0.008 **
			(0.002)	(0.004)
Region Fixed Effects (21)	No	No	Yes	Yes

Note: Coefficients of the dummy variables for areas are not reported.
Columns (2) and (4) control for individual random effects.
*   : Statistically significant at the 10% level
** : Statistically significant at the 5% level
*** : Statistically significant at the 1% level

Table 5: Structural Estimates

Independent Variables	Coefficient	Std. Dev.
Constant	-0.823	(0.262) ***
Distance	0.013	(0.002) ***
Age	-0.009	(0.004) **
Age^2	0.000	(0.000)
No education	-0.127	(0.059) **
Has a partner	-0.070	(0.046)
Number of children	-0.014	(0.010)
Number of rooms in housing unit	0.115	(0.029) ***
Tenure	0.377	(0.080) ***
Selben index	-0.026	(0.006) ***
σ_ε	1.706	(0.315) ***
σ_υ	0.036	(0.038)

The discount factor β has been normalized to 0.98.
The data consists of a panel of 970 rural households over 12 months.
The corresponding sample size is 11,040.
Standard errors in parenthesis.
* : Statistically significant at the 10% level
** : Statistically significant at the 5% level
*** : Statistically significant at the 1% level

Table 6: Percentage of beneficiaries that collect the transfer in any given month*

	Model	Sample
Overall (*unconditional*)	88.7%	88.7%
Months since last payment (*conditional*):		
One	88.5%	88.4%
Two	89.9%	91.3%
Three	91.1%	84.8%
Four	100.0%	100.0%

* The *unconditional* share corresponds to the percentage of beneficiaries who decide to cash their benefit in any given month. To estimate the *conditional* shares, we restrict the sample to those individuals who have received their last payment one, two, three, or four months ago.

Table 7: Economic value of the subsidy if home-to-agency travel time decreases by 60 minutes*

Travel time to closest town with payment agency (in minutes)	Economic value of the subsidy for a representative rural household ($)	Percentage increase in program's value when travel time decreases
120	791.1	3.8%
90	805.4	3.9%
60	820.8	4.1%

* These are estimates for a representative rural household. The observed characteristics correspond to the mean of our sample with the exception of the home-to-agency travel time.

Table 8: Differentiated transfers in rural areas to compensate households for their travel costs *

West (*Costa*)		Highlands (*Sierra*)		East (*Oriente*)	
Province	**Monthly transfer ($)**	**Province**	**Monthly transfer ($)**	**Province**	**Monthly transfer ($)**
El Oro	14.94	Azuay	15.13	Morona Santiago	15.45
Esmeraldas	15.05	Bolivar	15.57	Napo	15.44
Guayas	15.06	Cañar	15.38	Pastaza	15.65
Los Rios	15.06	Carchi	15.03	Zamora Chinchipe	15.47
Manabi	15.33	Chimborazo	15.29	Sucumbios	15.39
		Cotopaxi	15.65	Francisco De Orellana	15.26
		Imbabura	15.15		
		Loja	15.46		
		Pichincha	15.14		
		Tungurahua	15.13		

Notes:

* To construct this experiment, we first compute the value of the BDH program for a representative family that has the option to receive $15 per month. The representative family has the mean characteristics of our sample of rural households, except for the home-to-agency travel time. This variable has been set to zero, since we are interested in computing the value of the program for a family that lives in an area with a payment agency. Then, we find the transfer that the average household in each Province should receive to match the value of the program of the former representative family.