Revised Research Proposal

Do the Poorest among the Poor Benefit Less from Active Labor Market Programs? Evidence from PROJOVEN

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1. Abstract

In many developing economies, while substantial progress has been made to strengthen the democratic system, liberalize the economy, implement responsible macroeconomic policies, and expand basic social services, much is yet to be done to identify causal relationships for policy interventions to improve the lot of the poor.

The evaluation of training programs has played a central role in studying the effectiveness of active labor market policies. The paradigm of the representative agent that assumes that all treated individuals have the same impact from a public policy has produced a vast array of empirical work that focuses on mean training impacts (Heckman, Smith, and Todd 2001). Even when some studies have emphasized the importance of considering how people differ in their responses to the same policy (Heckman, Smith and Clement 1997, Heckman 2001, Bitler, Gelbach, and Hoynes 2004), we have almost no empirical evidence about whether the program benefits less the poorest among the poor.

We investigate heterogeneous treatment impacts of the Youth Training Program PROJOVEN on labor participation and earnings of disadvantaged individuals using a set of parametric and nonparametric econometric techniques. The primary goal of this program is to facilitate the labor market participation of poor individuals through training and employment opportunities.

The availability of data for six different cohorts in a program operating for almost a decade has created an extraordinary opportunity to investigate: (i) heterogeneous treatment impacts across the “poverty index” distribution, (ii) the long-term sustainability of the treatment effects (iii) the extent of differentiated treatment effects by gender, and

(iv) the existence of “cream-skimming” in the program’s selection mechanisms that may create large treatment effects at the cost of less equity.

2. The Program and Main Research Questions

The Youth Training Program PROJOVEN was implemented in 1995 with the goal of increasing the employability and productivity of disadvantaged young individuals aged 16 to 25 years throughout basic training courses. The treatment consists of a mix of formal and practical training organized in two phases. The first stage consists of three hundred hours of formal classes at the training center locations distributed in daily classes of five hours each for about three months. After completing this stage, training institutions must place trainees into a paid on-the-job training experience in productive firms for an additional period of three months. Since its creation, and for almost a decade, over 30,000 out-of-school unemployed poor individuals aged 16 to 25 years have been selected as beneficiaries of PROJOVEN across different calls.

The Beneficiary Selection Process

The selection in PROJOVEN is a multistage process where different actors -target individuals, bureaucrats, and training centers - govern each stage of the program participation process. The program awareness strategy constitutes the first formal effort to reach out the target population and aims to inform them about the benefits and rules governing the program. This first “filter” focuses only on those neighborhoods with high concentration of households below the poverty line. Those prospective participants attracted by the expected benefits and perceived opportunity costs of participation voluntarily show up in the registration centers where qualified personnel determine their eligibility status. A standardized targeting system based on five key observable variables (poverty status, age, schooling, labor market status, and pre-treatment earnings) determines who is eligible and who is not. This process concludes when the total number of eligible individuals exceeds in around 90 percent the total number of slots available in each call.

The eligibility status does not guarantee participation in the program. The enrollment in the program depends on both training centers and applicant's willingness to pursue the application process to its conclusion. Eligible individuals are invited to an orientation process, where they choose the courses they want to attend following the "first come first serve" criterion. This process concludes when the number of eligible individuals exceeds in around 75 percent the number of available slots for each course.

Finally, the training institutions decide who benefits from the program and who does not among the pull of eligible applicants sent by the program operator. This final step does not follow a standardized criteria since each institution apply its own rules.[1] It is important to notice that because the ratio eligible/beneficiary is around 1.75, the problem of cream-skimming" is latent.

The Selection of Training Services

The selection of training services follows a two-step standardized process. The first step targets the selection of training institutions. Before determining the eligibility of prospective young beneficiaries, the program operator opens a training directory called RECAP where all training institutions that want to participate in the program have to enroll. To be part of the RECAP, the training centers must pass a minimum quality threshold following standardized instruments that mostly evaluate the legal status

[1] It is against the program's rules to select individuals based on age, race, sex, and schooling.

