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THE EFFECT OF INCOME REDISTRIBUTION ON POVERTY REDUCTION IN BOLIVIA

Darwin Ugarte Ontiveros and Osmar Bolivar Rosales*

ABSTRACT

This document evaluates the impact of the conditional cash transfer programs (CCT), Juancito Pinto, Juana Azurduy and the Dignity Rent, on poverty reduction in Bolivia. The study is based on information from the 2013 Household Survey and the application of impact evaluation techniques. Results suggest that the implementation of these programs reduced the incidence of moderate poverty in Bolivia in 8.2pp and extreme poverty in 9.6pp, for the group which received these transfers.

JEL Classification: I38, D04, C21
Key Words: Social Conditional Cash Transfer Program, Impact Evaluation, Poverty

* Researchers of the Analysis and Fiscal Studies Unit of the Ministry of Economy and Public Finances. The content of the present document is sole responsibility of the authors and does not compromise the opinion of the institution to which they belong. Send all comments to: osmar.jsmpf@gmail.com or darwinismo@hotmail.com

I. INTRODUCTION

Historically Bolivia has been characterized for having high levels of poverty. Data from the 2002 National Population and Housing Census indicate that 65% of the population lived in poverty, and almost 40% in extreme poverty in that year. These characteristics highlighted the country as one of the poorest countries in Latin America; see World Bank (2006) for a description of the poverty characteristics in Bolivia during that years. Currently, data form the 2013 Household Survey indicate that the ratio of the population in extreme poverty was 18.8% whereas moderate poverty was reduced to 39.1%. This pattern of poverty reduction allowed to Bolivia, meet the first one of the Millennium Development Goals (MDG): to reduce extreme poverty to a 24.1% by 2015, in 2011, four years earlier than the established term.[1]

These results can be understood as the consequence of the social policies implemented in recent years in the country, being the most important the conditional cash transfer programs (CCT), namely, the Juancito Pinto program, the Juana Azurduy program and the Dignity Rent. The Juancito Pinto program consists of a single annual payment of Bs.200 to all elementary and high school students who attended at least 80 percent of the classes. The Juana Azurduy program is an economic incentive to pregnant mothers of Bs.1820 paid in installments, which encourages the use of maternal and infant health services along the pre and postnatal cycles. The Dignity Rent is a non-contributory lifetime pension to the population older than 60 years with monthly payments of Bs.250 for no rentiers and Bs.200 for rentiers.

These policies were developed in the framework of the Economic Social Communitarian Productive Model and the new role it assigns to the State in the economy since 2006.[2] The new view of economic policy sustains that the State must have the ability to generate economic surplus and its redistribution to the most vulnerable sectors. Namely, it must avoid the concentration of income, must redistribute and thus seek the participation of the excluded economic agents. Moreover, note that poverty decline is a concern of the State established in the Political Constitution of the Plurinational State of Bolivia.[3]

The objective of this work is to evaluate the impact of the social policy in Bolivia, estimating the impact of the income redistribution policies (Juancito Pinto Bonus program, Juana Azurduy Bonus program and Dignity Rent), on poverty decease. In order to accomplish this, information from the 2013 Household Survey was used and impact evaluation technics were applied. The results suggest that the implementation of these programs reduced the incidence of moderate poverty in 8.2pp and in 9.6pp the extreme poverty in Bolivia, for the group which received these transfers.

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[1] In 2000, the 189 member countries of the United Nations agreed to accomplish by 2015 certain goals centered on a common program: approach the poverty problem in a multidimensional way, these goals were called Millennium Development Goals, MDG

[2] A review of the social policy evolution in Bolivia is found in Monterrey (2013).

[3] The Article 316, number 7 of the Political Constitution of the State, 2009, establishes that part of the Estate's functions in the economy is to eradicate poverty in its multiple dimensions.

An explanation for the results obtained in this document can be found in recent literature which emphasizes the externalities that emerge from redistribution programs; therefore, for example, there are works which suggest the impact of social transfers on households recipients' economic growth. The mechanism is the impact of social transfers on productive ability of the beneficiaries in terms of human capital, the accumulation of physical and financial assets, and job offer; see Barrientos (2011) for a review. Similarly, Sadoulet et.al. (2001) show that social transfer programs have multiplier effects on income as they are regularly inverted and in this way they become a new source of income for the future. Davies and Davey (2008) show the multiplier effect of social cash transfers on the local economy taking as study case the Dowa Emergency Cash Transfer (DECT) in Malawi. Moreover, in Asian countries there is evidence suggesting the effects of transfer programs on domestic demand (Asian Development Bank Institute, 2010). Therefore, while the Juancito Pinto and Juana Azurduy programs have goals related to education and health, respectively, the money obtained becomes disposable income and as such it can be used to satisfy the economic needs.

On the other hand, during last decade in developing countries different types of social transfer programs intended to reduce poverty have been implemented, and there is a wide literature that examines their effectiveness, see Fiszbein et. at. (2009), and Villattoro (2005) for a review. In general, the results of these evaluations suggest that these programs have a great potential to reduce poverty and vulnerability in developing countries. The mechanism of transmission is disposable income, as these transfers increase the spending capacity and allow the access to goods and services that improve the beneficiaries' life conditions. In the same vein, other branch of the literature discusses the benefits of conditioning the social programs, Rawlings and Rubio (2005) and Barrera-Osio et. al. (2011) among others, show that money transfers are more effective when they are conditioned to some action. Coady et. al. (2004) in turn suggest the need to focus these programs on the poorest to make them more effective.

In Bolivia there are few studies which have rigorously analyzed the effect of social programs, Escobar et.al. (2013) using a non-experimental design and a model of 9.158 people and 2.748 households, analyzed the impact of Dignity Rent on poverty, the study concludes that this program contributed to diminish the incidence of poverty in 13.5pp for those households with older adults. Yañes (2012) uses ex-ante impact evaluation techniques and through microsimulations, using the 2005 Household Survey, suggests that the Juancito Pinto program has a positive impact on reducing schooling drop-out, on the decrease of the indigence levels and on the revenue distribution (especially in the rural sector). Hernani (2013) suggests that the Juancito Pinto program has succeeded in increasing school attendance only for children between 6 and 8 years old, particularly girls. Similar results were recently obtained by Aguilar (2014).

