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by

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Abstract

This paper analyzes the characteristics of beneficiaries that drop out of the Mexican conditional cash transfer program Oportunidades to determine if dropping out of the program is a result of self-targeting by the non-poor, the exclusion of the target poor population or a combination of both. The analysis, which uses a duration model, indicates that it is the wealthier beneficiaries that have greater odds of dropping out suggesting that conditionality acts as a screening device. Results also indicate that administrative factors and the particular provider of health services to beneficiaries have an important influence on dropouts.

Key words: Cash transfer programs, conditionality, Oportunidades, Latin America, Mexico, hazard models

JEL classification: I30, O22

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A study of the effects of conditionality on dropouts

1. Introduction

Conditional cash transfer programs (CCTs) have become a common tool for poverty alleviation and human capital formation among the poor, especially in Latin America.[1] Subsidies are given to poor families in order to: i) have a direct poverty alleviation effect by increasing total household income and thus their consumption, and ii) to elicit a behavioral change in these families so that a certain impact, such as increased investment in the human capital of the children of the poor, will take place. Impact evaluations of these programs have concentrated on verifying the behavioral changes and their related effects.[2] Much discussion has ensued related to whether conditioning of the subsidy is absolutely necessary to elicit the behavioral change and thus the impact. It has been difficult to shed light on this question given that the counterfactual, a randomized unconditional transfer, has not been possible to implement (Davis et al., 2006). While the lack of data makes it impossible to make a clear statement on the role of conditionality, the consensus seems to be that behavioral changes are correlated with the type of conditions that each program requires (Das, Do & Özler, 2005).

Conditions have other consequences beyond the effect on beneficiaries' behavior. In some programs, failing to meet the program's conditions implies that the recipients would receive a reduced payment or possibly be dropped from the program's roster. Therefore, conditions on the receipt of transfers may also encourage self-selection out of the program, thereby acting as a screening mechanism (Das, Do & Özler, 2005). Such screening mechanisms have been used in workfare programs by placing work requirements on program recipients that lead to self-selection into the program by those that are unemployed (Jalan & Ravallion, 2003; Galasso & Ravallion, 2003). In this paper, using data from Mexico's *Oportunidades* program, we evaluate the role of conditionality in CCTs in inducing self-selection and increasing the efficiency of the targeting system of the programs.

In targeting beneficiaries, *Oportunidades* employs a carefully constructed system to determine eligibility[3]. This system is designed to minimize the errors of omission – excluding the poor who should be eligible for the program – and the errors of inclusion – including the non-poor in the program.[4] Specifically, the program uses a combination of geographic and household proxy means test to classify families as poor, and thus eligible to participate in the program. First, potential recipient communities are ranked based on an index of marginality developed from the national population census. The marginality index is a proxy for the degree of access to basic goods and services at community level and thus gives a sense of how remote, and correspondingly poor, a community is. After communities are identified, the second step is to select households for participation in the program based on data collected from a household

[1] Among some are Mexico's *Oportunidades*, Honduras *PRAF*, Nicaragua's *Red de Protección Social*, Jamaica's *Path*, Colombia's *Familias en Acción*, Ecuador's *Bono Solidario*, Brazil's *Bolsa Escola* and *Bolsa Familia*, and Argentina's *Ingreso para el Desarrollo Humano* and *Jefas y Jefes*.
[2] For a summary of the estimated impacts of Mexico's Progresa program – the name of Oportunidades prior to 2001 – see Skoufias (2005). For an evaluation of the Nicaragua's *Red de Protección Social* see Maluccio & Flores (2004).
[3] Programa de Desarrollo Humano Oportunidades (2001-2005) Rules of Operation. www.oportunidades.gob.mx
[4] See Cornia & Scott (1995).

census within the community. A proxy means test is calculated for each household using discriminant analysis and households above the cut-off point are deemed eligible as beneficiaries. The key factors used to discriminate between the poor and non-poor are observable household assets that indicate relative wealth. Once families are incorporated, they remain in the program, and receive benefits, if they follow the protocol of conditions placed on receipt of the subsidies.

While the targeting of beneficiaries is carefully designed, the program may include the non-poor for two reasons[5]. First, the creation of a wealth index using discriminant analysis is at best an approximation of income or consumption poverty and it may be the case that this index allows the inclusion of non-poor households. Second, the program has been in operation for a number of years and the benefits of the program may results in some households no longer being considered poor. Similarly, the exclusion of the poor may be related to two factors. Given the initial geographic targeting of the program to marginal communities, the poor that happen to live in better off communities may be missed at least in the earlier years of operation. Furthermore, new poor households may form in communities after the roster has been created leaving out new households. To manage these issues of dynamic changes in the welfare status of beneficiaries, the program returns to survey the communities every three years, and, based on a proxy means test, verifies the eligibility of current recipients and determines if new households in the community are eligible for the program.

In addition to administrative rules and actions to update the roster and verify continual eligibility, households may self-select out of the program. That is, through failing to meet the conditions of the program or failing to pick up their checks, a significant number of households get dropped from the roster and lose their eligibility for transfers. If this is simply the result of the quasi-poor opting out of the program because the opportunity costs of conditionality are too great, conditionality is acting as a screening mechanism that minimizes the errors of inclusion and thus improves targeting. However, dropping out of the program may be related to a completely different phenomenon. It could be the case that conditionality places unreasonably high costs on very poor households making them unable to receive the transfer and therefore working against the program's objective of protecting the most vulnerable. For example, the costs associated with enrolling and attending school, attending health lectures or visiting health clinics may be high for poor households, particularly those in distant, marginal communities where transport costs are high. If this is the case, dropouts may then increase the errors of omission by making ineligible the very households that the program is intending to target.

The purpose of this paper is to examine the characteristics of households that drop out of the program to determine if these are a result of self-targeting by the non-poor, the exclusion of the target poor population or a combination of both. Towards this end, section 2 discusses the *Oportunidades* program in detail including a description of the eligibility requirements and the conditionality associated with the program. Section 3 then describes the data set used to evaluate dropouts. The analysis uses the administrative data from the program, including data from the household census conducted to determine eligibility, as well as administrative data on the length of time households remained in the program. Section 4 presents the empirical approach used in the analysis. In particular, we estimate a discrete non-repeatable one-way duration model that explains the hazard rate, $h(t)$, or the risk of dropping out of the program at time t, given that the

[5] For an analysis of targeting errors in the rural sector see, Skoufias, Davis & de la Vega, (1999). For an evaluation of targeting in urban areas se,e Coady and Parker (2004).

event did not occur before time *t*. In section 5, the results of this analysis are presented. Finally, conclusions and policy implications are presented in section 6.

2. The effect of program eligibility and conditions on dropouts

The targeting system *Oportundidades* used to identify beneficiary households is described in the introduction. Within those household declared eligible, in most cases payment is provided directly to mothers under the assumption they are more likely to use the resources to benefit their family and children. The degree of eligibility and therefore the amount of transfer is dependent on the composition of the household and in particular on the number and age of children. *Oportunidades* has two different forms of cash transfers: a basic transfer composed of a food grant, to which school scholarships grants are added if children in the family are of school age. Each type of transfer is linked to separate and independent conditionality requirements.