(formality) and the existence of some acceptable level of human resources and infrastructure.

In the second step, the program operator invites institutions enrolled in the RECAP to participate in public bidding processes where the selection of training courses rather than training institutions takes place. Because of tight government budgets, the program operator selects those courses with the relative highest scores at the best competing prices.[2]

To measure the effectiveness of each call, the program operator merges a random sample of beneficiaries to a non-experimental comparison group sample. The construction of the comparison group is based on one-to-one matching, where each beneficiary is paired to an eligible not participant neighbor (out-of-school unemployed poor individual aged 16 to 24 years living in the same neighborhood). This costly strategy is rewarded with the full balance of several observable variables in both populations. In addition, the neighborhood variable controls some unobservable characteristics (e.g., geographic and social segregation, transportation costs, labor demand concentration, etc.) that may affect both the propensity to work and the potential outcomes.

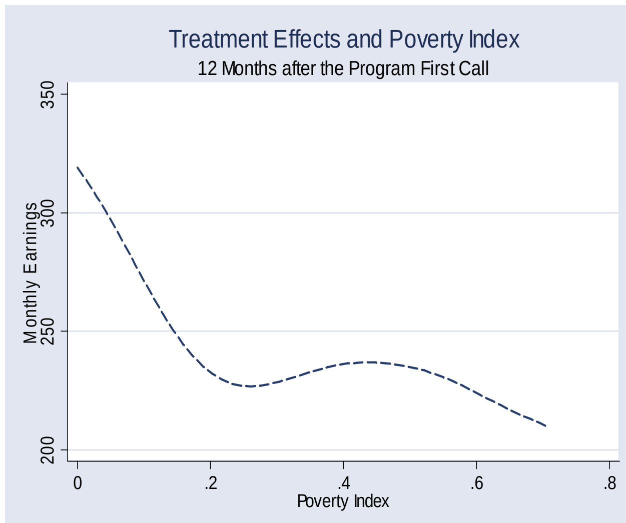
Some studies have been conducted to evaluate the program's effects on the population of interest.[3] Three patterns emerge from these studies:

(i) PROJOVEN's treatment effects are positive, ranging in size from 12 to 100 percent, (Galdo 1998, Ñopo, Saavedra, and Robles 2002). These are average treatment effects that assume that all treated individuals have the same impact

[2] The number of selected courses depends on the available training slots that are determined ex-ante.
[3] Galdo 1998, Burga 2001, Chacaltana 2001, Ñopo, Saavedra, and Robles 2002.

from the program. Yet, does the program have the same effect on everyone? Preliminary evidence suggests the poorest among the poor beneficiaries benefit less from the program:

Figure 1



(ii) These "common effect" estimates emerge from different econometric techniques and different parameters of interest. For instance, Ñopo, Saavedra, and Robles (2002) implement nearest-neighbor matching and difference-in-differences estimator, whereas Burga (2001) uses kernel regression matching. In addition, most of these studies focus only in short-term impacts (six months after the program) and not medium term effects (twelve and eighteen months after the program). Is the short-run treatment impacts higher than the medium-run treatment impacts for the poorest among the poor and less poor participants?

(iii) These studies overlook the potential problem of “cream-skimming” in PROJOVEN that may cause large treatment effect at the cost of less equity. This feature emerges from the analysis of the selection of beneficiaries in the program, which reveals that the training institutions may select the “best” individuals among the sample of eligible individuals.[4] Therefore, is the “cream skimming” feature intrinsic to demand-drive training designs?. How does it affect equity considerations?. Table 1 shows the distribution of schooling between eligible participants and participants. The main result that emerges from this table is the significant difference in the school distribution between these two groups, which shows that training institutions tend to select those individuals with higher potential outcomes.