This document is structured as follows: in the following section the social programs of interest and the evolution of the poverty in Bolivia are characterized, the third section describes the methodology used to analyze the effects of social transfers on poverty, the fourth section analyzes the results and the fifth section concludes.

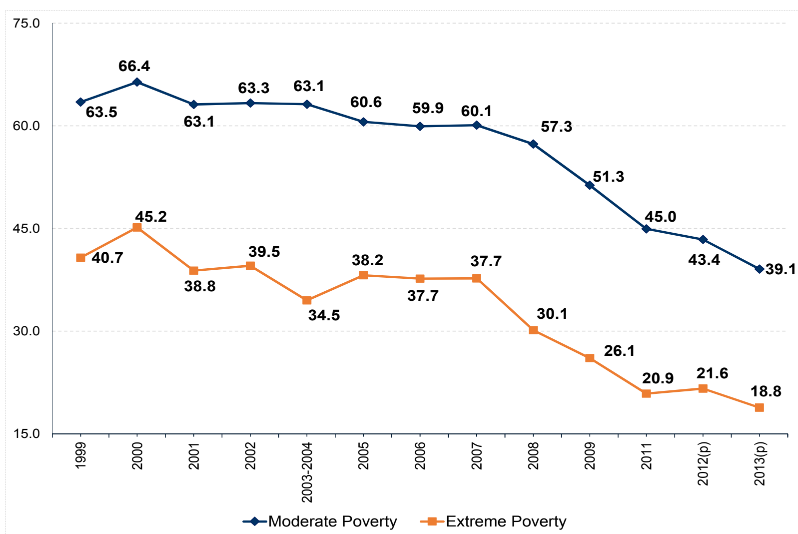
II. POVERTY IN BOLIVIA AND THE REDISTRIBUTION PROGRAMS

a. Poverty in Bolivia

Last two decades display different perspectives in terms of poverty in Bolivia, at the beginning of the 21st century, the country was characterized by high poverty levels and was one of the most unequal in income distribution in Latin America. In 2006, Bolivia started historic changes which significantly modified the economic and social characteristics of the country, so in 2010 Bolivia became a middle-income country, it is currently in a decided process of social gaps reduction, and in 2011 achieved the Millennium Development Goals of poverty reduction, four years before the established deadline.

As it can be observed in Graph 1, in recent years the poverty and indigence indicators presented a decreasing tendency, moderate poverty incidence diminished from 63.6% in 1999 to 39.1% in 2013 (24.1pp), similarly, extreme poverty decreased from 40.7% in 1999 to 18.8% in 2013 (21.9pp), that is, extreme poverty fell to more than half of its initial value.

Graph 1: Moderate and Extreme Poverty in Bolivia 1999-2013(p)
(Percentage)



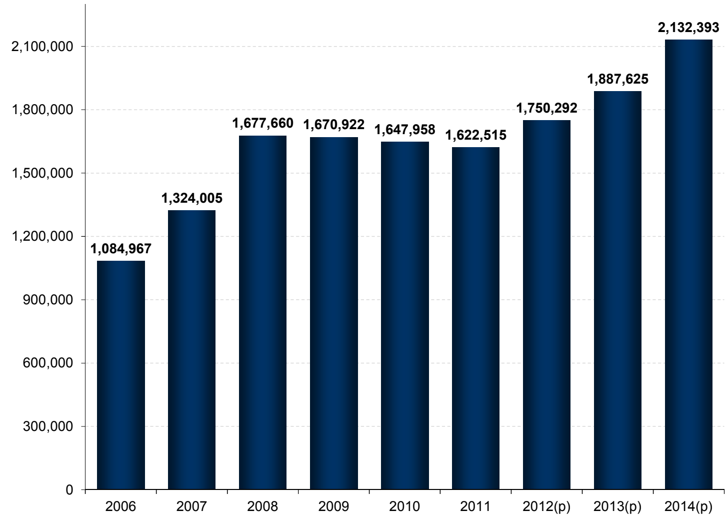
(p) Preliminary
Source: Ministry of Economy and Public Finances based on data from the National Institute of Statistic

It is important to highlight that the decrease of extreme poverty has accelerated since 2006. Between 1999 and 2005, moderate poverty declined only in 2.9pp (from 63.5% to 60.6%) whereas between 2006 and 2013 it reduced 20.9pp (from 59.9% to 39.1%). Similarly, extreme poverty, between 1999 and 2005 decreased in 2.6pp while in the period of 2006-2013 it diminished by 18.9pp. These figures reveal an important break in social policy effectiveness in Bolivia, same that is correlated, among other measures, with the implementation of the three redistribution conditional programs of interest: Juancito Pinto, Juana Azurdy and Dignity Rent.

b. Three redistribution programs

The Juancito Pinto program is a conditional cash transfer program established in October 26th, 2006 by the Supreme Decree N° 28899, with the purpose of promoting enrollment, permanence and culmination of the schooling year in the student population. This bonus consists of a single annual payment of Bs.200 to all elementary level and high school students who attended at least 80 percent of their classes. The coverage benefit of this program has been expanding progressively since 2006. In its beginning this transfer was directed to students from first to fifth elementary grades and currently it covers all primary and secondary students from public schools and the so-called agreement schools. As it can be appreciated in Graph 2, the number of recipients of this program has increased exponentially over time, in 2006 around one million students benefitted from the program, while in 2014, it is estimated that two million students were benefitted. At the same time, it is necessary to note that the financing sources for the payment of this program come exclusively from nationalized enterprises.

