WELL-BEING AND SOCIAL POLICY
VOL 5, NUM. 2, pp. 85-108

IMPACT ON EARNINGS, EMPLOYMENT PROSPECTS AND TIMING OUT OF UNEMPLOYMENT OF MEXICAN PROGRAMS TARGETED AT UNEMPLOYED INDIVIDUALS: CHALLENGES FOR FUTURE EVALUATIONS OF SICAT AND SAEBE

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Abstract

This paper presents estimates of the impact of programs for unemployed workers on the performance of program beneficiaries in Mexico. We emphasize the significance of applying methodologies capable of avoiding statistical bias attributable to unobserved variables when measuring the impact on earnings and allowing to us properly estimate unemployment duration and work status after exiting from unemployment.

Using a technique that combines the matching method with the double difference method (pre and post-intervention differences in differences between the treatment and control group) we measure the impact of SICAT on unemployed males with previous working experience who participated in the 2002, 2003 and 2004 programs. Outcomes using this method do not support the hypothesis that SICAT has a positive impact on the earnings per hour of program participants three months after finishing the training provided by the program. Furthermore, when the impact is statistically significant, such as in years prior to 2004, the effect was the opposite to the one that was expected, as if those participating in SICAT had been stigmatized in the labor market to the extent that it turns out to be counterproductive.

* The author thanks Leobardo Mata for his assistance and comments.

For the SAEBE program, we measured whether the probability of finding employment in the formal sector increases for program beneficiaries and whether they exit from unemployment faster when, in addition to financial assistance, they are provided employment services.

The purpose of these estimates is to identify the challenges future evaluations will have to face to be able to measure the impact of the SAEBE and SICAT programs on beneficiaries in a more adequate and accurate fashion. Among them, we emphasize the need to change the way surveys are conducted and control groups identified, improving data collection of job statuses trajectories, and the need to incorporate general equilibrium conditions in the labor market when measuring the impact of programs that cover a significant number of unemployed workers.

Key words: programs evaluation, public policies for the unemployed, formal and informal labor market in Mexico.
JEL classification: J08, C21, J18, J64.

Introduction

The Mexican government has two different programs to help unemployed workers who are looking for a job. Both are under the responsibility of the Ministry of Labor and are known as SICAT and SAEBE, acronyms for Job Training System and Economic Assistance for those Searching for Employment, respectively. The differences in their design and operation reflect the heterogeneity that characterizes unemployed individuals in a developing country.

On the one hand, there are those who have no skills or human capital to keep a job and thus constantly transition from unemployment to casual jobs, characterized by their short duration and very little training at the workplace. On the other hand, there are those who have previous work experience in the formal work market and previously acquired skills. Thus, they do not require additional training to get a new job where they can be as productive or even more productive than in their previous job but lack the resources to finance their search.

SICAT, formerly PROBECAT, has been providing assistance to the first group of unemployed workers for over twenty years; it offers participants financial incentives, for up to three months, so they can attend the training courses that are fully financed by the program. SAEBE has been operating since 2003 providing assistance to unemployed individuals in the second group through two components. The first is cash assistance, up to two payments of $1,900 each, and the second is employment services.

These cash payments help them finance their work search process (telephone cards, transportation expenses and any other related expenses beneficiaries might consider pertinent) and make it possible for them to maintain consumption levels required to meet basic family needs while they find a job. The second component provides them access to vacancy information and guidance using infrastructure managed by the Ministry of Labor’s National Employment System.

Until now, every evaluation of the impact of these programs on beneficiaries has used survey strategies designed to make treatment groups available as well as control groups which are not very adequate from a statistical point of view. On the one hand, retrospective surveys are applied to SAEBE and SICAT participants to form the treatment group and on the other hand, quarterly follow up panel surveys conducted by the National Institute of Statistics and applied to a representative sample of the country's labor force are used to measure national employment rates. Unemployed workers who could have participated in these programs but did not are selected from these surveys to form the control group.

This procedure produces significant statistical bias when estimating the impact on the performance of program beneficiaries. It arises because participant characteristics (observed and non-observed) and control group characteristics have different distributions.

A first step to reduce this bias is using the matching method to balance the statistical distribution of each observed variable eliminating distribution differences between the treatment and the control group. This procedure is not enough to eliminate statistical bias issues when estimating impact because there is still the issue of bias attributable to unbalanced distribution of unobserved variables (by the analyst) between both groups. (For example, when the decision to participate in the program is associated to unobserved individual characteristics).

Therefore, the parameters of interest in an evaluation are biased and can even have opposite signs to the ones that would be obtained when the right method to correct the source of the problem is applied or when a random evaluation is made.

In other papers (Calderón-Madrid 2006 and 2010), we indicate the appropriate method to correct theses biases due to unobserved individual heterogeneity when measuring program impact on permanence in unemployment and in the employment found after participating in the program.