Table 1

	Sixth Round		Eighth Round	
	Treated	Eligible	Treated	Eligible
No schooling	0.04%	0.02%	0.00%	0.00%
Incomplete primary	0.41%	0.93%	0.84%	1.12%
Complete primary	1.12%	2.06%	0.90%	1.96%
Incomplete secondary	16.14%	19.85%	14.01%	17.86%
Complete secondary	**82.29%**	**77.14%**	**84.25%**	**79.05%**

We will assess the extent of “cream-skimming” in PROJOVEN by measuring observable differences between eligible and beneficiary samples.

[4] The program operator defines the targeting criteria and identifies eligible individuals based on first come first serve. The number of eligible individuals is set in 75 percent – 90 percent larger than the number of available training slots. The training institutions finally decide who is assigned to training (participant) and who does not (ineligible participants). If the training institutions maximize their returns, then, they should select those individuals that on average are expected to have higher potential outcomes.

Core Research Objectives

The goal of this research project is fivefold:

1. To estimate overall heterogeneity of program impacts considering the poverty dimension. By doing so, we investigate whether the poorest among the poor have the same treatment impacts within and across different calls. We examine the program targeting mechanism to find heterogeneity in the eligible population along the criteria used for beneficiary selection.
2. To investigate the long-term sustainability of the treatment effects. In particular, we are interested in measuring whether the effects of the poverty index are steady across time. We compare short-term effects - six months after the program - to medium and long-term effects - twelve and eighteen months after the program.
3. To document the extent of differentiated treatment effects by gender and age. Previous studies show that female beneficiaries present larger training returns than males do. We want to extend the existing work by considering the poverty dimension in this discussion and by documenting whether this gender gap is constant across time within call.
4. To present evidence of "cream-skimming" in PROJOVEN. Preliminary analysis of the data shows important differences in the distribution of observable variables between eligible individuals (those who pass the targeting criteria in the local offices), and beneficiaries (individuals selected by the training centers among the sample of eligibles). This important feature, related to the institutional context of the program, may cause a trade-off between the size of the treatment effects and equity considerations.

5. To merge the empirical findings with a comprehensive analysis of institutional factors affecting the targeting mechanism. This step would allow us to address the lessons we have learned after a decade of PROJOVEN.

3. Scientific Contribution

The main contribution of this investigation is the identification and estimation of heterogeneous treatment impacts using nonparametric econometric techniques. In general, the estimation of varying effects is a pending work for most policy interventions (see Imbens 2004). Some steps have been taken in this direction in the last few years, following the lead of Bitler, Gelbach, and Hoynes (2004), and Djebbari and Smith (2004). In this respect, our research we will be one of the first studies that deal with heterogeneous treatment impacts in a developing country.

From a methodological perspective, the propensity score matching method (see Heckman, Lalonde and Smith 2001) shows that treatment impacts are very sensitive to the specification of the propensity score. Parametric propensity score models that pass standard balancing tests are regarded as valid because they balance the distribution of pre-treatment covariates between matched units conditional on the propensity score (Rosenbaum et al. 1985, Lechner 2000). The main limitation is, however, that alternative standard balancing tests may yield different answers, particularly in small samples (Smith and Todd 2005). Henceforth, we adopt an efficient nonparametric approach to estimate the propensity score using a novel kernel method with mixed continuous and categorical data. We give details of this technique in the methodological section.

4. Policy Relevance

The Youth Training Program PROJOVEN corresponds to a new array of demand-driven training programs implemented in Latin America in the mid 1990s in the midst of structural reforms in the labor markets. Similar programs have been implemented in Argentina (Proyecto Joven), Chile (Chile Joven), Uruguay (Opcion Joven), and Colombia (Youth Training Program). Therefore, our findings about the effectiveness of this particular program exceed the evaluation of the Peruvian local labor market.

This "last generation" of active labor market policies is based on market-based approaches where public resources are assigned to training institutions via public bidding processes. In this context, knowing whether this program is cost-effective or not constitutes a test about the effectiveness of market-based approaches to improve the employability and productivity of disadvantaged individuals.