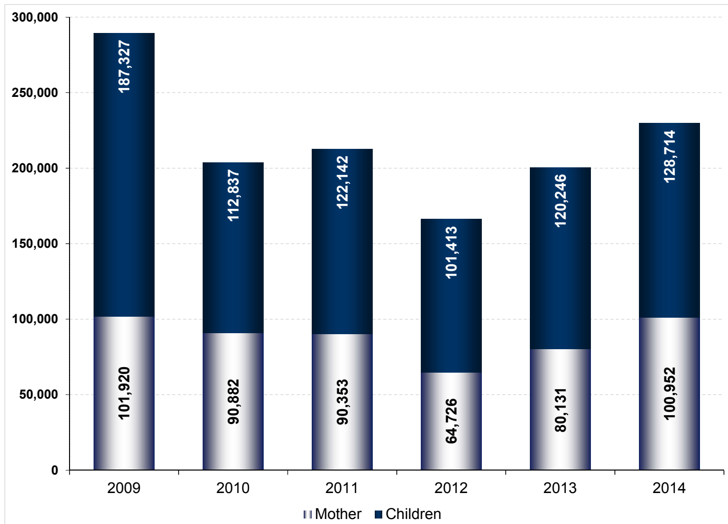
Graph 2: Recipients of the Juancito Pinto program, 2006 – 2014(p)
(Number of beneficiaries)



(p) Preliminary
Source: Created by Ministry of Economy and Public Finances based on data from Ministry of Education

The Juana Azurduy program, established by Supreme Decree N° 066 of April 3th, 2009, is a social program which has the goal to better the health and nutrition of pregnant women and children younger than two years of age. This bonus is an economic incentive that promotes the use of the maternity and infant health care services by mothers as follows: Bs.50 for each one of the four prenatal care visits (Bs.200 total), Bs.120 for assisted delivery certified by health personnel, Bs.125 for each one of the 12 post-delivery medical visits every two months (Bs.1500 total from birth to two years of age). In the entire process the amount received after 33 months is Bs.1.820, which benefits annually around 200 thousand people on average (see Graph 3). The funding resources for this program come, among other sources, from the investment of the international reserves profits.

Graph 3: Recipients of the Juana Azurduy program, 2009 – 2014(p)
(Number of recipients)

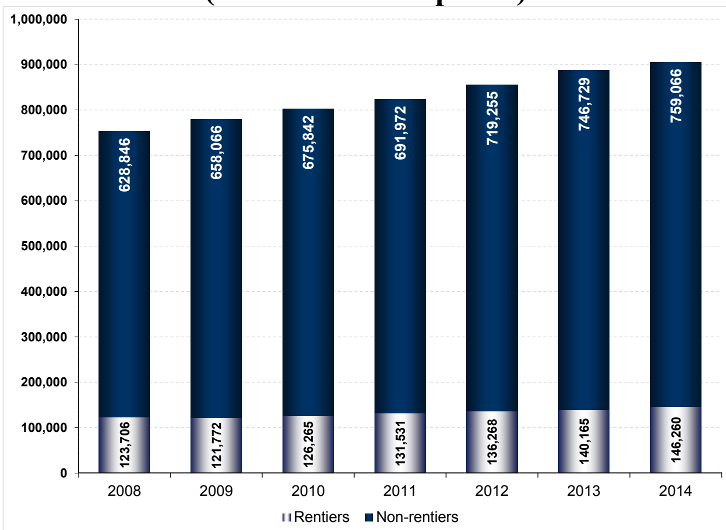


(p) Preliminary
Source: Ministry of Economy and Public Finances based on data from Ministry of Education

The Dignity Rent program, established on November 28, 2007, by Law N° 3791, is a non-contributory lifetime payment intended to benefit all population older than 60 years old. The payment is effective monthly for an amount of Bs.250 for no rentiers and Bs.200 for rentiers (people who receive a retirement income). Annually the accumulated payment is equivalent to Bs.3000 and Bs.2400, respectively. Up to 2014 this program benefitted 1,091,966 elder adults, with a paid sum of Bs.13,337 million. Graph 4 shows that the number of recipients per year is close to one million of elder adults. On the other hand, it can be mentioned that the main funding source of these transfers are the Direct Hydrocarbons Tax revenues (IDH in spanish).[4]

[4] Following Escobar et.al. (2013), the Dignity Rent is covered by the Universal Old Age Pension Fund (UOAP) whose funding sources are: i) 30% from the Direct Tax of Hydrocarbons, ii) dividends from the capitalized enterprises and iii) returns of the UOAP equity investments, which were equivalent to 1.9% of the GDP during 2012.

Graph 4: Dignity Rent beneficiaries, 2008 – 2014(p)
(Numbers of recipients)



(p) Preliminary
Source: Created by Ministry of Economy based on data from the Audit and Regulation of Pensions and Insurance Authority

III. METHODOLOGIC STRATEGY:

a. The impact evaluation problem

In order to calculate the impact of the conditional cash transfer programs on poverty reduction in Bolivia, two impact evaluation techniques were used: propensity score matching and instrumental variables. The "ideal" method for analyzing the impact of social programs, randomized experiments, requires a data generation process (sample design, and the design of the experiment, etc.). In a scenario of absence of resources to implement these strategies, the impact evaluation literature offers different alternatives, all of them based on different assumptions. For the purposes of this research, in the framework of the available information, the 2013 Household Survey: the suitable methodological strategies are the use of the matching techniques and the instrumental variables. However, to trust these calculations, it is necessary to adequately evaluate the assumptions behind these techniques. Which is done in section IV. Note that other strategies as discontinuous regression or the difference-in-difference method do not apply for the characteristics of the data.

In impact evaluation, the objective is to identify the cause-effect relationship between some implemented program and the outcomes obtained. The fundamental problem in the evaluation of these programs arises from the fact that it is not possible to observe both conditions at the same time for the same observation, that is, the situation in the case of participation and in the case of no participation in the program (in this study: having received a cash transfer or not); so one of the status is counterfactual. Therefore, it is necessary to define, in addition to the sample of participants which received the intervention (treatment group) another sample for comparison purposes (control group). It means that it is necessary to define an identification strategy which can generate adequate counterfactuals, in the framework of experimental information absence.

During last decades, there have been notable advances in the econometric analysis of causal effects; for a review of the various methods to estimate the average impact of a binary treatment, see Imbens and Wooldrige (2009). To understand the impact evaluation problem and the way in which the techniques used in this work deal with it, hereafter there is a description of the traditional approach of potential outcome developed by Rubin (1974). In this approach each observation $i = 1 \ldots n$ has two potential outcomes (Y_t°, Y_t^1) for a treatment. Y_t^1 is the result if the observation i participates in the program (belongs to the treatment group), and Y_t°, is the result if observation i does not participate in the program (belongs to the control group); in the framework of this study, it means to receive a social cash transfer or not. Note that each observation belongs to only one group: $T_i = 0$ if the observation belongs to the control group and $T_i = 1$ if the observation belongs to the treatment group. At the same time, each observation has a vector of characteristics X_i which is not affected by the treatment (covariates, pre-treatment or exogenous variables). Thus, for each observation there is the set: ($Y_i; T_i \in \{0,1\}; X_i$), where Y_i is the realized outcome: $Y_i = T_i Y_i^1 + (1 - T_i) Y_i^0$. In this framework, the average treatment effect (ATT) on the treated will be: $\tau = E[Y_i^1 - Y_i^0 \mid X_i, T_i = 1]$.

b. The matching method

As stated above, unfortunately it is not possible to observe both results, (Y_t°, Y_t^1) for each observation. Therefore, to estimate the average treatment effect, it is necessary to estimate the unobserved potential outcome for each sample observation. The simple difference between the average outcome in the treatment and control group would not identify the treatment effect because this difference may be contaminated by the effects of some variables which are correlated with the treatment, T_i, as well as the potential outcomes, Y_t°, Y_t^1. The presence of confounder factors could bias the estimated effect.