The food grant, which is the same amount for each beneficiary household, is conditional on health check-ups for all family members and attendance by the recipient to public health lectures. At registration, households set up a schedule of health appointments for all relevant household members for the year. This information is given to the health provider and attendance records are maintained. Along with these check-ups, transfer recipients are also asked to attend health and nutrition talks at the health clinic. The health provider is required to fill in a form every two months certifying beneficiary attendance at these talks. This results in a report to the *Oportunidades* administrators indicating the beneficiary family is in compliance with the conditions of the basic food transfer or is not. Failure to be compliant for four consecutive months (two bimonthly periods) or for six non-consecutive months out of any twelve months (three bimonthly periods out of six) results in the family being dropped from the program.

School scholarships are linked to specific children and thus differ by household. The grants are awarded to beneficiaries during the school calendar year and all children over 7 and under 18 (for grades 3 through 9) are eligible. Children must register and ensure regular attendance (a monthly attendance rate of 85%) to receive the award. School officials verify registration by signing a form for each family and certify attendance through submitting attendance forms to the proper authorities. If attendance requirements are not met, the amount linked to that particular child is deducted from the bimonthly total payment to the family. Failure to meet the conditions associated with children's schooling, therefore, does not result in expulsion from the program but rather in a reduced payment.

The health and schooling conditions described above are clearly not without costs. The principal cost for the household of meeting conditions is the opportunity cost of time. Being present at public lectures, scheduling and making health check-ups and attending school all require using valuable household labor time. The time involved in getting to the health centers and schools can also represent a significant amount of time. It is also likely to incur a direct cash cost for transportation, particularly for more remote households. The expectation then is that those households with the greatest opportunity cost of time are the most likely to fail to meet the conditions of the program; namely; those with other economic opportunities which are likely to be the relatively better off households. This is the screening mechanism described in the introduction that may lead to self-targeting. Additionally, however, given the costs of transportation, it may be the case that more marginal households with limited infrastructure access or who are cash constrained could potentially also find it difficult to meet the conditions of the program; that is, the extremely poor. Thus, we may find that both the better off and poorest households may find themselves leaving the program as a result of their actions.

Thus far, we have assumed that only the actions of households can lead them to dropping out of the program. There are other mechanisms other than failing to meet conditions that can lead to being dropped out. First, reporting mechanisms to enforce conditions rely on health personnel filling in forms to inform the program of noncompliance on the part of families. In such a situation with such a large program, this in itself may lead to some problems. In fact, as shall be seen in the subsequent sections of the paper, the efficiency of the health provider may influence reporting of compliance and thus the ability of beneficiaries to stay in the program. Another reason that may lead to drop out is failing to pick-up the transfer payment two periods in a row. By rules, this leads to the recipient being dropped. However, while this can be the result of recipient behavior and could be linked to the opportunity cost of time and the costs associated with transportation, it can also be the result of administrative problems. For example, to pick up a check requires having an identification card that is supplied by the program. If for some reason, the program fails to deliver in time all proper identification to the recipient, they cannot pick up their check and thus could be dropped out. Additional mechanisms that may lead to being dropped form the program are related to other aspects of the administration of the program. The program regularly has audits of the procedures and an audit may find that a recipient should not have been eligible.

To summarize, three triggers lead to a recipient being dropped from the program: i) reported as failing to meet health conditions two periods in a row or for three out of six periods; ii) failing to pick-up payments two periods in a row; or iii) administrative audits. Note that not all dropouts may be due to the behavior of households, in all of the above administrative glitches, or "shocks" could be playing a large role in the survival function of households in the program. To ensure the analysis properly assesses the influence of behavioral factors, in the analysis below, we are careful to control for these other factors.

3. *Oportunidades*' administrative data

The data used in this analysis comes from the administrative information of the *Oportunidades* program. The program collects information on when beneficiaries enter the program as well as if and when they drop out. For each rural community in which *Oportunidades* operates, the program conducts a census of households in the community – referred to as the ENCASEH – to determine eligibility. The questionnaire used for the census consists of detailed socio-economic information, including the characteristics of the recipient and household, measures of household income and sources, and receipt of public assistance programs. The administrative data also includes the community marginality index, used for the geographic targeting noted above, and the score (or *puntaje*) used for the household targeting. Finally, the administrative information includes other data such as the health provider used by the beneficiary household for check-ups.[6] Once constructed into a single data set, the data includes significant details on the characteristics of the beneficiary households at the time of entry into the program as well as administrative details.

[6] Health providers are the state health secretariat services or the Instituto Mexicano del Seguro Social´s IMSS-Oportunidades program.

As of 2005, *Oportunidades* had incorporated 5 million participants including over 3.3 million in rural areas. For this analysis, we focus on rural areas since this is where there is greater concern that conditions may lead to households dropping out and where most of the extreme poor in Mexico reside. Given the volume of data, it was necessary to take a subsample of the administrative data to analyze. First, we decided to work only with the four cohorts that entered the program in 1998[7], rather than all of the cohorts that entered the program between 1997 and 2004. The choice of this set of cohorts is based on the following reasons: i) these cohorts had been in the program for a significant amount of time allowing for longer-term analysis of dropouts; ii) the program was dramatically expanded in 1998 so these are large cohorts (1.6 million households) with national coverage; and iii) taking four cohorts instead of one helps to reduce cohort specific issues while working with a reduced number of cohorts allows us to more easily control for cohort and time-specific events. In total, a one percent sample of the cohorts was constructed creating a data set of 16,017 households.[8] Eight percent belongs to the cohort that entered in the first bimonthly period of 1998 (January-February), 61 percent in the fourth bimonthly period (July-August), five percent in the fifth (September-October), and 26 percent in the last bimonthly period of the year (November-December).

Oportunidades is organized around a bimonthly payment. While entry into the program depends on when *Oportunidades* enters the communities and initiates the program, beneficiaries are not required to meet program conditions immediately and therefore are not at risk of dropping out until the next (or second) period begins. Beneficiaries have the entire two-month period to meet conditions and can only be dropped out or drop out by failing to meet conditions at these discrete two-month intervals. Thus, the first time beneficiaries can be dropped out is at the end of the second period of risk and after this they can only be dropped from the program at the end of these two-month intervals. The risk of dropping out of the program at time *t*, given that the “dropout event” did not occur before time *t* – that is the hazard rate – is defined as the total number of dropouts over the risk set in a given two-month period. Since beneficiaries enter the risk set one period after they are incorporated into the program, we calculate the conditional probability distribution for dropping out from the second bimonthly period of 1998 (March-April) to the fourth bimonthly period of 2004 (August-September) which is the last period for which data is currently available. This gives up to 39 observation points in time for each household. In total, we end up with a sample of 514,972 observations for the 16,017 households. Before analyzing this data in detail, we will characterize the basic behavior of dropouts over time and provide descriptive statistics of the covariates of the model.

[FIGURE 1 HERE] [FIGURE 2 HERE]

Figure 1 shows the dropout rates over the discrete periods in question while Figure 2 is a smoothed version of the hazard function.[9] The figures show that the pace at which beneficiaries leave the program is not constant over time. Dropouts accelerate until reaching a peak in period 14 and the risk of dropping out stays relatively high until it begins to decrease after thirty bimonthly periods. The discrete hazard function shows the existence of significant peaks at

[7] Note that while there are six potential bimonthly periods per year, in 1998 new recipients only entered in four of them – January-February, July-August, September-October and November-December.