In contexts of tight public budgets, the knowledge about who benefits more from the program is itself a relevant policy question. The results of this paper will heighten the public debate about the trade-off between equity and efficiency when designing active labor market policies in developing countries. In addition, the results will let the program operator to redesign both target strategies and selection mechanisms depending upon either equity or efficiency considerations are favored.

The availability of data for measuring short and long-term treatment impacts allows us to address a fundamental policy issue: the sustainability of the treatment impacts over time. In particular, long-term estimates are crucial inputs for credible cost-benefit analysis. Likewise, the availability of data for a program operating for almost a decade has created an extraordinary opportunity to investigate treatment impacts for different cohorts. This feature in the data is policy relevant because allows us to assess the “external validity” of our findings.

Finally, the potential existence of “cream-skimming” in the program’s selection process directly addresses the trade-off between impact effectiveness and equity considerations. This is and old yet interesting policy problem present in every policy intervention.

5. Methodology

The aim of solving the evaluation problem is to find consistent and unbiased counterfactuals for those units that received the treatment. The problem arises because evaluators observed mutually exclusive states for the individuals: treatment (*G=1*, associate to outcome Y_1) or non-treatment (G=*0*, associate to outcome Y_0), but not both states at the same time. Therefore, estimating the outcomes that would have been observed for participants in the program had they not participated, Y_0, is the evaluator’s task.

Denoting Δ_i as the individual gain of moving from state 0 to state 1, we cannot identify the impact of participating in the program, $\Delta_i = Y_{1i} - Y_{0i}$, because of the missing data problem. We can only identify mean or distributional gains under some exogeneity assumptions. In this paper, we focus in the mean impact of treatment on the treated, which estimates the average impact among those participating in the program:

$$\Delta_{TT} = E(Y_1 - Y_0 \mid X, G=1) = E(Y_1 \mid X, G=1) - E(Y_0 \mid X, G=1)\,. \qquad (1)$$

While $E(Y_1 \mid X, G=1)$ may be estimated from the observed treated sample, the right-hand side of the equation (1) contains the missing data $E(Y_0 \mid G=1, X)$. If we know for certain the outcome that would have been observed for participants in the program had they not participated, $Y_0 | G = 1$, we have solved the evaluation problem. In this context, using non-participants' outcomes, $Y_0 | G = 0$, to approximate the counterfactual missing participants' outcomes creates mean selection bias because those who participated in the program may have different levels of Y_0, even in the absence of receiving any program services,

$$SB = E(Y_0 | G = 1, X) - E(Y_0 | G = 0, X). \qquad (2)$$

To estimate unbiased and consistent treatment effects we need to pick those econometric estimators that solve the type of selection specific to each program. A preliminary analysis of the selection process in PROJOVEN shows that both selection in observables and selection in unobservables are present since the selection of eligible individuals is based on observed targeting criteria; however, the selection of beneficiaries is based on characteristics observed only by the training centers and not by the evaluator. Therefore, cross sectional estimators such as the propensity score matching, in the standard version, are discarded.

We implement two different econometric estimators to identify the average treatment effects under the assumption that the distribution of unobservables is allowed to vary across groups but not over time within groups: $\varepsilon \perp T | G$, where $T = \{1, 0\}$ indicates the before-after time dimension, and $G = \{1, 0\}$ indicates the treated-untreated states. This is the standard assumption behind difference-in-differences models.