A branch of literature has developed statistic techniques to estimate the treatment effect under the assumption that by comparing treatment and control groups, considering observable differences, the bias in the comparisons between both groups are eliminated. Assumption denominated as of ignorability, selection-on-observables or conditional-independence, see Imbens (2004) for a discussion. Under this assumption, matching methods have become a valuable tool for the evaluation of treatments in observational studies; see Smith and Todd (2005) and Dehejia (2005). These methods seek to compare the situation of each participant with those individuals who are similar in their set of attributes, that is, the method seeks for each observation other sample observations whose covariates are similar but were not exposed to the same treatment group. To assure that the matching estimators consistently identify and estimate the treatment effect, the following assumptions are considered: (i) the assignment to the treatment group is independent to the outcomes conditional to the covariates. $(Y_i^0, Y_i^1) \perp T_i \mid X_i$, usually referred to as selection-on-observables or conditional-independence; and (ii) the assignment probability is limited between zero and one, $\varsigma < P(X_i) \equiv P(T_i = 1 | X_i) < 1 - \varsigma$, for some $\varsigma > 0$, also known as the overlap assumption; for a discussion about these assumptions see Imbens (2004).

As mentioned before, matching estimators replace the non-observed potential outcome using the average outcomes of observations with similar values in the covariates. However, when there are too many covariates it is not practical to match directly over them due to the denominated course of dimensionality. Thus, it is necessary to reduce the multiple covariates in a single measure, one metric $m(X_i)$, an scalar which measures the closeness or similitude of two observations. This metric, following Rosenbaum and Rubio (1983), is a function of the observed covariates in a way that the conditional distribution of X_i conditional on $m(X_i)$ is the same for both treatment groups. The most well-known metric in the literature is the Mahalanobis distance, $D(X_i) \equiv \|X\|_S = (X'SX)^{1/2}$, which is the norm of the covariate's vector, the positive matrix S corresponding to the inverse of the variance-covariance matrix. Another metric is the Propensity Score, $P(X_i) \equiv P(T_i = 1 | X_i)$, which is the predicted probability that $T_i = 1$ given the covariates X_i. So, conditioning on the covariates $D(X_i)$, or conditioning on the Propensity Score, $P(X_i)$, will make sure that the distribution of the covariates in the treatment and control groups are the same.[5] This is the Balancing Hypothesis, which can be presented as $T_i \perp X_i | m(X_i)$. If it is satisfied, observations with the same metric must have the same distribution of observable characteristics (and non-observables) independent from the treatment status.

Under these assumptions, there is a great variety of matching estimators suggested in the literature. In this work the estimators considered are those with good finite sample properties and demonstrated asymptotic properties, see Frölich (2004) and Busso et. al. (2009, 2014). Thus, the bias-corrected matching estimator of Abadie and Imbens (2011)[6] is selected. Busso et. al. (2014) show that this estimator has good properties in small samples and in case there are weak overlapping scenarios, moreover it has exact formulas for their robust to heteroskedasticity standard errors, and the asymptotic properties of these estimators were established by Abadie and Imbens (2006).

3.3 Instrumental variable method

Additionally, the existence of other non-observed factors which explain the participation in the program is possible, such as the access to information, opportunity costs, motivation, skills, etc. Thus, even having controlled by all the observable pre-existing characteristics among participants and non-participants considered in the selection process, it is probable that non-observed attributes make participants and non-participants in the program to differ before the treatment is

[5] See Zhao (2004) for comparisons and information requirements for both metrics.

[6] The Matching estimator based on the covariates intends to remove the bias coming from the inexact matching of the nearest neighbour matching in small samples. It adjusts the difference in the matching with the differences in the values of their covariates using regression functions; see Abadie and Imbens (2011) for details about this method.

applied, which would bias the impact estimation. In order to address the risk arising from non-observable characteristics, in addition to the matching method we call for instrumental variables.

In order to estimate consistently instrumental variables, there are necessary external variables that satisfy the criteria of relevance and validity, the so called instruments. It means, a group of variables which are very correlated with the participation in the program and that do not directly explain the poverty level. Let Z_i be the vector that contains the instruments, Imbens and Angrist (1994) demonstrated that the instrumental variables estimator in the framework of potential outcomes analysis can be expressed as follows:

$$\phi = \frac{E\left(Y_i \mid T_i = 1\right) - E\left(Y_i \mid T_i = 0\right)}{E\left(T_i \mid Z_i = 1\right) - E\left(T_i \mid Z_i = 0\right)}$$

Meaning that ϕ represents the average local treatment effect (LATE), which measures the average impact for people who change their participation condition as a result of a change in the instrument Z_1.

c. Impact evaluation of multiple programs

In this paper, in addition, the impact of the three conditional cash transfer programs as a whole are estimated in order to know the aggregate impact of the redistribution programs. To that end, the estimation is based on the impact evaluation of multiple programs under the conditional independence assumption (CIA), for more details of the estimator, see Viet Cuong (2008) and Lechener (2001). In this case, the participation vector has tree binary variables that represent each of the programs of interest.

$$T = \begin{pmatrix} T^1 \\ T^2 \\ T^3 \end{pmatrix}$$

Therefore, for example, $T^1 = 1$ if the person received the treatment 1, e.g. Juancito Pinto program and $T^1 = 0$ otherwise. In this framework, the set of potential treatments has the following values:

$$\mathrm{T} = \left\{ \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \right\}$$