[8] For three percent of households, there was incomplete information in the corresponding ENCASEH and the household was therefore not included. There is no reason to suspect losing these observations leads to any systematic problems with the data.

[9] The smoothed version of the hazard function is created using a kernel function.

certain periods suggests that dropouts may be linked to factors other than self-selection out of the program. In particular, in evaluating the data there is some concern that dropouts in certain periods are related to changes in administrative procedures. For example, note in Figure 1 that the largest dropout occurs during the first risk period, or when *Oportunidades* administrators possibly fail to turn in all paper work and instructions in time to eligible beneficiaries. Detailed discussions with *Oportunidades* administrators noted a number of operational issues that may have affected the probability of dropping out. Since the program was launched, the procedures to monitor whether beneficiaries are meeting conditions have improved significantly. Two important changes happened during the periods in question: (i) the introduction of guidelines of operational rules (*'Reglas de Operacion')* in mid-1999 and, (ii) the introduction of a *just-in-time* monitoring system[10] in mid-2000. Additionally, there were changes in the *puntaje* to make it national in scope that implied reclassifying the eligibility status of many families, as well as changes in the payment system from cash payments to the individual to direct deposits in bank accounts set up for some families.

Each of these occurrences may influence the probability of dropping out of the program and thus need to be controlled for in the subsequent analysis. In each case, these are time-specific events; that is, they occurred at specific calendar time periods and can thus be controlled for in regression analysis with appropriate dummy variables. These variables were thus included in the data set with those described above. Specifically, two dummy variables are created to account for the introduction of the operational guidelines (dummy equals 1 after 1999.4), and changes in the monitoring system of the program (dummy equals 1 after 2000.4). These two dummies identify if there was an upward or downward shift in the hazard function after these two changes. Furthermore, we have the following calendar time-specific dummies to deal with other administrative issues: (i) implementation of guidelines (1999.4), (ii) distribution of new identification cards (*Hologramas)* (2000.3 and again in 2001.3), (iii) problems with payment withdrawals (2002.6), (iv) no delivery of debit card or no signature of *Bansefi* contracts (2003.2), and (v) correction of inclusion errors (2003.4, 2003.5 and 2003.6). Unlike the introduction of the operational guidelines and monitoring system, these were single events at a point in calendar time and are thus controlled for with dummies for the specific calendar time.

[FIGURE 3 HERE]

Figure 3 shows the survivor function, which suggests that on average approximately 0.5% of households in the program dropout every bimonthly period. Furthermore, over the 39 periods or 6.5 years nearly one out of every five participants that entered the program in 1998 has dropped out.

[FIGURE 4 HERE]

As noted previously, the principal goal of this paper is to determine whether relatively poor or rich households are leaving the program. Although this issue is examined in detail later in the paper, as an initial examination of this issue we decompose the dropout survivor function by wealth category. As noted, targeting at the household level is done through the *puntaje*, which is a wealth index based on the assets of the household. At the beginning of the program, different regional models of the index coexisted, which classified the households as "eligible" or "non-eligible" based on its relative regional position. In 2001, *Oportunidades* started to operate with a unique national model to create the *puntaje* and reclassified households accordingly. In order to

[10] This system is known as the *Sistema Integral de Información (SIIOP).*

make the *puntaje* comparable among all the 1998 cohorts and following *Oportunidades'* practice, we re-classified the households using the national *puntaje* model. Using this reclassification, Figure 4 presents the survivor functions by the top and bottom three wealth deciles. The figure shows that the richest beneficiaries (deciles 1 to 3) have steeper survivor functions than the poorest ones.

[FIGURE 5 HERE]

Along similar lines, we examine the survivor functions by marginality index. The marginality index is the index used for the geographic targeting of communities in the program and measures community remoteness and poverty. Figure 5 shows the survivor functions of the top and bottom three deciles. As can be seen from the figure, household in the richest communities (deciles 1 and 2) are leaving the program faster than the households from the poorest ones. Taken together, these findings suggest that poorer households and households in poorer communities tend to be less likely to dropout than richer households and households in richer communities thus supporting the hypothesis that conditionality is leading to wealthy households self-selecting out of the program. This is explored in greater detail below.

[TABLE 1 HERE]

Before proceeding to the detailed analysis, Table 1 presents summary statistics of the characteristics of the households in the sample prior to entering the program. The data is also divided by households that have dropped out and households that are still in the program with initial tests of difference. Results indicate that the recipients of the dropout group relative to the active group are characterized by: a higher proportion of males, older, more average years of education, a higher proportion non-indigenous, a lower proportion that are married and a higher proportion that works. Households that have dropped out of the program tend have fewer members, a lower dependency rate and less poor (as measured by the *puntaje*) on average than the households that remain active. Moreover, receiving income from a relative that does not live in the same household is more usual among households that have dropped out. Furthermore, receiving any kind of other public assistance is more likely in the group that stays in the program. At the community level, households that have dropped out on average belong to richer communities than the ones that are poorer. Finally, households that use the health provider *IMSS Solidaridad* appear to have a low level of dropouts.

4. Analyzing dropouts: the empirical approach

To evaluate the reasons beneficiary households drop out of the *Oportunidades* program, a duration model is employed. This type of model is appropriate when trying to evaluate events in which a change from one state to another occurs and the timing of this transition between states is of interest. Duration models, which is also referred to as survival analysis or event history analysis, are used to examine similar types of transitions, such as the length of time a worker remains unemployed, the time a person remains married or the survival time of a terminally ill patient, that is studied here (Greene, 2003). In our case, we are interested in determining the factors influencing both the probability of dropping out and examining the timing of dropouts. Furthermore, as noted in the previous section, there are certain administrative events that occurred at points in calendar time. A duration model allows us to examine these factors of interest while controlling for these calendar-specific administrative events.

As noted in the project description above, the *Oportunidades* program is organized around a bimonthly payment program. While entry into the program depends on when *Oportunidades* enters the communities and initiates the program, beneficiaries are not required to meet program conditions immediately and therefore are not at risk until the next period begins. Beneficiaries have the entire two-month period to meet conditions and can only be dropped out, or drop out by failing to meet conditions, at these discrete two-month intervals. As such, the appropriate model for analysis is a discrete duration model (Box-Steffensmeier & Jones, 2004). Since data is available for all beneficiary households from the onset of the program, there is no left-censoring or left-truncation of the data. However, communities were entered in a staggered pattern so that new cohorts are included in the program at different initial time periods, which implies flow sampling. All beneficiaries either drop out or remain in the program and since data is for a limited period of time the data is subject to right censoring with those observations that are right-censored being those that did not drop out of the program in the period in question. Finally, beneficiaries do not reenter the program once they have dropped out and are thus only observed for a single spell.[11]

Given the discrete nature of the data and the other characteristics mentioned above, the analysis of the data can be conducted using standard discrete dependent variable models such as the logit or probit. There are no clear reasons to choose one over the other and in this case a logit model is used.[12] The data are organized in such a way so that in each period beneficiaries are at risk they receive a zero if they did not drop out and a one if they did drop out. Beneficiaries that never drop out receive a zero in every period for which they are at risk. Dropouts are explained by both time invariant and time variant covariates. In a discrete model, duration is incorporated into the model by including a time variable in the regression. The manner in which this is included depends on assumptions about the form of the baseline hazard function; that is, the expected shape of the pattern of dropouts. If a certain form is assumed, the parameters of that form can be estimated. Alternatively, a nonparametric approach such as including dummy variables for each period of hazard is reasonable, particularly if the analysis is principally focused on explaining dropouts and not predicting the hazard function (Box-Steffensmeier & Jones, 2004). While we are primarily interested in explaining dropouts and not the hazard function, we do wish to use the function to examine differences in hazard rates for certain categories of the sample. As such, we examined both parametric and non-parametric approaches. The results are robust across specification and we focus our attention on the approach in which a polynomial is used to represent the hazard function.