5.1. Parametric Difference-in-Differences Estimation

Our starting point is to estimate the average treatment effects for all rounds within call using a parametric difference-in-difference model. We proceed by estimating,

$$Y_{it} = \alpha_0 + X_{it}'\alpha_1 + \alpha_2 \mathrm{G}_i + \sum_{t=1}^{3} \alpha_{3t} \mathrm{T}_{it} + \sum_{t=1}^{3} \beta_{1t} \mathrm{T}_{it} * G_i + \varepsilon_{it}\,, \qquad (3)$$

where Y represents the outcome variable (*earnings and labor market participation*), *X* is a vector of covariates that includes individuals' demographic and socio-economic characteristics, as well as macroeconomic control variables, *T* is a dummy variable representing the time dimension, *G* is a dummy variable for participation, and ε the error term. The parameter of interest is β_{1t}, which represents the difference-in-difference estimate of PROJOVEN on the labor outcomes of beneficiaries. The advantage of this specification is that we can recover the short-term (β_{11}), medium-term (β_{12}), and long-term (β_{13}) treatment effects from the same estimation within round. This estimation considers all samples, males and females, which allows us to measure the extent of differentiated treatment effects by gender within round.

A natural way to extend this standard model to a world of heterogeneous treatment effects is by adding additional terms and interactions that use information regarding the poverty index,

$$Y_{it} = \alpha_0 + X_{it}'\alpha_1 + \alpha_2 \mathrm{G}_i + \alpha_3 S_i + \alpha_4 G_i * S_i + \sum_{t=1}^{3} \alpha_{5t} \mathrm{T}_{it} * S_i + \sum_{t=1}^{3} \beta_{1t} \mathrm{T}_{it} * G_i * S_i + \varepsilon_{it}. \qquad (4)$$

where again *X* is a vector of covariates that includes individuals' demographic and socio-economic characteristics, *T* is a dummy variable representing the time dimension, *G* is a dummy variable for participation, *S* is the poverty index that *is* constructed using factor analysis that group together socio-economic variables that are collinear to form a composite indicator capable of capturing as much of common information of those variables as possible, and ε the error term.[5] It is worth noticing that α_4 is the coefficient for the interaction between participation and the poverty index, α_5 is the coefficient for the interaction between time and poverty status, and β_1 the coefficient for the interaction of time, treatment status and poverty index. We test then whether there is any program impact on the outcome by evaluating the following joint hypothesis:

$$Ho : \delta_2 = \beta_{it} = 0.$$

Then, we test whether the program impact along the poverty index is the same for all individuals by testing the following hypothesis

$$Ho : \beta_{it} = 0.$$

Rejecting this null hypothesis is evidence of heterogeneous program impacts along the poverty index. In order to test whether the impacts are decreasing or increasing along the index, we examine the sign of the coefficients on the interactions terms in equation (4).

5.2. <u>Difference-in-Differences Nonparametric Propensity Score Matching</u>

A more flexible approach considers difference-in-differences kernel regression matching. To implement the treatment effect on the treated, polynomial kernel matching on the propensity score imputes the counterfactual for each treated unit through a weighted average of the outcome variable in the comparison sample and, then, estimates a simple means difference between the two samples over the common support region. In that sense, matching resembles an experiment; no functional assumptions for the outcome equation are required:

[5] We use exclusively data from the baseline sample to construct the poverty index to avoid using confounding variables.

$$\Delta_{TT}^{M} = \frac{1}{n_1}\sum_{i_1=1}^{n_1}\left\{ (Y_{1it} - Y_{1it-1})I^{CS} - \left\{ \sum_{i_0=1}^{n_0} W(i,j)(Y_{0jt} - Y_{0jt-1})I^{CS} \right\} \right\}, \qquad (7)$$

where Y_{1i} and Y_{0j} are the outcome for the *ith* treated and the *jth* untreated units; I^{CS} is an indicator function that takes the value 1 if the unit is in the common support region, 0 otherwise; and n_1 and n_0 are the sample of treated and comparison units. The key variable is $W(i, j)$ that depends on the distribution of the propensity scores between the treated and untreated populations, and its functional form defines various matching estimators.

The identifying assumption justifying this matching estimator is that there exists a set of conditioning variables *X* (or the propensity score) such that after conditioning on it, the outcomes for treated and untreated individuals follow a parallel path. In this respect, the detailed baseline data contain individual and household information for both treatment and control groups. Besides including common variables used in the evaluation of training programs such as labor market outcomes, schooling, age, sex, marital status, children, etc, these data also contains information about parent's education, dwelling characteristics, household income, household size, among others. Therefore, our estimates treatment impacts are purged of any effects coming from demographic, socio-economic, and family differences.