And the potential outcomes will be $\Upsilon = \{Y_{111}, Y_{100}, Y_{101}, Y_{110}, Y_{011}, Y_{000}, Y_{001}, Y_{010}\}$. The conditional independence assumption which allows the use of matching method will be: $\Upsilon \perp \mathrm{T} \mid X$. Thus, following Viet Cuong (2008) as the programs under consideration are independent of each other, then it is possible to estimate the joint effect of the three transfer programs in a similar way to the estimation of the individual effect, namely:

$$E\left(Y_{111} \mid X, T^1 = 1, T^2 = 1, T^3 = 1\right) = E\left(Y_{110} \mid X, T^1 = 1, T^2 = 1, T^3 = 0\right) = E\left(Y_{101} \mid X, T^1 = 1, T^2 = 0, T^3 = 1\right)$$

e. Data

The information used comes from the 2013 Household Survey. This database, collected by the National Institute of Statistics (INE, in spanish), provides information on socioeconomic and demographic variables, and on life conditions of the households in Bolivia.[7] Among them, this survey holds information about receiving or not the three programs under consideration.

In order to show the usefulness of this survey for the purposes of this research, the first line of the following table presents the number of people who received the bonus according to the 2013 Household Survey. The second line presents the same information but implementing the expansion factor, specifically, its representation in the universe. In the third line we have the official number of individuals who received these programs in Bolivia. When comparing the information from the second and third line, it is noted that the sample representation in the universe is very close to the population data. Which suggests that the sample used in this survey is highly representative of the population who received the conditional cash transfer programs.

Table 1: Comparison of the treatment sample with the population data

N° individuals benefitted:	Juana Azurduy	Juancito Pinto	Renta Dignidad	Moderate Poverty incidence	Extreme Poverty incidence
Household Survey (EH) 2013	863	5,784	3,375	34.9	14.7
EH 2013 w/ expansion factor	258,463	1,770,325	1,069,542	39.0	18.7
Total Bolivia, oficial data	200,377	1,887,625	886,845	39.1	18.8

Next on Table 2, it is shown the households which participate in the treatment and control groups of the programs of interest. Note that households are the unit of analysis in this study.

Table 2: Number of households in the treatment and control groups by program

Programs:	Juana Azurduy	Juancito Pinto	Dignity Rent	Any of the three programs
Households benefitted	628	3,358	2,520	5,717
Households non benefited	8,925	6,195	7,033	3,836

On Table 3 it is detailed the main characteristics of the 2013 Household Survey data; there it can be noted that: (i) 30% of the households in the model are poor and 12% of the households live in extreme poverty; (ii) the difference in the proportion of poor households it is not too clear for the beneficiaries and non-beneficiaries of the Dignity Rent, but yes it is for the recipients and non-recipients of the Juancito Pinto and Juana Azurduy programs. These results may suggest the existence of self-selection for latter programs, aspect which justifies the use of instrumental

[7] The survey holds information on 9,553 households and 35,693 people interviewed throughout the Bolivian territory

variables; (iii) the difference in remaining characteristics between the beneficiaries and non-beneficiaries households, in general, is small; this characteristic may suggest that the treatment assignment in the sample is random; (iv) the behavior of the spending variable and the index of material wealth[8] are coherent among themselves and with the poverty indicators.

Table 3: Characteristic of the sample

	Juancito Pinto		Juana Azurduy		Dignity Rent		Any of the three		Total
	No	Yes	No	Yes	No	Yes	No	Yes	
Poverty	0.21	0.45	0.28	0.46	0.30	0.28	0.18	0.37	0.30
Extreme Poverty	0.08	0.19	0.11	0.23	0.12	0.11	0.06	0.15	0.12
Head of the Household reads	0.93	0.96	0.94	0.97	0.97	0.85	0.97	0.92	0.94
Gender of Head of H. (1=man)	0.73	0.76	0.73	0.85	0.77	0.66	0.75	0.73	0.74
Head of Household works	0.81	0.92	0.85	0.92	0.93	0.63	0.91	0.81	0.85
Schooling of the Head	10.48	8.91	9.98	9.26	10.77	7.60	11.91	8.61	9.93
N° Members inthe H.	2.99	5.11	3.64	5.11	3.91	3.26	3.05	4.20	3.74
Age of the Head of Household	38.95	24.02	48.39	36.88	40.93	66.20	41.47	51.73	47.63
Total Spending (Bs.)	5,831.80	5,688.05	5,842.62	4,910.91	6,051.76	5,030.78	6,453.84	5,333.40	5,781.15
Nonfood Expenditure/Total Expenditure	0.53	0.42	0.49	0.49	0.49	0.51	0.53	0.47	0.49
Nonfood Expenditure (Bs.)	3,920.54	3,162.58	3,692.16	3,105.47	3,759.44	3,359.54	4,283.39	3,234.15	3,653.45
Material Wealth Index	0.18	-0.10	0.33	-0.02	0.09	-0.03	0.14	-0.20	0.00

IV. RESULTS

a. Propensity score matching results

In Table 5 we have the results of the estimations. However, before interpreting the coefficients, the following aspects must be mentioned: (i) that the results do not differ if the propensity score or Mahalonobis distance is used as metric to define similitude, hence only the results using propensity score are presented. (ii) As previously mentioned, the chosen matching algorithm is the finite sample bias corrected matching method of Abadie and Imbens (2011), since this estimator has good properties in small samples, their asymptotic properties are established and there are calculation formulas for their variance robust to heteroskedasticity. (iii) Each observation in the treatment group is compared with the four nearest neighbors. (iv) In order to achieve good overlapping between treatment and control distributions of the propensity score, extreme values are trimmed from both distributions. (v) The standard errors are robust to the heteroskedasticity. (vi) The households considered are those whose income is less than the median. Finally, (vii) the specification for the Propensity Score contains the covariates described in the following table:

[8] This index was built applying the Multiple Correspondence Analysis on the following variables, if the household owns: a computer, sound equipment, refrigerator, motorcycle, automobile, internet, telephone, gas, piped water, cement house and house property.

