

***Active Labor Market Policy impact in a context of high informality: The evaluation of the
PAE program in Bolivia****

This version: 10th of November 2018

Abstract.

In low and middle-income countries, jobseekers face barriers affecting their access to formal labor markets. Two of the most important barriers identified are: (i) limited skills obtained in the education system and (ii) information barriers to labor market entry (Berniell & de la Matta). In the case of Latin America and the Caribbean, job seekers have additional difficulties because most of them only have labor experience in the informal sector, so it is difficult to screen their productivity level to employers. Can formal job experience impact such barriers? The present paper evaluates the impact of an on-the job training program on formal enterprises in Bolivia on three labor market outcomes: employment, formality and monthly earnings. Using data from a telephonic survey and administrative datasets and using a combination of matching and difference in difference estimators we find that the program improves employment in 8 pp. for treated and the access to formal employment in 4 pp. The impact of the intervention on monthly earnings, as high as 85%, is basically explained by the improvement of the earnings of those who already had working experience. We also identify that the impact of the PAE is higher for those with higher education (tertiary education) and those older than 28 years. These results are consistent with the hypothesis that information barriers, particularly in a context of high informality are a major barrier for access to formal employment.

* Document in elaboration. Rafael Novella & Horacio Valencia

Introduction

The lack of access to employment, especially to formal ones, is probably one of the main concerns by low and middle-income countries. In this context, Latin American and Caribbean (LAC) faces additional difficulties since an important share of the economy is informal¹, therefore access to formal employment seems to be restricted only to more educated workers (Attanasio et al., 2011). As a policy challenge, informality and unemployment are not only contemporary problems, they also would have impacts in the medium and long term through imposing pressure to fiscal balance, social security scheme and poverty and inequality goals.

Regarding labor market issues, there are two reasons identified behind the lack of access to formal employments: (i) the limited skills obtained in the education system; and (ii) information barriers to labor market entry (Berniell & de la Mata, 2017). These problems are greater in the context of LAC economies. Even more, these difficulties are bigger for vulnerable job seekers, such as youths, women and people with lower levels of formal education.

In this context, Active Labor Market Policies (ALMP) have gained importance as an instrument to generate formal and productive jobs (Pignatti, 2016; Kluve, 2016)². In LAC, the application of these programs is long-standing and most of them have been implemented as training programs designed to job seekers³. The way in which ALMP in the region were implemented is heterogeneous (Gonzales et al., 2012) and their success or failure could be explained by the combination of different components and the importance of building integrated skills training structures (Kluve, 2016).

Despite the growing interest in analyzing the effectiveness of ALMPs, only recently relevant evidence of their effectiveness become available in developing countries (McKenzie, 2016). Evidence from developed countries shows that training policies generally has small effects, especially for young people (Card et al., 2010). However, the results of evaluations of these policies are more auspicious in developing countries, particularly in LAC (Betcherman, 2007, Ibararán & Rosas, 2008, Gonzales et al., 2012, Attanasio et al., 2011, Kluve 2014; Kluve, 2016).

The present document aims to support the understanding of the impact of having access to a formal work experience over the access to an employment and the quality of them. Answering this question is relevant considering the little evidence about the impact of these type of ALMPs in the literature, particularly in the region. Is particularly important to understand the impact of these type of ALMPs in a context of high informality, in order to do this, we analyze the case of Bolivia, a small and open economy in LAC.

In this sense, the document studies the impact of an access to formal experience through the Employment Support Program in Bolivia (PAE by its acronym in Spanish). PAE is a training program in which job seekers registered in the Public Employment Service (PES) were matched into vacancies in formal companies and in which the program paid a training stipend between 1 and 1.5 minimum salaries up to three (3) months. Since the assignment to the program is not random, combining a propensity score matching and difference in difference estimators we are able to isolate the impact of the on the job training over different labor market variables: employment, formal employment and earning income.

This document uses three sources of information: administrative data from PES, administrative data from the Program itself and data from a telephone survey. The telephone survey was designed to capture

¹ The share of Informal workers is about 62% in the region (Alaimo et al., 2015). Defining informal as those workers who doesn't contribute to social security.