We estimate a fully nonparametric propensity score using multivariate kernel methods with mixed categorical and continuous data. Indeed, the propensity score is a conditional probability density function, $f(T \mid X) = f(T, X)/f(X)$, which uses a sufficiently rich set of pre-treatment covariates *(X)* to attain the conditional independence assumption. Following Li and Racine (2003), we estimate a multivariate kernel conditional density function with the joint *PDF* estimated by:

$$\hat{f}(T,X) = \hat{f}(Z) = n^{-1}\sum_{i=1}^{n}\tilde{K}_{h,\lambda}(z_i, z), \qquad (8)$$

where $Z = \{T, X\}$, $n = n_1 + n_0$ is the total number of treated and comparison units, and $\tilde{K}_{h,\lambda}$ is a well-behaved multivariate kernel function which depends on the distribution of the z_i vector evaluate at z, and a vector of optimal bandwidths for continuous and categorical variables $\{h, \lambda\}$, both converging to zero as $n \to \infty$. We estimate the multivariate kernel function $\tilde{K}_{h,\lambda}$ by "hybrid" product kernels in which each univariate kernel corresponds to each data type,

$$\tilde{K}_{h,\lambda}(z_i, z) = \prod_{j=1}^{c} K_{h_j}(z_{ij}, z_j) \prod_{j=c+1}^{d+c} K_{\lambda_j}(z_{ij}, z_j) \qquad (9)$$

where K_{h_j} and K_{λ_j} are the univariate kernel function for categorical and continuous data, and c and *d* are the number of continuous and categorical covariates.

After estimating the propensity score, we can estimate the average treatment effects on the treated using local constant and local linear polynomial kernel regressions for each round. A final step is the estimation of treatment effects considering the poverty dimension. In doing so, we assign treated units into different quintiles, where the quintiles are defined by the distribution of the poverty index *(S)*. Then, we proceed to estimate the average treatment effect within quintiles.

5.3 Quantile Regression

This alternative estimator allows us to estimate the treatment effects across the entire distribution of the outcomes. To that end, we use quantile regression that is a useful and widely used econometric technique (Koenker and Bassett 1978). This semiparametric approach allows the estimation of treatment impacts at various points of the distribution without relying on the normality assumption of the error terms. An important application is the work of Bitler, Gelbach, and Hoynes (2004) that finds evidence of program impact heterogeneity in response to welfare reform in U.S following the quantile approach.

For any variable Y having *cdf* $F(y) \equiv \Pr[Y \leq y]$, the q^{th} quantile of F is defined as the smallest value y_q such that $F(y_q) = q$. If we consider two distributions F_T and F_C, we may define the quantile treatment effect as $\Delta^{QTE} = y_q(T) - y_q(C)$. As a simple example, estimating the quantile treatment effect at the 0.50 quantile involves taking the sample median for the treatment group and subtracting the sample median for the control group. To ensure finite-sample balance across all observable pre-treatment variables, we weight each observation by its inverse propensity score (Bitler et al. 2005).

6. Description of the Data

We employ rich, longitudinal, and representative samples of both treatment and control individuals for each call. To measure the poverty dimension we use administrative pre-program data that capture socio-economic information for both treatment and comparison individuals. These data include schooling, labor earnings, age, sex, unemployment history, marital status, number of children, number of household members, household income, parents' education, home's infrastructure (floor, walls, and ceiling), access to telephone, access to water, access to water sewage, access to electricity, participation in welfare programs, among others.

Then, we proceed to match this administrative data to the follow-up evaluation data that aim at measuring two labor outcomes: labor participation and labor earnings. Twenty-four different datasets composed our evaluation data, corresponding to the first, second, fourth, sixth, eighth, and eleventh rounds, with a baseline survey and three follow-up surveys within round. Table 3 shows the timing of each dataset.