Table 4: Variables used in the model specification

Variables	
Dependent	Moderate and extreme poverty indicators estimated by the INE taking into account the difference between the income level with the poverty line (1= poor household, 0 = not poor household).
Treatment	An indicator which describes the household as recipient of the Juancito Pinto transfer program (1= beneficiary household, 0= non-beneficiary household) An indicator which describes the household as recipient of the Juana Azurduy transfer program (1= recipient household, 0= non-recipient household) An indicator which describes the household as recipient of the Dignity Rent (1= recipient household, 0= non-recipient household) An indicator which describes the household as recipient of some of the three programs (1= household recipient of at least one transfer, 0= household which did not receive any of the transfers)
Household Characteristics	The head of household knows how to read and write, the head of household´s gender, the head of household works (yes or no), the head of household´s education level (schooling), number of members in the household, and the average age of the household.
Economy	Total household spending; index of material wealth
Regional Characteristics	Zone (urban or rural), States (a dichotomous variable for each state)
Characteristics that describe them as potential recipients.	There are older adults over 50 years old in the household There are children between 6 and 14 years old in the household There were recent pregnancies in the household in last two years.

Focusing on the estimations, the results are reported in Table 5, there it can be noted that the three conditional cash transfers have a statistically significant and negative effect on poverty. Among them, the one that has the biggest effect on poverty is the Dignity Rent, aspect that can be explained by the higher frequency in the assignation of this monthly transfer.

The first column of Table 5 indicates that the Juana Azurduy program reduced by 3.7pp the incidence of moderate poverty and by 4.0pp the incidence of extreme poverty in the recipient group of this program.[9] Last column suggests that having received one of the three programs, reduced on average 7.2pp the incidence of moderate poverty for the subset of the population that in fact benefitted from any of these three programs in 2013, the extreme poverty proportion was reduced by 8.9pp on average.

Table 5: Propensity score matching impact of the CCT programs on poverty in Bolivia

	(1) Juana Azurduy	(2) Juancito Pinto	(3) Dignity Rent	(4) Any of the three
Dependent variable: Moderate poverty				
ATT	-0.037*	-0.033*	-0.049**	-0.072***
	t=-1.66	t=-1.73	t=-2.01	t=-4.22
Dependent variable: Extreme poverty				
ATT	-0.040*	-0.044*	-0.053**	-0.089**
	t=-1.65	t=-1.93	t=-2.52	t=-2.02

Statistical significance: *** at 1%, ** at 5%, * at 10%
t statistic robust to heteroskedasticity

As it was previously mentioned, matching methods are based on the conditional independence assumption (CIA), which states that the covariates used in the specification allow to control by all those factors that explain at the same time the treatment (received a social cash transfer) and the outcome (poverty status). In case there is a non-observed variable that influences both variables, the outcomes can be biased. To verify if this is the case for the present results, the sensibility analysis proposed be Rosenbaum (2002) is implemented. Instead of testing the validity of the CIA assumption, Rosenbaum (2002) proposes superior and inferior limits to find out what happens with the estimated results (if they are over or under estimated) in case of deviations from the CIA. The calculations of these limits for Table 5 results suggest that these are not sensible to the deviations from the CIA, since the hypothesis of over and under estimation are rejected in the existence of scenarios with deviation of CIA. These results are reported in Appendix.

Furthermore, it is necessary to check if the matching process accomplished was able to balance the distribution of the relevant variables in the control and treatment groups. In that case, after implementing the matching, there should not be significant differences in the covariate of either group. For this reason, tests of differences in the mean of the covariates between the treated households and their assigned controls by the matching method were applied. The results suggest

[9] Note that these results are applied to those households which are similar between them, only that one participates in the program and the other does not.

lack of existence of significant differences in the covariates of both groups. These results are in Appendix.

b. Instrumental Variable method results

As explained on previous section, to avoid comments on the impossibility that all dependence between the treatment selection and the potential values of the dependent variable are explained by observed variables, the participation variable is considered endogenous and the impact of the redistribution programs are estimated through the instrumental variable method.

The instruments used to explain the receiving of the program are a combination of two sets of variables: (i) the first group includes the following variables, if there are children in the household, if any female member of the household was recently pregnant and if there are older adults in the household (over 50 years old). These variables instrument the Juancito Pinto, Juana Azurduy and the Dignity Rent, respectively. These instruments are highly correlated with the possibility of receiving a program and can be considered exogenous to the poverty level once controlled by the other covariates. (ii) Additionally, instruments generated by the heteroskedasticity of the first stage are used, following the work of Lewbel (2012). Lewbel demonstrates that it is possible to generate internal instruments based on the heteroskedasticity of the first stage residuals.[10] Thus, by increasing the number of identification restrictions over identified models are estimated.

The combination of both sets of instruments satisfy the relevance and validity properties needed to deal properly with the endogeneity problem. In order to verify these properties the following tests are applied: (i) the Kleibergen-Paap Wald Test to verify if the instruments are properly correlated with the endogenous explanatory variable (benefited from a program). The critical values of this test are not standard and were calculated by Stock and Yogo (2005). Two null hypothesis stem from these statistics, the first one is that the relative bias of Instrumental Variables relative to Ordinary Least Squares is less than 5%; the second one, that the size of the Wald test is less than 10% (the size of a test represents the probability of making a Type I error). ii) To test validity, the Hansen J of over-identification restrictions is reported, the null hypothesis is that the instruments are orthogonal to the errors.

[10] ε_i y v_i be the error of the second and first state, respectively, the parameters of the second stage can be identified if it is satisfied that: $E(X_i, v_i)=0$, $Cov(X_i, \varepsilon_i v_i)=0$, and $Cov(X_i, v_i^2) \neq 0$. Under these conditions, Lewbel (2012) demonstrates that vector $(X_i - \overline{X})\hat{v}_i$ can be used as a set of inside instruments, where ε_i y $\hat{v}_i$ are the remainders of the second and first stage, respectively. The first assumption, $E(X_i, v_i)=0$, implicates the exogeneity of the regressors, the second assumption, implicates that $(X_i - \overline{X})\hat{v}_i$ is a "valid" instrument because it is independent from ε_i. The third one implicates "relevance" and this one will depend on the covariance of the instruments with v_i (the level of heteroscedasticity in the first stage). Therefore, Lewbel suggests that the product of regressors centered on its average with the remains of the first stage will have important information for the identification if there is clear evidence of heteroscedasticity (in regards to the regressors).