5. Factors influencing drop outs

Table 2 presents the results for the analysis of dropouts based on the duration model described in the previous section. Odds ratios are reported instead of coefficients for ease of interpretation. The results indicate a number of characteristics of the beneficiary influence the odds of dropping out and we begin by looking at the characteristics of the individual beneficiaries themselves. If the recipient is male, the odds of them dropping out are significantly higher. Male recipients are less than 10% of the recipient population and usually indicate that an

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[11] There is some possibility that households reentered the program later if they reapplied in the subsequent entry round. However, *Oportunidades*' officials suggested the incidence of this appears low and should not be important in this analysis.

[12] Results for the probit model mirrored those of the logit model indicating the choice of logit is unimportant.

adult female is not in the house. Older recipients also have higher odds of dropping out although this effect appears to slightly diminish with age. This suggests that those below a certain age are more likely to drop out. As the number of years of education increases, the recipient is significantly less likely to drop out suggesting the higher educated are more likely to stay in the program. Recall that on average recipients have only 2.9 years of education and that 37% have no formal education. The result may indicate that, controlling for other factors, those with some education may see the value of education and are more likely to want to take advantage of *Oportunidades*. Beneficiaries that are indigenous – as defined by the fact they do not speak Spanish – are more likely to drop out. There is some concern that language barriers may limit the ability of households to comply with conditions so this issue is explored further below. Single-headed households are also found to have greater odds of dropping out which may indicate that such families have a harder time meeting conditions with only one primary adult in the family. Finally, those recipients who were working outside the home at the time of the initial survey are found to have greater odds of dropping out. This is most likely because the opportunity cost of time is high and they are thus unable to meet conditions as easily.

[TABLE 2 HERE]

Moving to household variables, the results indicate that households with a higher dependency ratio and greater household size have lower odds of dropping out indicating that the composition of the household influences drop outs. There is some concern that these households may be more likely to drop out because of the greater burden of conditions that require all household members to receive check-up and even more for certain children, but the results indicate this concern is unfounded. Similar to the results for recipient employment, those that received private transfers from family members (mostly remittances) are more likely to drop out. This is possibly because they have less of a need for *Oportunidades* transfers, and prefer to substitute a conditional transfer for an unconditional one. Those that were receiving public assistance from the government before *Oportunidades*, however, are less likely to drop out. Those receiving such assistance are likely to be the extreme poor and thus are expected to be less likely to drop out.

[FIGURE 6 HERE]

As discussed previously, a principal concern of this paper is determining the relationship between wealth – as measured by the *puntaje* index – and dropping out with our hypothesis being that the richest and poorest households may be most susceptible to dropping out of the program. To test this hypothesis, it is necessary to include the *puntaje* variable in a nonlinear form and for the regression linear, squared and cubed terms are included. Results presented in Table 2 support the hypotheses that wealth matters (all three variables are significant) and indicate a nonlinear relationship between dropping out and the *puntaje*. In order to see this relationship more clearly, Figure 6 graphs *puntaje* against the predicted probability of dropping out.[13] The graph indicates that the likelihood of dropping out is highest at low levels of the *puntaje* (relatively wealthier recipients) and declines at a diminishing rate as the *puntaje* increases. The results support the hypothesis that conditionality is leading to self-selection out of the program and is thus acting as a targeting mechanism. Note, however, that while there is a small increase in dropouts at the poorer end of the distribution, the level of dropouts is relatively

[13] This is calculated using the mean predicted probability of dropping out for the relevant range of values of *puntaje*.

small. Thus, it appears concerns that conditionality may be pushing out the extreme poor are unsupported by evidence.

While the *puntaje* measures individual wealth, the marginality index examines how marginal a community is and this variable is included to determine if dropouts are more likely in more or less marginal communities. The results indicate that the community level of marginality does not influence dropouts. These results hold even when nonlinear specifications are included (results not shown). Along with the aforementioned concerns, there is also some reason to be concerned that in less marginal communities recipients may be less likely to dropout since they are fewer in number and thus have less social interaction with other recipients and may have more difficulty in interacting with *Oportunidades*. To examine this hypothesis, the regression presented in Table 2 is rerun with all the presented variables as well as dummy variable to represent households with low marginality indices (from better off communities) and high marginality indices (from worse off communities). The dummies were included along with interaction terms between these dummies and the *puntaje* variables. The results (not shown) were significant for both sets of interaction terms suggesting the relationship between the *puntaje* and the probability of dropping out depends on how marginal a community is. To view the results, Figure 7 shows the predicted probability of dropping out for the range of values of the *puntaje* for households in low and high marginality communities. Examining the graph the pattern for high marginal communities is similar to those found in general (see Figure 6). For highly marginal communities, it does appear, however, that poorer households are more likely to drop out. This is potentially a source of concern and should be further explored.

[FIGURE 7 HERE]

As noted, there are two main providers in the areas covered by *Oportunidades*: (i) *Secretaria de Salud (SSA)* – the public health system of the Health Secretary of Mexico – and, (ii) *IMSS Solidaridad/Oportunidades* (IMSS) – a program managed by the Mexican Institute for Social Security that serves the rural poor not in areas covered by social security protection. It might be that beneficiaries from different providers face a different likelihood of dropping out depending on access to services and monitoring of conditionality. The results indicate that recipients using IMSS as a health care provider are much less likely to drop out than those using SSA. This could be solely because of the fact that IMSS tends to be a more stable health provider. Recent graduates from medical schools, who are deployed to these health posts for duration of less than a year, often staff SSA. This may lead to increased mistakes in monitoring of conditions and of reporting failure to meet conditions. It may also be that IMSS staff get to know recipients better and are thus more likely to follow through to ensure recipients meet conditions. In either event, this is problematic in that it suggest the health care provider, who is required to report on whether conditions are met, has a significant influence in whether households dropout. This is explored more fully below.

The next set of variables control for changes in administration of the program. In some cases, these administrative factors were designed to improve the monitoring of the program and in others they are administrative difficulties. In general, the expectation is that they will increase the odds of dropping out since they are improvements in the monitoring of conditions of the program. With the exception of the initial introduction of guidelines in 1999, all of the other administrative factors increased the odds of dropping out. The results indicate that administration of programs can have a substantial influence on whether recipients stay in the program. This is only problematic if these administrative changes result increased inefficiencies.