The first section of this document presents another method used to correct bias attributable to unobserved characteristics (by the analyst) when measuring impact on the salary per hour of program participants. We took advantage of the fact that data collected for surveyed individuals includes not only the remuneration received and the number of hours worked in the job found after participating in the program, but also in the last job held before becoming unemployed; that is, we have pre and post-intervention data on the salary per hour both for individuals in the treatment group and in the control group. This allows us to combine the matching method with the double difference method to eliminate bias when estimating the parameters of interest attributable to unobserved characteristics (by the analyst), which, in addition to being invariable over time, are also specific to each individual, whether they belong to the group of program participants or to the control group.[1] Outcomes using this method do not support the hypothesis that SICAT has a

[1] Heckman et al. (1998) proved that this method is a useful tool to control for bias from both observables and unobservables.

positive impact on the earnings per hour received by program participants three months after finishing the training provided by this program. Additionally, when the impact is statistically significant, such as in years prior to 2004, an effect that is the opposite of the one that was expected is suggested, as if SICAT participants had been stigmatized in the labor market to the extent that it is counterproductive.

Using these outcomes, we would like to highlight the inadequacy of evaluation designs until now and that databases obtained have serious measurement problems. This program has had almost 5 million beneficiaries since it was implemented and not a single evaluation has been able to find, convincingly and with statistical strength, that training provided to the unemployed in Mexico is effective to improve beneficiary outlooks in terms of income. These observations also apply to other program objectives such as the employment prospects of individuals (See Samaniego 2002).

From these information problems we can infer that a challenge to future evaluations of this program is the need to overcome the obstacles that have made it impossible to conduct adequate surveys of both program participants and non-participants, based ideally on an experimental design that makes it possible to perform counterfactual analysis without the serious statistical bias issues experienced until now.[2]

The second section of this paper estimates SAEBE's effectiveness in increasing the probability of program beneficiaries re-entering the formal sector of the economy. We also estimate the effectiveness of State Employment Services by providing, in addition to financial assistance, job vacancy information and guidance to help program participants find employment faster compared to those who are only receiving financial assistance for their job search process.

Mexico has no unemployment insurance providing assistance to workers who have lost their jobs. The Federal Labor Law establishes that anyone fired "without cause" is entitled to severance pay from their employer (equivalent to three months salary plus twelve days for each year worked). In practice, the number of workers that receive compensation when they lose their job is reduced; hence, one of the topics of the economic policy debate in Mexico is the advisability of transitioning from the current social protection system with severance pay for unjustified termination of employment, towards a more flexible one with unemployment insurance, as in Brazil, Colombia and Chile. In these countries, the size of the informal sector of the economy is substantial; consequently, unlike in industrialized economies, unemployment insurance only covers formal sector workers and aims to reduce their risk of finding work only in the informal sector of the economy when they lose their job.

For a developing country, the design and operating mechanisms of the SAEBE program have certain characteristics of unemployment insurance. Some of these are that only unemployed individuals who have contributed to social security (which identifies them as belonging to the formal sector of the economy) are eligible and providing them cash to finance a job search process

[2] Evaluations of assistance and training programs for the unemployed in Santo Domingo (Kugler et al. 2009) and Colombia (Card et al. 2007) have been made made using experimental designs.

that will allow them to remain in the formal sector. That is why measuring the impact of the SAEBE program on beneficiary performance is useful not only to find out its effectiveness but also to enrich the debate on the advisability of transitioning from the current social protection system with severance pay towards a more flexible one with unemployment insurance.

Using the empirical exercise presented in this paper we can identify the challenges to properly evaluate it in the future. First, obtaining accurate responses from individuals in the control and treatment groups regarding their period of unemployment, duration and type of employment (formal or otherwise) in jobs held after participating in the program. Secondly, properly addressing the issue of unobserved heterogeneity as a determinant of permanence in each employment status since, as pointed out by Eberwein, Ham, and Lalonde (1997), even if the control group and the treatment group are selected using experimental designs, the use of adequate techniques is required to correct bias.

The paper is divided in 4 sections in addition to this introduction. Section 1 describes the programs and Section 2, the data; the variables used in our estimates are also defined here. Section 3 presents statistical models used and Section 4 discusses the outcomes. Finally, conclusions and comments are presented.

1. Program Characteristics

SICAT is a program that provides training courses to participants for up to three months. Depending on their profile, they are awarded an allowance of between one and three minimum salaries, transportation expenses and all participants are provided free training courses (instructors, tools or material) and accident insurance. In 2004, the program offered the following training modalities:

a) Work skills training, in coordination with the productive sector taking advantage of its infrastructure as a means of learning to promote the development of qualifications;

b) Work training doing actual work, in coordination with micro and small enterprises; targeted at individuals between 16 and 30 years of age.

c) Training for self employment, providing assistance to beneficiaries with personal initiative to generate their own employment options;

d) Training coupons, allowing beneficiaries to decide which course better suits their needs among those provided by private training centers certified by the Ministry of Education or the Ministry of Labor.

e) Training for technicians and professionals, offers courses for unemployed professionals and technicians with or without work experience.

SAEBE targets unemployed formal sector workers who are looking for a job. It provides up to two assistance payments of $1,900 each (a total of approximately three minimum salaries) to subsidize their job search process (transportation, telephone calls and living expenses while looking for work). In addition to financial assistance, State Employment Services provides vacancy information and guidance to most SAEBE beneficiaries. Using the surveys of the representative group of participants that comprise the treatment group for the 2004 evaluation, we found that 20% did not have access to these services during 2004. This heterogeneity in the provision of services allows us to estimate the impact of this SAEBE component on the average time to find a job compared to the time it would have taken had they only been provided financial assistance to subsidize their search.