The following table shows the results using instrumental variables, as can be observed the results are similar to the ones obtained in last table. That is, the conclusion in Table 6 is that the implementation of the programs had a negative effect on poverty.[11] In the first column the Juana Azurduy program contributed to reduce moderate poverty in 4.7pp and extreme poverty in 5.3pp. Similarly, the second column shows that the money offered by the Juancito Pinto program had a negative effect on moderate poverty of 5.4pp and of 6.2pp on extreme poverty. In the third column it can be seen that the Dignity Rent had an effect of 5.9pp in the decline of moderate poverty and of 7.1pp on the decline of extreme poverty. Last column shows that the aggregate effect of the three programs was a reduction of 8.2pp on moderate poverty and a reduction of 9.6pp on extreme poverty. The tests mentioned on previous paragraph, reported below each coefficient, show that the instruments are highly correlated with the participation variables (are relevant) and are exogenous (valid), which support the statistic properties of these results.

Table 6: Instrumental variables impact of the CCT programs on poverty in Bolivia

	(1) Juana Azurduy	(2) Juancito Pinto	(3) Dignity Rent	(4) Any of the three
Dependent variable: Moderate poverty				
IV estimation of the impact	-0.047*	-0.054*	-0.059*	-0.082**
	t=-1.75	t=-1.68	t=-1.72	t=-1.97
Kleibergen-Paap test	136.2	134.6	81.9	75.2
Hansen test	p=0.56	p=0.10	p=0.19	p=0.35
Dependent variable: Extreme poverty				
IV estimation of the impact	-0.053*	-0.062*	-0.071**	-0.096**
	t=-1.89	t=-1.67	t=-2.02	t=-1.96
Kleibergen-Paap test	157.8	104.7	92.1	105.5
Hansen test	p=0.10	p=0.41	p=0.21	p=0.19

Statistical significance: *** at 1%, ** at 5%, * at 10%
t statistic robust to heteroskedasticity

V. CONCLUSIONS

In early 2000, Bolivia was characterized by high levels of poverty. In 2006, Bolivia began historical changes which significantly transformed the economic and social characteristics of the country. The State acquired a redistributor role and one of its central concerns became the decline in poverty. Therefore, different social policies were implemented to improve population life

[11] Note that these results correspond to the effect on poverty "for the households" which received the social transfers (who participated in the program).

conditions in the country, the most important, the conditional cash transfers programs: Juancito Pinto, Juana Azurduy and Dignity Rent.

At present time, Bolivia has become a middle income level country, it is in the midst of a firm process of diminution of social gaps and it has already met the goal of poverty reduction before the deadline established in the 2000 Millennium Development Goals.

The objective of this work was to evaluate the impact of these conditional cash transfer programs in Bolivia on poverty reduction. Information from the 2013 Household Survey and impact evaluation techniques were used with this purpose. The results suggest that the implementation of these programs, reduced the incidence of moderate poverty in Bolivia in 8.2pp and extreme poverty in 9.6pp in the group who received these transfers.

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APPENDIX:
TEST OF MEAN DIFFERENCES BETWEEN THE TREATMENT AND CONTROL GROUPS

Dependent variable: Poverty	**Dignity Rent**			**Juana Azurduy**		
	Mean		**Ho: Diff=0**	**Mean**		**Ho: Diff=0**
Explanatory variables	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**
Head of Household know how to read & write (Yes=1, No=0)	0.78	0.77	0.28	0.97	0.97	0.99
Head of Household Gender (Man=1, Woman=0)	0.63	0.62	0.41	0.85	0.84	0.15
Head of Household works (Yes=1, No=0)	0.74	0.76	0.19	0.93	0.92	0.69
Average Age of the Household	46.90	48.10	0.21	18.40	17.90	0.43
Number of members in the household	2.44	2.46	0.51	4.67	4.87	0.25
Education Level of the Head of Household (schooling)	6.08	5.92	0.30	7.61	7.68	0.61
Material wealth index	0.72	0.69	0.17	0.54	0.59	0.28
Total Expenditure in the Household	2591.04	2741.53	0.15			
Nonfood spending/Total spending				0.46	0.45	0.44
Area (urban, rural),	1.47	1.48	0.19	1.40	1.42	0.17
There are elderly adults in the household (over 50 years old)	0.78	0.91	0.00			
There were recent pregnancies in the household in recent years				0.91	0.97	0.00

Dependent variable: Poverty	**Juancito Pinto**			**Any of the three programs**		
	Mean		**Ho: Diff=0**	**Mean**		**Ho: Diff=0**
Explanatory variables	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**
Head of Household know how to read & write (Yes=1, No=0)	0.95	0.94	0.41	0.89	0.88	0.49
Head of Household Gender (Man=1, Woman=0)	0.76	0.75	0.39	0.75	0.74	0.19
Head of Household works (Yes=1, No=0)	0.93	0.92	0.16	0.89	0.87	0.43
Average Age of the Household	24.09	23.66	0.14	33.95	34.69	0.09
Number of members in the household	3.93	4.00	0.14	2.94	3.11	0.08
Education Level of the Head of Household (schooling)	7.16	6.99	0.16	7.12	6.99	0.14
Material wealth index	0.49	0.51	0.19	0.55	0.56	0.48
Total Expenditure in the Household	3892.96	4065.70	0.09	3291.82	3459.82	0.08
Area (urban, rural),	1.39	1.41	0.29	1.41	1.42	0.38
Number of children between 6 and 14 year old in the household	1.51	1.65	0.00	0.78	1.06	0.00
There are elderly adults in the household (over 50 years old)				0.35	0.44	0.00
There were recent pregnancies in the household in recent years				0.24	0.25	0.67

Dependent variable: Extreme Poverty	**Dignity Rent**			**Juana Azurduy**		
	Mean		**Ho: Diff=0**	**Mean**		**Ho: Diff=0**
Explanatory variables	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**
Head of Household know how to read & write (Yes=1, No=0)	0.76	0.77	0.21	0.95	0.97	0.62
Head of Household Gender (Man=1, Woman=0)	0.61	0.62	0.39	0.83	0.84	0.23
Head of Household works (Yes=1, No=0)	0.73	0.76	0.12	0.94	0.92	0.24
Average Age of the Household	45.20	48.10	0.09	18.63	17.90	0.18
Number of members in the household	2.39	2.46	0.43	4.53	4.87	0.17
Education Level of the Head of Household (schooling)	6.14	5.92	0.23	7.58	7.68	0.11
Material wealth index	0.73	0.69	0.11	0.53	0.59	0.09
Total Expenditure in the Household	2567.25	2741.53	0.10			
Nonfood spending/Total spending				0.43	0.45	0.20
Area (urban, rural),	1.47	1.48	0.26	1.41	1.42	0.28
There are elderly adults in the household (over 50 years old)	0.79	0.91	0.00			
There were recent pregnancies in the household in recent years				0.89	0.97	0.00