² Solving the described problems require a combination of policies. Structural reforms to boost the creation of employment, specially the formal ones, and encourage education systems to train future workers with the set of skills required by the market (Gonzales et al., 2012). At the same time, it is necessary to have policies to improve the efficiency of the labor market by reducing the search and contracting costs (Alaimo et al., 2015) and policies to improve the relevant skills of the current workers.

³ The literature has identified that traditional ALMPs are divided in three main categories: training programs, employment subsidies and search and matching assistance programs.

information regarding the employment characteristics of workers at the time of their registration in the program and the time of the survey.

The results show that the program has a positive impact on access to employment of 8 pp. in relation to the control group. A positive impact of 4 pp. over access to formal employment (understanding formal employment as access to social security) and an impact of 8% on labor income. These results are consistent with the impacts found in different ALMPs in the region and are consistent with the impacts found by Berniell & de la Mata (2017) in a very similar program in Argentina.

We were able to identify that the improvement of the earnings is explained by those who already had working experience. We also identified that the impact of the PAE is higher for those with higher education (tertiary education) and those older than 28 years. We perform several robustness checks in order to verify the validity of the assumptions. The results are consistent with the hypothesis that information barriers, particularly in a context of high informality economy, are a major barrier for access to formal employment.

The rest of the document is organized as follows: Section 2, literature review; Section 3 describes the background and a description of PAE Program; Section 4 describes the data and identification strategy; Section 5 presents the results; Section 6 presents the robustness check and finally in Section 7 conclusions.

Literature Review *

Despite the growing interest in analyzing the effectiveness of ALMPs, only recently relevant evidence of their effectiveness become available in developing countries (McKenzie, 2016). Evidence from developed countries shows that training policies generally has small effects, especially for young people (Card et al., 2010). However, the results of evaluations of these policies are more auspicious in developing countries, particularly in LAC (Betcherman, 2007, Ibararán & Rosas, 2008, Gonzales et al., 2012, Attanasio et al., 2011, Kluve 2014; Kluve, 2016).

It is possible to summarize the two major ALMP programs implemented in the region in two categories⁴: Those designed for vulnerable job seekers, especially for youths, that include classroom and on-the-job training. The premise of such programs is that the lack of technical skills is the reason why particular individual are unemployed or in informal jobs. The assumption behind is that skills can be taught and learnt in a relevant short period of time (McKenzie, 2016). The second model of intervention implemented in the region has focus on firm training. The premise behind these interventions is that the lack of relevant information about the level of skills that the job-seekers have is the main reason why individuals are unemployed or informal, the gaining experience in formal firms could give them the necessary screening over its productivity to boost their careers.

Because of its nature, much more evidence is available about training policies that include classroom training in the region. Attanasio et al. (2011), shows a positive impact on paid employment in the formal sector from a training program for disadvantaged youths introduced in Colombia in 2005. Card et al. (2011) found positive impact on formal employment conditional on being employed and in wages for a program implemented in 1999 in Dominican Republic. Both programs have long term evaluations that show the positive impacts identified in the short run maintain after 8 years or more (Attanasio et al. ,2015; Ibararán et al., 2016).

On the other hand, programs with emphasis on the job training had less evidence available, this fact is explained because of the design of these programs, most of them are self-targeted, and only few of them

⁴ *Mexico's Probecat* and *Chile Joven*, were established in 1984 and in 1991, respectively. These two programs laid the foundations for this new type of intervention. The design of these programs became a model to be replicated in later decades in the rest of the region (Gonzales et al., 2012)

had robust evidence through randomized impact evaluations⁵. In LAC, the only existing impact evaluation comes from the *Programa Primeros Pasos* (PPP) in Argentina (Berniell & de la Mata, 2017). The program has an excess of demand that made possible randomize the selection of beneficiaries. The PPP program support the improved employment by granting youths from 16 to 25 years a first formal job opportunity through a subsidy to on the job training for 12 months.