2. Data and Definition of Variables

This paper focuses exclusively on measuring the impact on males that had been unemployed for a period of less than 52 weeks before participating in the SICAT program in 2004, 2003 or 2002 or in the SAEBE program in 2004. Our databases use data from the “Surveys on the Employment Levels and Job Permanence of SICAT and SAEBE Beneficiaries”; surveys were applied to three samples of program participants. Table 1 shows the number of individuals interviewed, which for purposes of this study, constitute the treatment group, to estimate the impact of the services offered by these programs three months after finishing the training courses, for SICAT, and three months after receiving the services provided by the National Employment Service, for SAEBE.

Table 1
SICAT Beneficiaries and Individuals in the Control Group
Males with Previous Work Experience Unemployed for Less than One Year

	2004		2003		2002	
	Treatment	Control	Treatment	Control	Treatment	Control
Total	464	736	637	619	354	1229
Find employment	306	654	486	594	311	1069
Do not find employment	158	82	151	25	43	160

Data pertaining to eligible individuals who could have participated but did not do so are also shown in this table. They represent the control group, defined as men looking for jobs who have been unemployed for less than 52 weeks and come from the National Employment Survey conducted by the National Institute of Statistics (INEGI).[3] For all these individuals, we have the demographic variables that characterized them before receiving benefits form either program or when they became eligible (age, education, marital status, number of dependents, geographical location and number of weeks elapsed between the date their last employment was terminated and the starting date of the program) and variables regarding their previous job (type of contract, number of hours worked, type of work).

Using these characteristics we defined vector *X,* whose component comprises the variables defined below; with the exception of age, the rest are dummy variables that take the value of one or zero:

a) *Age.* It is included in the estimates as a discreet variable starting at 16 years of age and changes one year at a time; b) *educa1, educa2* and *educa3* are binary variables that take into account the individual's education and take the value of one if the individual only finished primary school, secondary school or high school respectively; otherwise, they take the value of zero;[4] c) *edovil*, its value is one if the individual is single and zero otherwise; d) *depen1*, *depen2* and *depen3,* number of dependents; they take the value of one if they have more than one but less than four, four or more or none, respectively; otherwise, they take the value of zero; e) *dura1, dura2, dura3, dura4* register the number of weeks elapsed between the date of termination of their employment and the starting date of the program. They take the value of one if it was less than four, between four and eight, between eight and twelve and more than twelve weeks, respectively; f) *hora1, hora2, hora3* are binary variables that capture whether their work shift was less than 30 hours, between 30 and 40 hours or more than 40 hours a week; g) *contra1, contra2, contra3* indicate the type of contract they had in their last job: open-end for an undefined duration, a verbal contract or a written contract for the performance of a particular task; h) *ocupa1, ocupa2, ocupa3*, *ocupa4,* and *ocupa5* represent binary variables according to their occupation in the last job held; i) *zona1, zona2, zona3, zona4,* and *zona5* are binary variables that capture the geographical location of individuals according to the part of the country they live in.

[3] Those interviewed during the first and second quarters were identified. Since this is a quarterly panel survey, we worked only with those we were able to follow for at least two quarters after they declared being unemployed, until November of the same year, when the survey of individuals in the treatment group was conducted.

[4] To consider the robustness of results, as an alternative in some of our estimates, the variable age was introduced as a set of binaries according to these four groups: less than 20, 20 to 25, 25 to 30 and higher than 38 years old. This was also the case with variable *educa1, educa2,* and *educa3;* variable *educa* also has the discrete values 1, 2 and 3.

For individuals who participated in SICAT and for those included in the control group, we construct the variable salary per hour in the first job held after participating in the program and salary per hour in the last job held before participating in the program.[5] An additional variable related to their previous job is also defined; it is a dichotomous variable that takes the value of one if it was a job in the formal sector and zero if it was not.

We identify the formal sector as the sector which provides non-salary related benefits such as social security, retirement funds and housing loans administered by the following government agencies: IMSS, ISSSTE, SAR and INFONAVIT. All the individuals who participated in SAEBE as well as those that form the control group had previously worked in this sector. For those who belonged to these groups and were employed three months after participating in the program, we identified whether their new job was in the formal sector or not. This information is shown in Table 2.