Table 3

Round	# Units	Baseline	1st follow-up	2nd follow-up	3rd follow-up
1	1507	January, 97	October, 97	August, 98	April, 99
2	1812	August, 97	January, 99	July, 99	January, 00
4	2274	October, 98	February, 00	September, 00	April, 01
6	2583	November, 99	May, 01	November, 01	June, 02
8	3114	January, 01	June, 02	December, 02	August, 03
11	1840	September, 03	January, 04	October, 04	-------

7. Dissemination Strategy

GRADE is a leading research institution in Peru and an important actor in the discussion, analysis, and evaluation of public policies in areas such as Labor, Health, and Social Programs. As such it has already well-established mechanisms to disseminate its research results, each one focusing in different types of audiences. Four such mechanisms will be used. First, we will divulge the results of our investigation through a formal seminar to be carried out at GRADES's headquarters with the presence of the academic community, policymakers, and the program operator. Another mechanism is the working paper series that GRADE publishes on a regular basis (four-six issues per year), and which now counts 48 issues. Our report will be published as part of these series. A third mechanism has a broader set of opinion leaders as a target audience and consists of a policy brief (5-6 pages long) that is disseminated in a series named *"Analisis & Propuestas" (Analysis & Proposals),* GRADE's quarterly publication, which reaches around 1,500 opinion leaders in Peru. Finally, GRADE publishes a bi-weekly column in a newspaper with broad nation-wide circulation, Peru.21. A two-page synthesis of the results will be published using this column. As far as the international academic community, a revised and final version of this research will submitted to a peer-reviewed journal for its consideration and eventual publication.

8. List of Team Members

Name	Age	Gender	Previous related experience
Miguel Jaramillo	43	Male	PhD in Economics, Senior Researcher at GRADE. Has worked in research, teaching as well as in policy-making. He worked in the Labor Ministry between 1996 and 999, first designing and then coordinating the Labor Information System Project. Was vice-minister in 1998. In research, he has worked on labor market and social program evaluation issues. Has participated in different projects in this area, including baseline studies as well as program impact evaluation.
Jose Galdo	33	Male	Ph.D. (ABD) in Economics. His doctoral dissertation focuses in programme evaluation. He was Research Associate in the Center for Policy Research at Syracuse University and Head of the Evaluation Unit in the Ministry of Labor and Social Promotion of Peru. He has evaluated several programs including the National Work Support Demonstration, the Kentucky Working and Reemployment Services, and PROJOVEN.
Cristina Rosemberg	24	Female	Bachelor in Economics, Research Assistant at GRADE where she has worked in topics related to rural development and impact of the remittances in Peru. She has also served as teaching assistant at Pontificia Universidad Catolica del Peru. Expertise in database management and econometric tools.
Angelo Ginocchio	22	Male	Undergraduate senior student in the Pontificia Universidad Catolica. Research Assistant at GRADE where he has been participating in Labor and Health research projects. Expertise in database management and econometric tools.

9. <u>Description of Research Capacities</u>

The study of causal effects for a program operating ten years is a challenging task that involves a good understanding of the institutional setting, targeting mechanisms, and econometric estimators. First, this investigation will give us the opportunity to deepen our understanding about the link between poverty and welfare programs in developing countries. The conventional wisdom is to believe that all poor individuals benefit the same from welfare programs. It is possible, however, that the effectiveness of welfare programs varies across a poverty index. If so, this research will allows us to understand better the institutional factors behind this result.

Second, this research will give us the opportunity to open a sincere dialogue with policy makers and the program's operator. In particular, we expect to maintain a close institutional relationship with both the Ministry of Labor and Social promotion and the technical team of PROJOVEN.

Finally, we will build a good understanding about the identification and estimation of several econometric techniques that can be used in future evaluations of different public policies. In particular, we need to excel the empirical estimation and programming of the following estimators: factor analysis, matching estimators, nonparametric propensity score models, difference-in-differences estimators, quantile regression.