[FIGURE 8 HERE]

Finally, the results on the time variables are considered. As noted previously, a polynomial is used for the hazard function and the results do not vary dramatically across specification of the hazard. Figure 8 shows the survival function controlling for the other factors that influence dropping out. The graph clearly shows a steady decline in dropouts over time and mirrors those shown in Figure 3. On average there is approximately a 0.5% rate of dropout for each period or around 3% per year which leads to a 20% in dropouts over the period in question.

[FIGURE 9 HERE]

The results in Table 2 indicated that whether a household is indigenous increases the odds of dropping out. To examine this more carefully, an additional specification was run in which the hazard function was interacted with the indigenous dummy variable to test whether dropouts vary across time between the two populations. The results (not shown) indicate that there is a significant difference in dropouts over time for the indigenous population. This can be seen in Figure 9. Indigenous people are dropping out at a slightly faster rate than the non-indigenous population. At the end of the period in question, 3-4 % more indigenous people had dropped out compared to non-indigenous.

[FIGURE 10 HERE]

Lastly, Table 2 indicates a difference in dropouts across health care provider. Following a similar procedure for the indigenous variable, the role of the health care provider in dropouts over time is examined. The results (not shown) again indicate a strong relationship suggesting a different rate of dropouts for those using IMSS versus SSA. Figure 10 shows the difference in dropouts over time across the health care providers. The results are rather dramatic with a greater rate of dropouts and a larger number for SSA versus IMSS. Nearly 25% of SSA recipients are expected to dropout over the 39 periods versus less than 10% for IMSS. It may be case that this variable is capturing something else about the households that receive health care through each provider so it should be viewed with some caution. However, the results are dramatic enough to strongly suggest examining in details the reasons for this occurring.

6. Conclusions and policy implications

In this paper, administrative data from Mexico´s *Oportunidades* program are analyzed to shed light on the following policy questions: i) could conditionality increase the targeting efficiency of the programs by acting as a disincentive to remain in the program indefinitely?; ii) are the poorest being overburden by program requirements?; iii) what characteristics of the program are increasing the risks of the poorest leaving the safety net?

Conditionality in cash transfer programs have been used for targeting resources to the poor by inducing self-selection into the program, so that beneficiaries of the targeted population participate in the program and others opt-out (Das, Do & Ozler, 2005). Workfare programs are a typical example, where wages paid are set below market minimum wage values for inferior goods (such as hardship in manual labor). While *Oportunidades* relies on proxy means tests to screen people into the program, results from this analysis indicate that conditionality seems to have an effect over the choice of opting out of the program and thus increasing the program’s overall targeting performance by screening out the non-poor. As such it satisfies two important criteria, that beneficiaries are willing to participate in the program and that the non-eligible population finds that the conditions places greater costs than the benefits derived from remaining in the program (Ravallion, 2003). Different measures of relative welfare, such as the proxy means score, high dependency families, receiving remittances, working outside the home, were all negatively correlated to the probability of dropping out of the program.

Conversely, the cost of the program's conditionality does not seem to be overly burdensome for the extreme poor as they do not appear to systematically dropout of the program. However, we found specific instances of concern where the program may be dropping out the extreme poor and thus increasing the vulnerability of these households and reducing their human capital accumulation. The two specific instances are in the case of indigenous populations and the case of the extreme poor in low marginality communities, where there is likely to be greater inequality. A further equity concern relates to the increasing odds of dropping out due to operational changes. If such changes increase the efficiency of monitoring conditions, they may improve the value of conditionality in screening out wealthier households If, however, these reflect operational inadequacies, they are of concern in that they are not correlated to any specific welfare level and can "shock" any number of extremely vulnerable communities.

The policy implications of the first finding argues for the inclusion of conditionality in program design in order to induce that beneficiary families that may have erroneously been included or have change their welfare status over time self-select out of the program. One must stress that this relationship should hold for a program in which conditionality is closely monitored and enforced such as the *Oportunidades* program. Galasso & Ravallion (2003) find that Argentina´s Plan Jefes y Jefas included a 20-hour community work requirement to act as a screening device of individuals who were already employed, and that the condition was only partially successful at screening the non-participation of employed individuals. They conclude that the requirement of 20 hours was not expensive enough for individuals employed in the informal sector to opt out, or to the opportunity cost of losing 20 hours of leisure. It could also be the case that if the 20-hour requirement was not closely monitored or enforced which de facto could have transformed the program in an un-conditional transfer scheme.

Secondly, there is some concern that in less marginal communities the probability of dropping out is slightly higher for the extreme poor. This finding combined with a reduced probability for indigenous groups of dropping out should be of careful review from program operators. In the last few years, *Oportunidades* has been actively engaged in establishing reentry mechanisms for these sorts of cases. Much of the fieldwork during the past two years in rural areas has been concentrated in resurveying communities and incorporating families that may have dropped out but are still highly vulnerable.

The third and related policy conclusion is that administrative "shocks", or changes of certain operational processes, have had an enormous impact on the probability that families faced of being taken off the roster and thus losing eligibility. For example, the ability of the program to deliver and renew the beneficiaries' identification cards has resulted in some instances in entire groups being dropout of the program. The magnitude of the shock is equivalent to covariate shock (droughts, floods, etc) that any of these rural communities may face and thus we conclude that even though the program has generated higher degrees of protection against various shocks that families faced[14], it has generated some of them itself by operational mishaps. In the last years, the program has reduced dramatically these types of shocks on the roster implementing

[14] Skoufias & Quisumbing (2005)

decentralized monitoring systems to prevent these occurrences. However, the cyclicality of misreporting on health conditionality, particularly for those families attending state secretariat services is of great concern.

References

Box-Steffensmeier, J. & Jones, B. (2004). *Event History Modeling: A Guide for Social Scientists*. Cambridge: Cambridge University Press.

Cornia, G. & Stewart F. (1995). Chapter 13: Two Errors of Targeting. In Van de Walle, D. & K. Nead (Eds.), *Public Spending and the Poor: Theory and Evidence*. Baltimore: Johns Hopkins University Press

Coady, D., & Parker S. (2004) An Evaluation of Targeting of the *Oportunidades* Program in Urban Areas. Mimeo. Instituto Nacional de Salud Pública de México.

Davis, B., Handa, S., Stampini, M. & Winters, P. (2006). Does it matter whether conditional cash transfers are given to women or men? Evidence from the PROGRESA and PROCAMPO programs in rural Mexico. In Alvarez, C. & F. Regalia (Eds.), *Safety Nets in Latin America: Tales from the Field. IDB's experience in program financing and evaluation*. Washington, DC: Inter-American Development Bank.

Das, J., Do, Q. & Özler, B. (2005). Reassessing conditional cash transfer programs. *The World Bank Research Observer, 20*(1), 57-80.

Galasso, E. & Ravallion, M. (2003). Social Protection in a Crisis: Argentina’s Plan Jefes y Jefas. *Policy, Research Working Paper No. WPS 3165*. Washington, DC: The World Bank.

Greene, W. (2003). *Econometric Analysis: Fifth Edition*. Upper Saddle River, NJ: Pearson Education.