Table 2
SAEBE 2004 Beneficiaries and Individuals in the Control Group

		Males		Male heads of household		Male non-heads	
		Treatment	Control	Treatment	Control	Treatment	Control
Total		571	268	440	125	131	143
Find employment	Formal	279	123	217	52	62	71
	Informal	179	112	139	62	40	50
Do not find employment		113	33	84	11	29	22

3. Statistical Models Used

3.1 Difference in difference matching (combining the double difference method with the matching method) to estimate impact on salary per hour

Matching program participants with individuals in the control group allows us to use the latter to measure participant outcomes had they not participated in the program. However, the method is valid only if certain restrictive assumptions are fulfilled. Among them, that program participation

[5] Only cases where individuals found work were used in estimates of program impact on earnings. This simplification is a source of inaccuracy and bias in impact estimates because reservation wages of individuals are a variable likely to be affected by the program.

not be associated to unobserved variables (by the analyst). This is a very restrictive assumption, particularly for the case under study in this paper. Therefore, we combined this method with the double difference method to estimate impact, allowing us to eliminate measurement errors attributable to unobserved characteristics (by the analyst) when these remain invariable over time (called individual fixed effects) or change, but do so at a constant rate.[6]

This combination is only possible when pre and post-intervention observations are available for all individuals. In this case, it is possible to combine the matching method with estimates based on the double difference method (that is, using the matching method to obtain an adequate control group and applying the differences between post and pre-intervention outcomes and between the treatment and the control group).

The assumption required to justify the use of the double difference method is that once you have controlled for a set of observed variables, *X*, which determine the earnings per hour and the decision of individuals to participate in the program, the difference between remuneration received in the job they got after their period of unemployment and the one received before becoming unemployed is the same for program beneficiaries had they not participated in the program. More specifically:

$$E\left(Y_{it}^{1} \mid X, D=0, t=1\right) - E\left(Y_{it}^{1} \mid X, D=1, t=0\right) = E\left(Y_{it}^{0} \mid X, D=0, t=1\right) - E\left(Y_{it}^{0} \mid X, D=0, t=0\right) \quad (1)$$

where Y_{it_1} and Y_{it_0} represent individual *i*'s salary per hour after t_1 and before t_0 the program, *D* is a variable that takes the value of one if the individual participated in the program and zero if he did not and *E* is the expected value.

For individuals in the treatment group and in the control group we have the following expressions:

$$Y_{it_1}^{1} = \gamma_{t_1}^{1} + U_{it_1}^{1} + \alpha D \ldots\ldots\ldots\ldots\ldots\ldots Y_{it_0}^{1} = \gamma_{t_0}^{1} + U_{it_0}^{1} \quad (2)$$

$$Y_{it_1}^{0} = \gamma_{t_1}^{0} + U_{it_1}^{0} + \alpha D \ldots\ldots\ldots\ldots\ldots\ldots Y_{it_0}^{0} = \gamma_{t_0}^{0} + U_{it_0}^{0} \quad (3)$$

[6] In particular, it is required that in the absence of treatment, salaries of both the treatment and the control group follow parallel trajectories over time. This assumption is violated when there are unobserved temporary components specific to an individual that influence the decision to participate in the program and when pre-treatment characteristics considered to be related with the dynamics of salaries are not balanced between the treatment group and the control group. This happens when participation is more likely if individuals are going through a temporary decrease in earnings just before the programs start. This implies that compared to individuals in the control group, participants expect higher earnings even without participating in the program. (this is known as "Ashenfelter's dip"). See Abadie 2005.

where supra index one indicates program participation and zero, non-participation. U_{it} represents the unobserved part in the determination of the variable of interest and is made up by two components, θ_i which represents an invariable characteristic over time that is specific to the individual and ε_{it}, which represents a temporary characteristic that is specific to the individual:

$$U^1_{it_1} = \theta^1_i + \varepsilon^1_{it_1} \qquad U^1_{it_0} = \theta^1_i + \varepsilon^1_{it_0} \tag{4}$$

$$U^0_{it_1} = \theta^0_i + \varepsilon^0_{it_1} \qquad U^0_{it_0} = \theta^0_i + \varepsilon^0_{it_0} \tag{5}$$

When the assumption (1) holds true, we have:

$$\Delta Y^1_{it} = \left(\gamma^1_{t_1} - \gamma^0_{t_1}\right) + \alpha D + \left(\varepsilon^1_{it_1} - \varepsilon^1_{it_0}\right) \tag{6}$$

$$\Delta Y^0_{it} = \left(\gamma^1_{t_0} - \gamma^0_{t_0}\right) + \left(\varepsilon^0_{it_1} - \varepsilon^0_{it_0}\right) \tag{7}$$

which means that specific characteristics invariable over time can be eliminated as the cause of measurement errors. In addition, the assumption used to justify the method implies that the decision to participate in the program is unrelated to temporary characteristics that are specific to an individual since: $\left(\gamma^1_{t_1} - \gamma^0_{t_1}\right) = \left(\gamma^1_{t_0} - \gamma^0_{t_0}\right)$, allowing us to obtain parameter of interest α free of measurement bias:

$$\alpha = \Delta Y^1_{it} - \Delta Y^0_{it} \tag{8}$$

When values for the variable of interest for the same individual at two different points in time are available, double-difference matching can be calculated as follows:

$$\hat{\alpha}_{DDM} = \frac{1}{n^1_{t_1}} \sum_{i \in I^1_{t_1} \cap S_p} \left\{ Y^1_{it_1} - \sum_{j \in I^0_{t_1} \cap S_p} W(i, j)\, Y^0_{jt_1} \right\} - \frac{1}{n^1_{t_0}} \sum_{i \in I^1_{t_0} \cap S_p} \left\{ Y^1_{it_0} - \sum_{j \in I^0_{t_0} \cap S_p} W(i, j)\, Y^0_{jt_0} \right\} \tag{9}$$

where $\hat{\alpha}_{DDM}$ represents the estimated treatment impact, S_p indicates the common support under which matching is made, *W(i, j)* is the weighted result for observation *j* and individual *i* and I_{t_1}, I_{t_0} represent the treatment and the control group, respectively.