The division of labor between the team members will be as follow:

(1) Baseline data processing:	Cristina, Angel
(2) Follow-up data processing:	Cristina, Angel
(3) Analysis of baseline data:	Cristina, Angel, Jose, Miguel
(4) Analysis of follow-up data:	Cristina, Angel, Jose, Miguel
(5) Estimation of poverty index:	Jose, Cristina, Angel
(6) Modelling Impact:	Jose, Cristina, Angel

(7) Analysis, discussion of results: Miguel, Jose, Cristina
(8) Preliminary Draft: Miguel, Jose, Cristina
(9) Final Document: Miguel, Jose, Cristina

This research proposal will take 8 months of work according to the following project timetable.

Tasks	**2005**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Baseline data processing	X	X						
Follow-up data processing		X	X					
Analysis of baseline data			X	X				
Analysis of follow-up data				X	X			
Estimation of poverty index			X					
Modelling Impact					X	X		
Analysis and discussion of results					X	X	X	
Preliminary Draft						X	X	
Final Document							X	X

10. <u>Ethical issues</u>

None

11. <u>List of past, current, and pending projects in related areas</u>.

Name	Projects
Miguel Jaramillo	"Transiciones globales y ajustes locales. Los mercados laborales y de capacitación en el Peru a inicios del s.XXI (co-authored) (ongoing) "¿Cómo se Ajusta el Mercado de Trabajo ante Cambios en el Salario Mínimo? Evaluando la Experiencia de la Última Década" (ongoing) Los Emprendimientos Juveniles en América Latina: ¿Una respuesta ante las dificultades de empleo? (past) "Baseline study for CID's Youth Entrepreneurship Program, Puno" (past) "An Experimental Evaluation of the Youth Entrepreneurship Program in Huancavelica, Peru", [with Sandro Parodi] (past) "Youth Entrepreneurs: Evaluating Promotion Programs", [with Sandro Parodi] "Evaluating the Effects of Minimum Wage on Employment and Other Labor Market Adjustment Variables" (past) "The Regulation of Labor Market in Peru" (past) "Impact evaluation of the Entrepreneurial and Vocational Training for the Urban Poor Project developed by CARE Peru" (past) "Impact evaluation of the Training for Young Micro-entrepreneurs Project developed by the Colectivo Integral de Desarrollo – CID" (past) Quantitative and Qualitative Evaluation of the Young Micro-entrepreneurs Project developed by the Colectivo Integral de Desarrollo – CID", [with Sandro Parodi] (past) "Impact evaluation for the Vocational Training Project in Southern Peru" "Economic Impact of Recent Labor Regulation Changes: youth labor training, labor services firms, and severance costs" (past) "The impact evaluation of the Training and Technical Assistance Project BONOPYME" (past)
Jose Galdo	"Treatment Effects for Profiling Unemployment Insurance Programs: Semiparametric Estimation of Models with Fixed Effects" (ongoing) "Evaluating the Regression Discontinuity Design Using Experimental Data" *[with Dan Black and Jeffrey Smith]*. (ongoing) "Bandwidth Selection and Treatment Effects with Non-Experimental Data" (Past) "Impact Evaluation of Training Programs on the Peruvian Labor Market: The Case of PROJOVEN". In: E. Vasquez (ed) "*Impact of the Social Investment In Peru*", International Development Research Center-Canada, Research Center of Universidad del Pacifico (Past)
Cristina Rosemberg	"Impact of remittances in Peru at a national and local level" (Ongoing) "Proposal on the Assessment of Environmental and Social Impacts for the Operations Phase of the Camisea Gas Field" (Past) (co-authored) "Impact assessment of the Alternative Development Program (ADP)" (Past).
Angelo Ginocchio	"Determinants of the household's out-of-pocket health expenditure: implications for the universal securing in Peru" (ongoing)

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