Dependent variable: Extreme Poverty	**Juancito Pinto**			**Any of the three programs**		
	Mean		**Ho: Diff=0**	**Mean**		**Ho: Diff=0**
Explanatory variables	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**
Head of Household know how to read & write (Yes=1, No=0)	0.92	0.94	0.39	0.87	0.88	0.41
Head of Household Gender (Man=1, Woman=0)	0.77	0.75	0.27	0.71	0.74	0.12
Head of Household works (Yes=1, No=0)	0.91	0.92	0.19	0.84	0.87	0.10
Average Age of the Household	24.56	23.66	12.00	34.10	34.69	0.34
Number of members in the household	3.84	4.00	0.10	2.98	3.11	0.29
Education Level of the Head of Household (schooling)	6.81	6.99	0.11	7.54	6.99	0.11
Material wealth index	0.47	0.51	0.14	0.54	0.56	0.21
Total Expenditure in the Household	3874.52	4065.70	0.09	3353.14	3459.82	0.16
Area (urban, rural),	1.40	1.41	0.57	1.40	1.42	0.36
Number of children between 6 and 14 year old in the household	1.49	1.65	0.00	0.83	1.06	0.00
There are elderly adults in the household (over 50 years old)				0.38	0.44	0.00
There were recent pregnancies in the household in recent years				0.18	0.25	0.00

SENSIBILITY ANALYSIS, DEPENDENT VARIABLE: POVERTY

Dignity Rent program

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	3.571	3.571	0.000	0.000
1.05	3.957	3.189	0.000	0.001
1.1	4.325	2.825	0.000	0.002
1.15	4.677	2.477	0.000	0.007
1.2	5.016	2.145	0.000	0.016
1.25	5.342	1.827	0.000	0.034
1.3	5.656	1.521	0.000	0.064
1.35	5.959	1.228	0.000	0.110
1.4	6.252	0.945	0.000	0.172
1.45	6.537	0.672	0.000	0.251
1.5	6.812	0.409	0.000	0.341

Juancito Pinto program

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	7.339	7.339	0.000	0.000
1.05	6.835	7.848	0.000	0.000
1.1	6.356	8.333	0.000	0.000
1.15	5.900	8.800	0.000	0.000
1.2	5.464	9.249	0.000	0.000
1.25	5.048	9.682	0.000	0.000
1.3	4.648	10.101	0.000	0.000
1.35	4.265	10.505	0.000	0.000
1.4	3.896	10.897	0.000	0.000
1.45	3.541	11.278	0.000	0.000
1.5	3.198	11.647	0.001	0.000

Juana Azurduy program

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	0.937	0.937	0.174	0.174
1.1	1.465	0.411	0.072	0.340
1.2	1.947	-0.068	0.026	0.527
1.3	2.392	0.328	0.008	0.372
1.4	2.805	0.736	0.003	0.231
1.5	3.191	1.116	0.001	0.132
1.6	3.554	1.473	0.000	0.070
1.7	3.896	1.808	0.000	0.035
1.8	4.220	2.125	0.000	0.017
1.9	4.527	2.426	0.000	0.008
2	4.820	2.712	0.000	0.003

Any of the three programs

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	6.018	6.018	0.000	0.000
1.1	4.799	7.245	0.000	0.000
1.2	3.690	8.373	0.000	0.000
1.3	2.673	9.418	0.004	0.000
1.4	1.734	10.393	0.041	0.000
1.5	0.860	11.308	0.195	0.000
1.6	0.044	12.171	0.483	0.000
1.7	0.645	12.988	0.260	0.000
1.8	1.368	13.765	0.086	0.000
1.9	2.053	14.507	0.020	0.000
2	2.703	15.216	0.003	0.000

SENSIBILITY ANALYSIS, DEPENDENT VARIABLE: EXTREME POVERTY

Dignity Rent

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	3.939	3.939	0.000	0.000
1.1	4.631	3.256	0.000	0.001
1.2	5.268	2.635	0.000	0.004
1.3	5.860	2.066	0.000	0.019
1.4	6.414	1.542	0.000	0.062
1.5	6.936	1.055	0.000	0.146
1.6	7.430	0.600	0.000	0.274
1.7	7.899	0.173	0.000	0.432
1.8	8.346	0.089	0.000	0.465
1.9	8.774	0.470	0.000	0.319
2	9.185	0.832	0.000	0.203

Juancito Pinto program

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	4,105	4,105	0,000	0,000
1.1	3.171	5.045	0.001	0.000
1.2	2.321	5.907	0.010	0.000
1.3	1.541	6.705	0.062	0.000
1.4	0.820	7.447	0.206	0.000
1.5	0.149	8.142	0.441	0.000
1.6	0.374	8.796	0.354	0.000
1.7	0.963	9.414	0.168	0.000
1.8	1.519	10.000	0.064	0.000
1.9	2.045	10.557	0.020	0.000
2	2.545	11.088	0.005	0.000

Juana Azurduy program

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	1.017	1.017	0.155	0.155
1.1	0.455	1.582	0.325	0.057
1.2	-0.059	2.098	0.524	0.018
1.3	0.362	2.573	0.359	0.005
1.4	0.799	3.015	0.212	0.001
1.5	1.207	3.427	0.114	0.000
1.6	1.588	3.814	0.056	0.000
1.7	1.947	4.179	0.026	0.000
1.8	2.287	4.524	0.011	0.000
1.9	2.608	4.851	0.005	0.000
2	2.914	5.162	0.002	0.000

Any of the three programs

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	4.362	4.362	0.000	0.000
1.1	3.353	5.378	0.000	0.000
1.2	2.436	6.311	0.007	0.000
1.3	1.595	7.175	0.055	0.000
1.4	0.818	7.982	0.207	0.000
1.5	0.095	8.737	0.462	0.000
1.6	0.484	9.449	0.314	0.000
1.7	1.119	10.123	0.132	0.000
1.8	1.717	10.762	0.043	0.000
1.9	2.284	11.371	0.011	0.000
2	2.824	11.952	0.002	0.000