3.2 Multilogit models to estimate impact on transition to formal employment versus informal employment

Measuring program impact on the probability of getting a job in the formal sector versus one in the informal sector when an individual exits from unemployment requires estimating a model including three states (defined as the individual's status three months after the individual received assistance: unemployment, employment in the formal sector and employment in the informal sector). Specifications for this model are:

$$p_{ij} = \exp\left(X_i' \beta_j + Z\gamma_j\right) / \sum_{l} \exp\left(X_i' \beta_l + Z\gamma_l\right) \tag{10}$$

where p_{ij} is the probability of exiting from status *i* (unemployment) to status *j*; the variables included in vector *X* were defined in the previous section and variable Z is a dummy indicating whether the individual received program benefits or not.[7]

This model requires identifying one of the states as a reference for the other two; so the probability of finding a job in the formal sector versus finding one in the informal sector represents the parameter of interest to answer the counterfactual question regarding the effectiveness of the program.

3.3 Estimating hazard rates to estimate impact of the program on time to find a job

Measuring program impact on the timing out of unemployment requires estimating what is known in statistics as hazard rates, by applying survival models. The starting point of these models is the density function for the timing out of unemployment to employment, *f(t)* and its related survival function for unemployment, defined as one minus the distribution function for the timing out of unemployment, *1-F(t);* or alternatively, as the probability that unemployment duration be equal or

[7] From the results, we subtract the coefficient associated to exit from the informal sector from the coefficient associated to dummy Z for exit to the formal sector. When this is statistically significant and the sign is positive, it is interpreted as evidence that the program has had the desired impact.

exceed value *t*. The coefficient of these two functions is known as the hazard rate, $h(t)$. This function is considered the timing out of unemployment since it is the probability (over time as Δt tends to zero) that the unemployment period will end at interval $(t, t+\Delta t)$, since *t* has been the duration in that state.

These rates can be specified and empirically estimated based on individual characteristics represented by vector X components and a dummy variable, *Z*, that indicates whether individuals received program benefits or not. Thus, it would be convenient to use the functional form known as proportional risks (Kiefer 1988) represented as follows:

$$h(t \mid X, Z) = h_0(t) \exp(X\beta + Z\gamma) \tag{11}$$

In this expression, β represents a vector for parameters to be estimated together with scalar γ.

4. Outcomes

4.1 Impact of SICAT on the salary per hour of program participants

Rosenbaum and Rubin (1983) established a procedure that makes it possible to reduce vector data related to observed individual characteristics to a scalar. According to the steps suggested by these authors, we estimated a probit model where the dependent variable takes the value of one if the individual belongs to the treatment group and zero if he belongs to the control group. The independent variables are those included in vector X, described in section 3, plus a binary variable that takes the value of one if interviewed individuals came from the formal sector and zero if they did not.[8] Propensity to participate in the program, defined as the estimated value of the probit model corresponding to each individual, was the scalar used for the different matches discussed below.[9] According to the formula (9), in difference in difference matching individuals in the treatment group can be matched either with a single individual in the control group or with a combination of "close neighbors" constructed based on applying the weighting procedure to one or two individuals in the control group. Table 3 shows the results of applying the weighting procedure to the four individuals in the control group closer to each individual in the treatment group (measured according to their propensity to participate in the program).[10]

[8] In principle, this vector should include the determinant variables that affect both the decision to participate in the program and the individual salary per hour.
[9] See Smith and Todd (2004).
[10] We followed the methodology developed by Abadie and Imbens 2002. We used the method suggested by these authors to obtain standard errors since it is more trustworthy than using the bootstrap method to obtain them.

Outcomes for the impact on the salary per hour of SICAT beneficiaries during 2004, 2003 and 2002 are shown in Table 3. They indicate that we can reject the null hypothesis that the program has a positive impact on this variable three months after the training provided concludes. Estimates suggest that 2004 SICAT program beneficiaries would have received the same earnings per hour worked if they had not participated in the program; for the other two years, they suggest that remuneration could be even lower.

Table 3
Impact of SICAT on the Salary per Hour
Four Nearest Neighbor Difference in Difference Matching

	2004	2003	2002
	0.58 (3.15)	-1.47 (0.88)***	-2.32 (0.48)*
By modality			
Work skill training	-2.75 (3.41)	-5.86 (1.06)*	
Work training doing actual work	2.42 (3.91)	-2.17 (1.07)*	-5.31 (0.53)*
For self employment		-5.96 (2.08)*	-1.99 (0.75)*
Training coupons	2.15 (5.10)		
For technicians and professionals	-5.09 (7.46)	-0.36 (0.86)	

Note: * and *** significantly different from zero at the level of 1% and 10% respectively. (Standard errors in parenthesis).