Jalan, J. & Ravallion, M. (2003). Estimating the Benefit Incidence of an Antipoverty Program by Propensity-Score Matching. *Journal of Business and Economic Statistics*, *21*(1), 19-30

Maluccio J. & Flores R. (2004). Impact Evaluation of a Conditional Cash Transfer Program: The Nicaraguan Red de Protección Social. *FCND Discussion Paper No. 184*. Washington, DC: IFPRI.

Skoufias, E. (2005). PROGRESA and its impacts on the welfare of rural households in Mexico. *IFPRI Research Report 139*. Washington, DC: IFPRI.

Skoufias, E., & Quisumbing A. (2005) Consumption insurance and vulnerability to poverty: A synthesis of the evidence from Bangladesh, Ethiopia, Mali, Mexico, and Russia. *European Journal of Development Research 17*(1), 24-58 .

Skoufias E., Davis B. & de la Vega S. (1999) Suplemento al reporte definitivo: Evaluación de la selección de hogares beneficiados por el Programa de Educación, Salud y Alimentación (PROGRESA) de México. Washington, DC: IFPRI.

Figure 1: Discrete hazard function

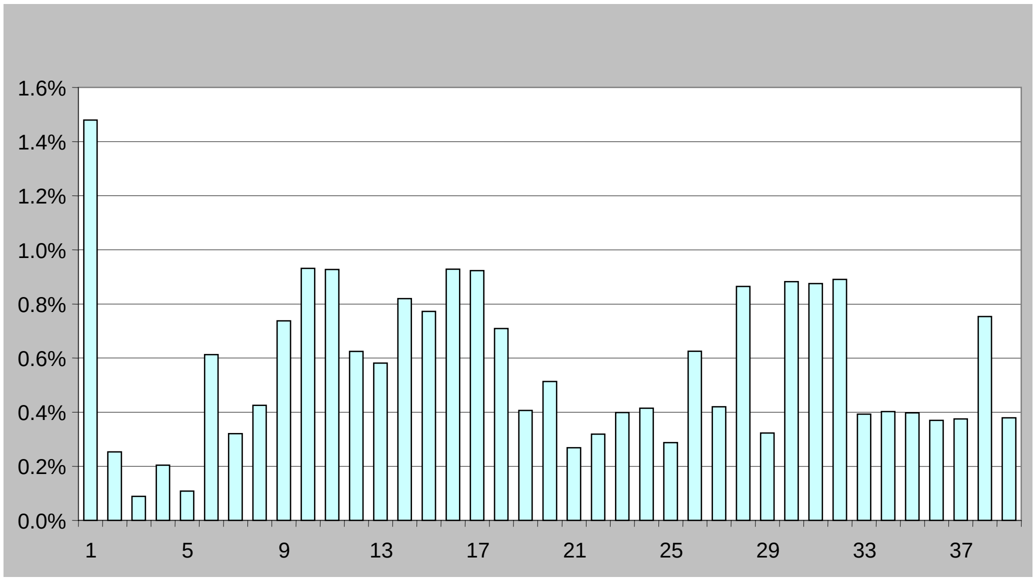

Figure 2: Smoothed hazard function

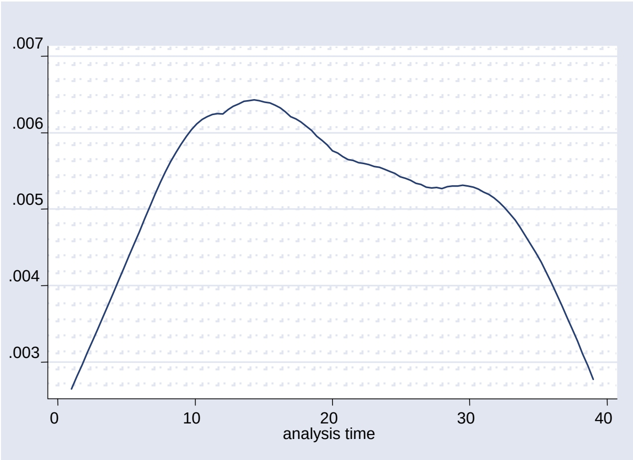

Figure 3: Survivor function

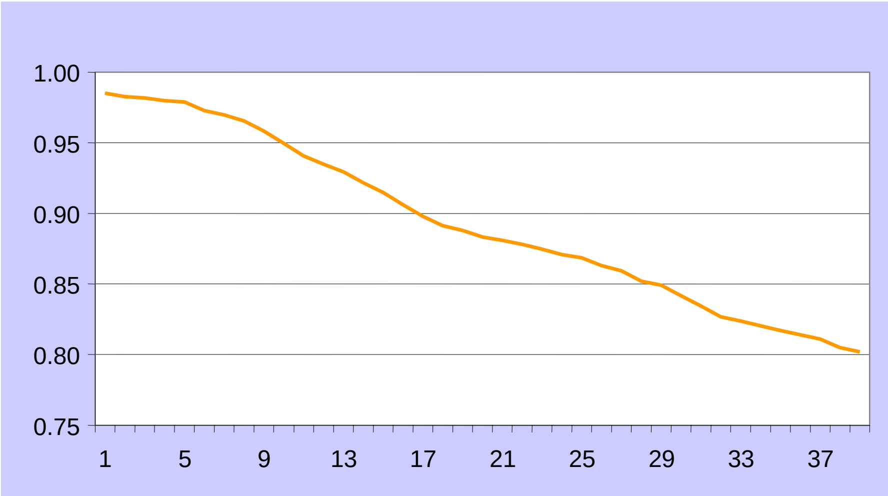

Figure 4. Survivor function by *puntaje*

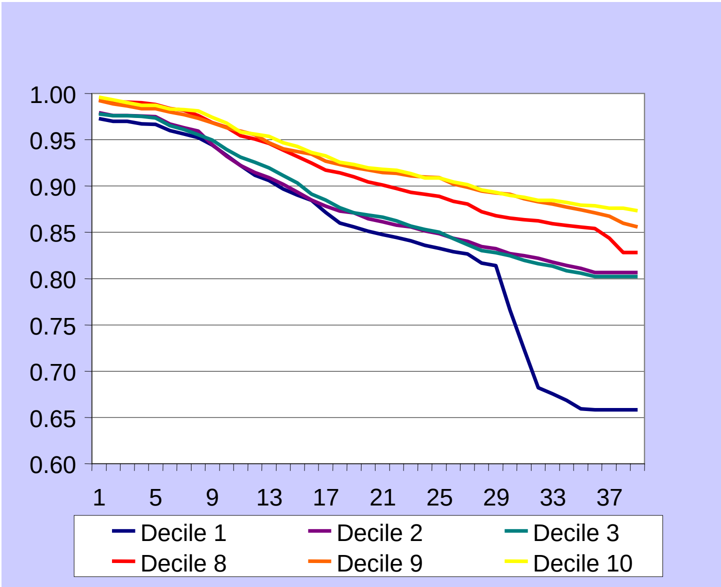

Figure 5. Survivor function by community marginality index

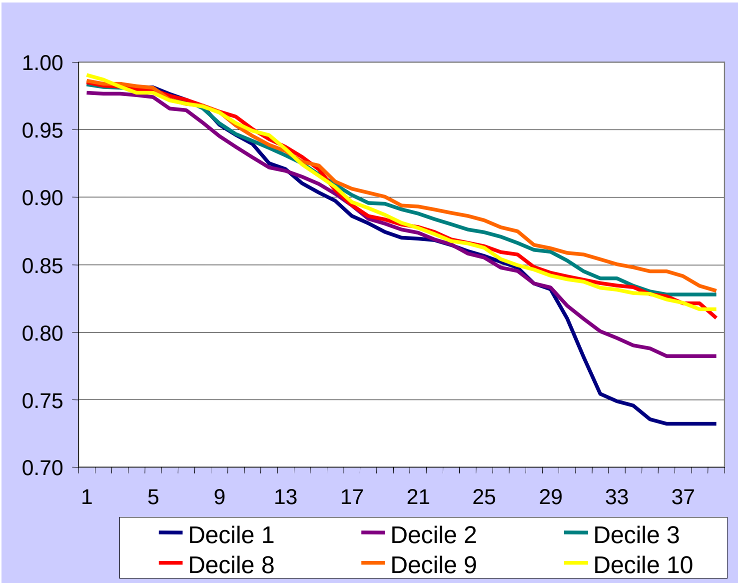

Table 1: Household charactersitics

	Total	Active	Dropout
Characteristics of recipient			
Male recipient	9.5%	8.8%	12.4%
Age	41	41	41
Years of education	2.9	2.8	3.2
Indigenous	7%	7%	6%
Single	35%	33%	43%
Works outside home	21%	20%	24%
Household characteristics			
Dependency ratio	1.2	1.3	1
Number of people	5.4	5.6	4.6
Public assistance	7.9%	8.2%	7.1%