As mentioned in the first section of this paper, participants are assigned to one of the different training categories provided by the program. To take into account the sensitivity of our outcomes to disaggregated estimates, we estimated the impact on the salary per hour of SICAT beneficiaries according to the category they were assigned to. Conclusions do not vary: in no category has the program a positive and statistically significant impact on the salary per hour received three months after finishing training.

We also resorted to alternative ways, always combining the matching method with the double difference method, to measure the impact on the earnings of beneficiaries during 2004. First, we separated individuals who are family heads from those who are not. Second, as an alternative to applying the weighting procedure to the matching of individuals in the control group with each individual in the treatment group, on the one hand, we used the closest neighbor approach and on the other hand, weighting based on a normal kernel and bandwidth of 0.06. Table 4 presents outcomes using these variations. Only in one case was it possible to reject the null hypothesis that the program has a positive impact on the earnings per hour of program participants. This is when the Caliper method is used, and only for the first variation. It consists in presetting a tolerance of 0.001 as the maximum distance between an individual in the treatment group and one in the control group; any observations that do not satisfy this criterion are left out of the analysis. In this case, the impact is positive (4.75 pesos per hour) and statistically significant at 7%, but this procedure means using only 25% of the observations for the control group and leaving out 46% of the observations for the treatment group.

Table 4
Impact of SICAT 2004 on the Salary per Hour
Difference in Difference Matching Method

	Propensity score[1/]	Kernel	Caliper (0.001)
Male household heads	1.88 (2.73)	0.88 (1.37)	4.75 (3.45)
Male non heads	2.35 (2.66)	1.58 (2.63)	-1.12 (1.78)

Note: 1/We used the stratified method proposed by Ichino. (Standard errors in parenthesis).

When differences in post-treatment salary per hour levels are considered, using the databases thus obtained and after having matched individuals in the treatment group with individuals in the control group, we consistently find that, in average, salary levels for the treatment group are lower than those for the control group. This suggests that alternative estimation methodologies are not likely to change the signs and make the impact statistically significant, as proven in an evaluation of the PROBECAT program using 1994 data (Calderón 2004), where bias attributable to unobserved variables that determine self-selection to participate in programs were explicitly modeled and estimated applying the techniques set forth in Heckman, Tobias and Vytlacil (2003).[11]

[11] Contrary to this position, the paper by Delajara, Freije and Soloaga (2006) suggests that despite the fact that the matching method (without resorting to difference methods) indicates a negative and statistically significant impact for 2002, 2003 and 2004, when the method developed by Heckman, Tobias, and Vitlacil is used, the sign is reversed and it turns out that the program is indeed effective in improving the remuneration paid to program participants.

Our results would lead us to conclude that the program does not help participants increase their income levels or that those who participate in the program are stigmatized to such an extent that it turns out to be counterproductive. This seems to be more the result of using data from surveys that have many flaws than of a trustworthy assessment. Data for the treatment group were obtained from a single retrospective survey that includes questions regarding their work status at the time of the interview and their last job before becoming unemployed; if it is not their first job after the training program, it includes questions regarding other jobs held. Data for the control group come from panel surveys that identify unemployed workers whose first round of interviews coincides with the date the group of beneficiaries began their training. As many as four additional surveys are used to follow these individuals and reconstruct their work history to make it compatible with information from the surveys applied to the treatment group.

4.1.1 Impact of SAEBE on the transition from unemployment to formal employment

To measure the effectiveness of the program in improving the probability of individuals being hired as workers in the formal sector, which is where they worked before they lost their jobs, we estimate the multilogit model including three states (defined as the status of the individual three months after receiving assistance: unemployment, employment in the formal sector and employment in the informal sector). Its specifications are given by (10) in the previous section, where variable Z is a dummy that indicates whether an individual received program benefits or not.[12]

The first two lines in Table 5 present the impact of SAEBE on the transition from unemployment to employment in the formal sector and unemployment to employment in the informal sector.[13] When the probability of finding a job in the formal sector versus finding it in the informal sector (given that a job is found), outcomes suggest the following: that three months after receiving support from SAEBE, household heads have a better chance of finding formal employment when they exit from unemployment than if they had not benefited from the services provided by this program. Those who are not household heads are less likely to go to the informal sector although the probability that they will continue searching for a job increases.

[12] This is the simples, although less accurate way to estimate models of this type. They can be developed incorporating individual heterogeneity by including random coefficients and even a more dyunamic specification that captures more than one transition to employment after having participated the program (See Card and Hyslop 2005).

[13] These outcomes are based on the multinomial logit model included in the Annex.

Table 5
Impact of SAEBE 2004 on the Type of Employment Found

	Impact on Formal Employment (change in the probability of finding employment in the formal sector)	Impact on Informal Employment (change in the probability of finding employment in the informal sector)	Impact on Unemployment (change in the probability of not finding employment)
Male household heads	6.6 **	-19.3 **	12.7 **
Male non heads	0.0 **	-10.3 **	10.7 **

Note: ** Significantly different from zero at the level of 5%.

4.2 Impact of vacancy information provided to SAEBE beneficiaries on their timing out of unemployment

Using the questionnaire applied to SAEBE beneficiaries three months after they participated in the program allows us to find out the time it took each of them to find a first job, provided they are not still unemployed. Unfortunately, the questionnaires applied to individuals in the control group do not include this information. This made it impossible to estimate program impact on their timing out of unemployment to employment, either formal or informal, versus what would have happened if they had not received the benefits provided by this program. Instead, using only individuals who participated in the program, we were able to estimate whether providing vacancy information in addition to cash assistance helps individuals find a job faster. This was possible since only 80% of them received both components. To this end, we estimated a proportional risk function like the one represented in (11) where individuals who only received financial assistance now constitute the control group and those who received both financial assistance and vacancy information now form the treatment group.

That is, technically, in this estimate we include treatment group members divided in two groups: those who had access to the employment service component in addition to financial assistance and those who only received financial assistance. In this case, the variable dummy Z takes the value of one when participants had access to vacancy information and zero if not. This procedure allows us to deduce whether program participants exit unemployment faster when they are also provided vacancy information versus only receiving SAEBE economic assistance.

Outcomes are shown in Table 6, separating household heads from non heads. These indicate that the impact of providing information in addition to financial assistance on the timing out of unemployment is statistically different from zero and in agreement with the objectives of this program component. According to them, male household heads require almost twelve weeks to find employment when they only receive financial support, up to $3,800, from SAEBE. The job search period for those who received vacancy information in addition to financial support was three weeks and six days shorter.[14]

Table 6
Impact of SAEBE on Timing Out of Unemployment

	Average number of weeks receiving only financial assistance	Hazard ratio (vacancy information coefficient)	Impact on weeks due to vacancy information
Household head and non household head males	11.68	1.33	2.9
Household head males	11.94	1.48	3.87
Non household head males	11.00	1.84	5.02

4.3 Final comments

The purpose of providing financial assistance to unemployed individuals under the SAEBE program is to help them conduct longer and more effective job searches to get better a job than the one had they would have been able to find had they not had the possibility of searching for a job.

It is for this reason that the effectiveness of the program depends not only on increasing the probability of re-entering the formal sector but also on affecting the individual's timing out of

[14] These outcomes were obtained using the hazard models presented in the Annex. Parameters were obtained based on reversing the hazard ratios in our estimates using the calculations described in Calderón–Madrid (2005).

unemployment to employment in the informal sector should he not be able to find formal employment. The question of how the timing out of unemployment impacts formal employment is also relevant to measure the effectiveness of this program.[15]

In this paper it was not possible to consider an analysis of this nature, for example, like the one made by Margolis (2008) for Brazil, due to flaws in the questionnaires used. Surveys applied to the control group for purposes of this SAEBE program evaluation do not include questions regarding the date they found a job to be able to construct the variable timing out of unemployment.

In addition to overcoming the limitations imposed by incomplete data for the control group, a more thorough evaluation of this program should include this variable to allow the use of statistical procedures that are more far-reaching than those used with the available data. If these were available, a study based on hazard functions with competitive risks could be made to adequately estimate the timing out of unemployment into two alternative states, the informal and the formal sector.[16]

Based on estimates made in this paper of the impact of the SICAT and SAEBE programs, we can infer other suggestions regarding what should be done to produce an evaluation as rigorous as required for conclusions to be useful in decision making. These suggestions are presented as three challenges for future program evaluation design. These are: firstly, a more adequate sampling design for treatment and control group members. It would be desirable to advance, as Colombia and Santo Domingo have already done, towards experimental designs and randomized treatment and control groups from a sub-group of unemployed individuals who manifest their decision to participate in the program. Should this be a very ambitious challenge, the minimum requirements would be a) for surveys of control group and treatment group members, preferably from similar geographical areas so labor markets are not subject to different shocks, be conducted on the same date; b) that the questionnaire used be the same for everyone; c) that at least one pre-intervention survey and one post-intervention survey be conducted and d) that the work history of individuals be measured. With respect to this last point, it would be important to follow individuals for at least two years to have more elements regarding the work trajectory of program participants. (See, for example, Bonnal, Fougère, and Serandon 1997).

[15] Unlike unemployment insurance; SAEBE does not allow individuals to prolong their unemployment period to continue receiving support, which is only provided on two occasions. The second payment is made 15 to 30 days after the first payment date or when beneficiaries declare they have already found a job, proof of which is required.

[16] See van den Berg, van Lomwel, and van Ours 2003 and Eberwein, Ham, and Lalonde 1997. A multilogit model does not consider the period of time elapsed before transitioning from unemployment to employment; hazard models, on the other hand, even allow a flexible functional form that can be different for timing out of unemployment into formal or informal employment.

Finally, but definitely not less important, is the challenge arising from the fact that the number of individuals receiving assistance from these programs is high and that perhaps assuming that there are no indirect effects on the rest of the labor market participants is not realistic. Should this be the case, one of the assumptions that allow us to make these partial equilibrium evaluations is violated. The challenge then is conducting an evaluation using a general equilibrium framework and not a partial equilibrium one as it has always been done. (See,for example, Lise, Seitz, and Smith 2003).