Transfers from family member	7.1%	6.6%	9.8%
Puntaje	2.5	2.6	2.1
Community characteristics			
Index of marginality	-0.04	-0.03	-0.11
Health provider			
IMSS Solidaridad	26%	29%	10%
Household observations	16,017	13,051	2,966

Table 2: Duration model of dropouts

	Odds Ratio	z-stat
Characteristics of recipient		
Male recipient	1.14	2.26
Age	0.90	-25.17
Age squared	1.00	22.11
Years of education	0.97	-4.11
Indigenous	1.22	2.36
Single	1.16	3.50
Works outside home	1.18	3.44
Household characteristics		
Dependency ratio	0.89	-3.39
Number of people	0.95	-3.84
Public assistance	0.83	-2.34
Transfers from family member	1.15	2.01
Puntaje	0.42	-14.81
Puntaje squared	1.24	6.79
Puntaje cubed	0.99	-3.23
Community characteristics		
Index of marginality	0.98	-0.56
Health provider		
IMSS Solidaridad	0.24	-22.40
Administrative factors		
Operation guidelines in effect (1999.4 onward)	7.48	18.18
Just-in-time monitoring system in effect (2000.4 onward)	4.07	12.03
Implementation of guidelines (1999.4)	0.62	-3.96
Distribution of identity cards (2003.3)	6.57	18.03
Distribution of identity cards (2001.3)	2.66	11.50
Problem with payment withdrawals (2002.6)	1.54	3.78
No delivery of debit card or no *Bansafi* signature (2003.2)	2.24	8.31
Correction of inclusion errors (2003.4-2003.6)	2.08	10.34
Hazard function		
Time	0.53	-18.35
Time squared	1.03	15.20
Time cubed	1.00	-12.48

No. of observations 514,972
Notes: Results for state fixed effects and date of entry fixed effects are included in the regression but not presented in the results

Figure 6. The relationship between wealth (*puntaje*) and dropping out

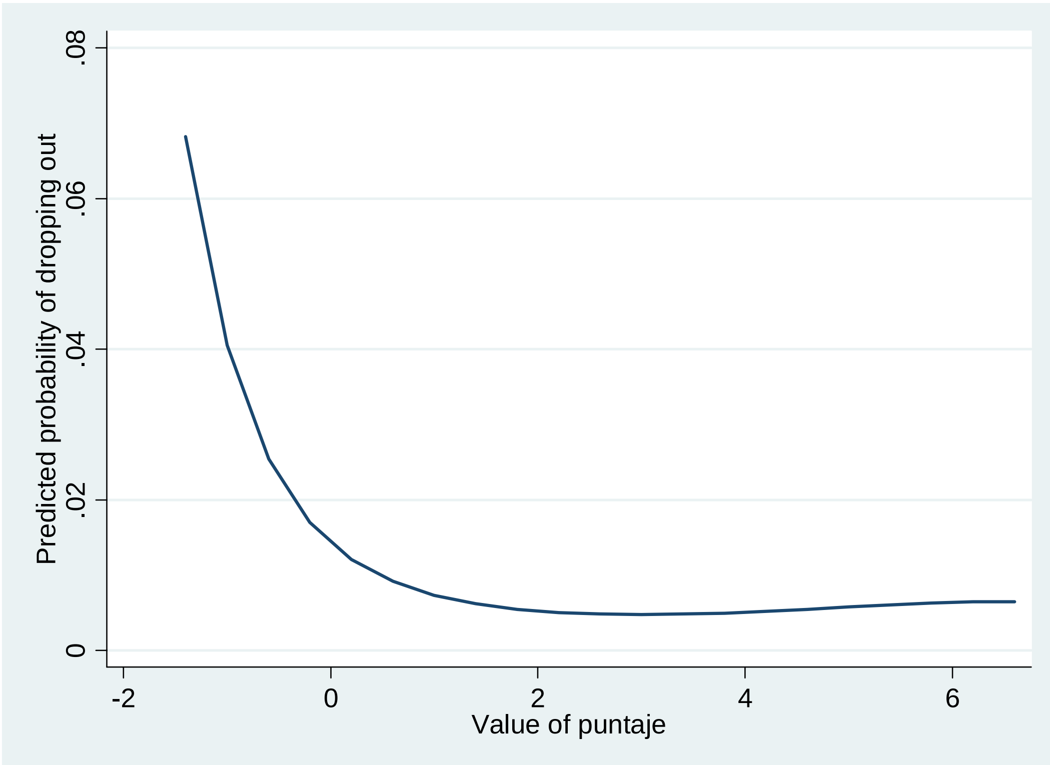

Figure 7. The relationship between wealth (*puntaje*) and dropping out in low and high marginal communities