Annex

Table 7
Probits for Propensity Score to Participate in the SICAT Program

	2002		2003		2004	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
age	-0.04***	0.01	-0.03***	0.01	-0.02***	0.01
educa1	-0.47***	0.13	-1.45***	0.12	-0.20	0.13
educa2	-0.36***	0.13	-1.80***	0.11	-0.27**	0.12
household head	6.23					
edovil	-0.05	0.15	0.12	0.14	-0.11	0.13
depen1	-5.73***	0.16	0.37**	0.15	0.16	0.15
depen2	-6.48***	0.18	-0.19	0.18	-0.65***	0.17
dura1	0.21*	0.12	-0.24**	0.11	-0.49***	0.11
dura2	-0.12	0.14	-0.72***	0.14	-0.64***	0.13
dura3	-0.14	0.16	-0.62***	0.15	-0.59***	0.15
formal_a	0.26***	0.10	-0.13	0.10	0.29***	0.09
hora1	-0.50**	0.22	0.67***	0.18	0.85***	0.18
hora2	-1.79***	0.11	-0.03	0.10	0.11	0.10
cons	1.02***	0.25	1.85***	0.25	0.57**	0.23
Pseudo R^2		0.123		0.36		0.351

Note: *, ** and *** indicates coefficient is significant at the level of 1%, 5% and 10% respectively.

Table 8
Multilogit Model to Measure the Impact of SAEBE 2004 on the Type of Employment Found

	Male household heads				Male non heads			
	Formal		Informal		Formal		Informal	
	Coef.	Std. Err.	Coef.	Std. Err	Coef.	Std. Err.	Coef.	Std. Err.
Z	-1.47***	0.06	-2.07***	0.06	0.24**	0.10	-1.81***	0.13
age	-0.08***	0.00	-0.05***	0.00	-0.07***	0.01	-0.01**	0.01
educa1	0.43***	0.07	0.96***	0.07	1.92***	0.18	-2.00***	0.18
educa2	0.47***	0.07	1.02***	0.08	1.21***	0.17	-2.53***	0.16
edovil	-0.82***	0.15	-1.36***	0.17	-1.18***	0.10	-2.28***	0.12
depen1	-14.81***	0.17	-19.65***	0.54				
depen2	-15.52***	0.17	-19.85***	0.54				
dura1	0.89***	0.07	1.42***	0.08	1.31***	0.13	-2.55***	0.16
dura2	0.78***	0.07	0.63***	0.07	3.18***	0.21	1.07***	0.21
dura3	0.40***	0.08	0.80***	0.08	1.63***	0.14	0.22	0.16
hora1	-0.11	0.11	0.54***	0.11	-1.07***	0.25	1.03***	0.22
hora2	0.16***	0.05	-0.26***	0.05	0.66***	0.10	-0.48***	0.11
ocupa1	-1.07***	0.11	-0.70***	0.11	-1.77***	0.24	-1.26***	0.25
ocupa2	0.06	0.08	0.03	0.09	-0.35**	0.17	-0.50**	0.21
ocupa4	0.45***	0.10	0.42***	0.10	0.19	0.14	-0.32**	0.15
ocupa5	0.09	0.09	0.36***	0.09	2.25***	0.21	-2.13***	0.27
ocupa6	-1.42***	0.09	-1.67***	0.10	-0.81***	0.15	-0.57***	0.16
contra1	0.19***	0.07	0.40***	0.07	1.49***	0.12	-1.34***	0.13
contra3	0.46***	0.08	0.53***	0.09	0.79***	0.14	-0.80***	0.15
zona1	0.40***	0.08	-0.30***	0.09	1.14***	0.15	3.09***	0.16
zona2	0.15*	0.09	-0.73***	0.09	1.05***	0.13	0.06	0.15
zona3	-0.70***	0.09	-0.90***	0.09	-0.11	0.12	0.04	0.14
zona4	-1.05***	0.12	-0.03	0.11	25.63***	0.35	20.95	
cons	19.62		23.08***	0.53	-0.65**	0.31	5.87***	0.32
Log likelihood				-19234				-4392
Pseudo R^2				0.147				0.405

Note: *, ** and *** indicates coefficient is significant at the level of 1%, 5% and 10% respectively.

Table 9
Impact of the SAEBE Program on the Timing Out of Unemployment
Hazard Function Estimates
Male Household Heads

	Haz. ratio	Std. Err.
Z	1.49 ***	0.05
age	0.98 ***	0.00
educa1	1.60 ***	0.05
educa2	1.53 ***	0.05
edovil	0.41 ***	0.04
dura1	1.77 ***	0.05
dura2	1.16 ***	0.04
dura3	1.14 ***	0.04
hora1	1.09 *	0.05
hora2	0.97	0.02
ocupa1	0.49 ***	0.03
ocupa2	0.86 ***	0.03
ocupa3	1.02	0.03
ocupa4	1.02	0.04
contra1	0.86 ***	0.03
contra3	0.84 ***	0.03
zona1	0.87 ***	0.03
zona2	0.74 ***	0.03
zona3	0.81 ***	0.03
zona4	0.73 ***	0.04
depen2	0.99	0.03
depen3	1.30 ***	0.12
Log likelihood		-78295.606

Note: *, ** and *** indicates coefficient is significant at the level of 1%, 5% and 10% respectively.

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