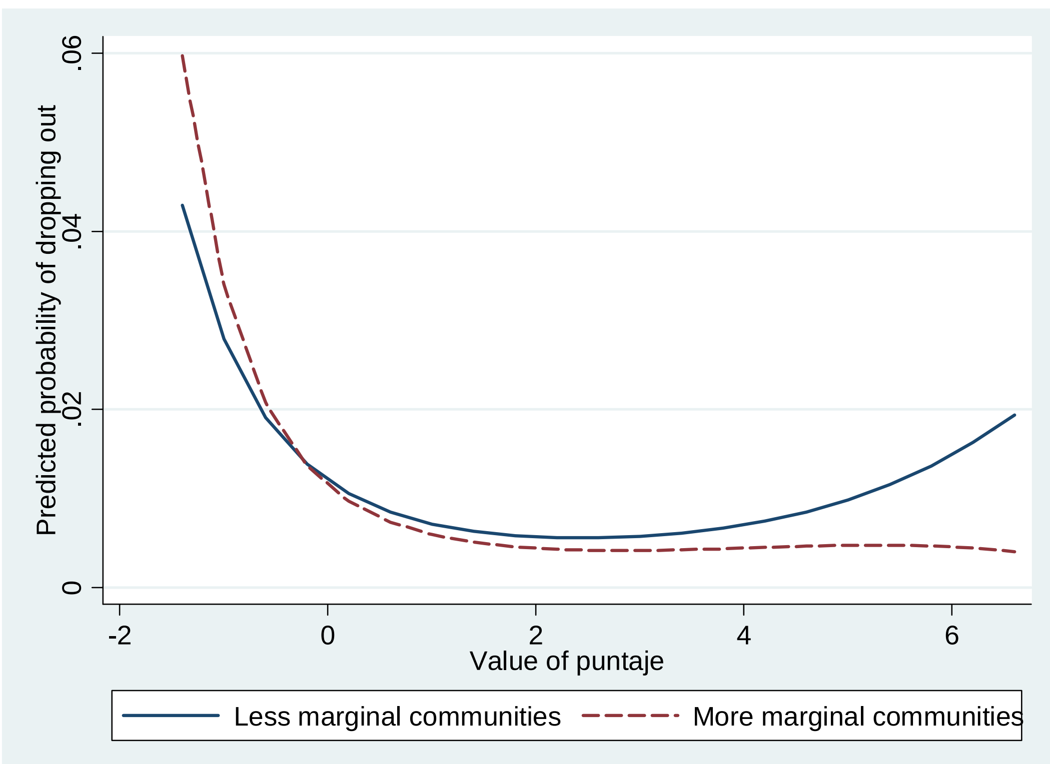

Figure 8. Survival controlling for other factors

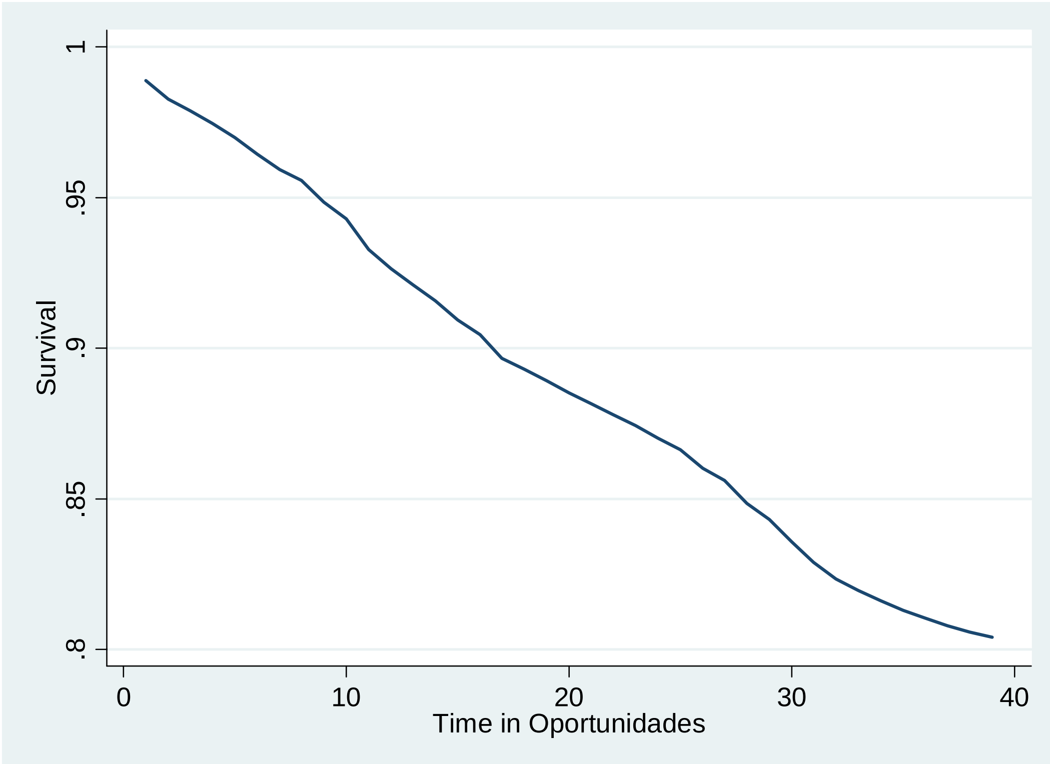

Figure 9. Survival by indigenous and non-indigenous

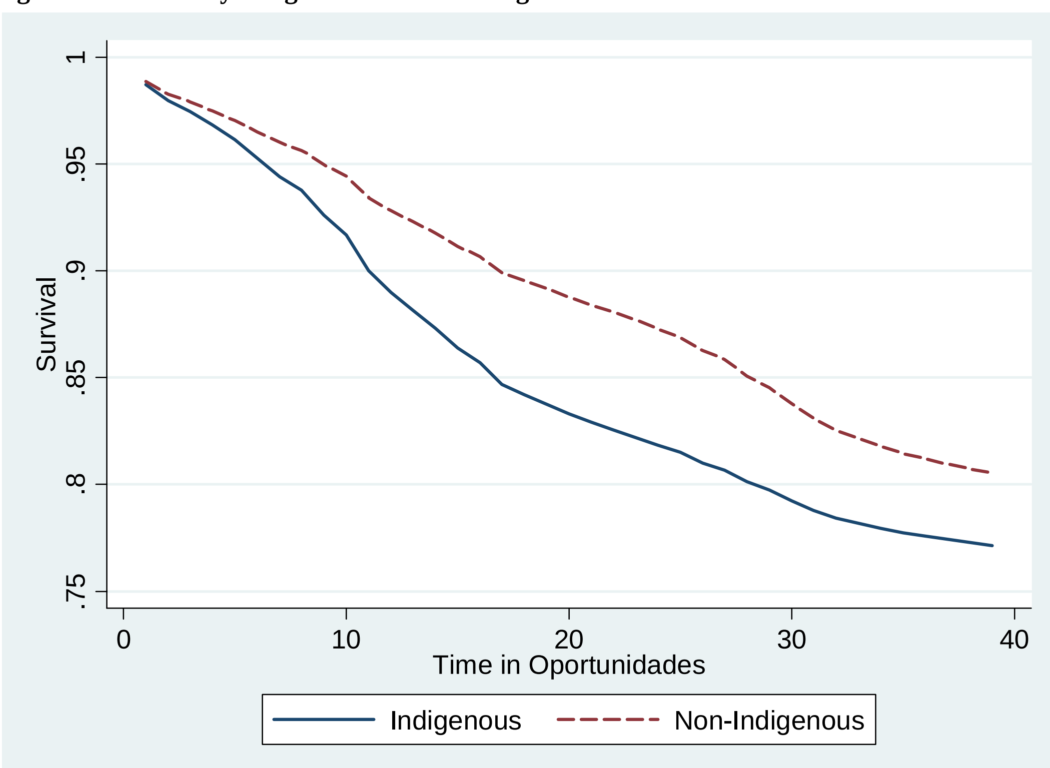

Figure 10. Survival by health provider