Background and Description of the Program

Since 2005, explained by a favorable commodity price context, Bolivia has experienced high levels of economic growth and poverty reduction. Nonetheless, this growth did not significantly improve its productivity neither the quality of the employments that job seekers can access. At the moment of the design of the Program (*circa 2010*), Bolivia had one of the lowest urban unemployment rates in the region (4.26% in 2009) and a high level of informality that reaches about 80% of the employees⁶ with a high percentage of them occupied as self-employed (43%). As expected, unemployment rate and informality rates were larger for the youth, women and people with lower levels of formal education.

In this context, starting in September of 2012, the Ministry of Employment started the Program to Support Employment (PAE by its acronyms in Spanish), financed through a loan of the Inter-American Development Bank (IADB). The aim of the program was to ease the placement of job seekers who have the required credentials but do not have access to a formal employment opportunity that would give them the experience needed to boost their careers.

PAE program operates as an internship to job seekers and provides a wage subsidy up to three months. The amount of the subsidy was between (1) one and one and a half (1.5) minimum wages defined on the skills requirements of the vacancy, which was entirely defined by the Program as described in Table 1. During its lifetime, the program serves 19,544 beneficiaries⁷, 55% of them were women and 49% of them had some level of tertiary degree (35% completed, 14% uncompleted).

Table 1. Stipend calculus (as a percentage of a minimum wage)

Sector	Education Level		
	High school or less	Technical Education	Bachelor's degree
	115%	130%	150%
	100%	115%	130%
	100%	100%	115%

To be eligible for the program, the only requirement was to have more than 18 years at the moment of registration in the PES and meet the requirements of the vacancy. Firms eligibility criteria for PAE required being formal (i.e. to has a tax code) and that the vacancy was credibly leading to a permanent hiring. Firms can only apply for a limited number of PAE stipends depending on their size and can only reapply to the program conditional on at least 50% of past stipends having been converted into contracts, and at least one year having elapsed since the end of the first PAE stipend.

The process to match a job seeker with a vacancy was made by caseworkers. Whenever a PAE vacancy is posted, the PAE caseworker makes an initial screening of candidates and compiles a shortlist. Shortlists typically include three or more jobseekers per vacancy. In the case of PAE, the shortlist is provided directly to the employer⁸. Employers contact and interview shortlisted jobseekers and select one of the candidates.

⁵ Most of the evidence comes from programs in developed countries, for example Gelber et al. (2015) analyze an internship in New York, they found that the program increases earnings and employment in the short run.

⁶ Understanding informality as the lack of access to social security.

⁷ Jobseekers only could participate once in their life time in the program.

⁸ For each jobseeker, shortlists provide national identity number, name and surname, date of birth, address, phone number and occupation sought. Jobseekers are listed by first-come, first-served basis.

Job interview and job offer decisions stay with the firm and job acceptance decisions with the jobseeker. Once an offer is accepted, and after some regularity checks, the PAE administers the program.

Data

Data for the present evaluation comes from three (3) sources. First, administrative data of the Public Employment Service of Bolivia (PES). This database contains socio-economic information reported by job seekers that serve to record the labor offer and vacancies. Second, administrative data of the PAE, which contains information on the beneficiaries of the program and the characteristics of their labor intermediation such as the amount of the stipend and some characteristics of the enterprise. Finally, the third source of information comes from a telephone survey carried out between November 2017 and February 2018 to job seekers registered in the PES between 2015 and 2017. We restring the analysis to this period because of the difficulties to contact job seekers in previous periods. In this sense, all the information used is restricted to that period (from 2015 to 2017).

The challenge associated with the manipulation of data in the current evaluation is explained by the poor quality of the administrative information at the PES database. The main problems are related to: (i) information with errors, inconsistencies and the lack of relevant information such years of education, employment status and others; (ii) the chaotic grouping of some variables⁹; and (iii) the lack of interconnection between different databases within the MTEPS. These problems have consequences in the relationship between the information of the PAE and the PES, which affects the linkage of information between both databases. Of the 19,544 registered PAE beneficiaries, only 17,975 could be found in the PES database, which implies a loss of 8% of the total beneficiaries.

In this context, from November 2017 to February 2018 a telephone survey was conducted to job seekers registered in the PES. The survey was designed with the objective of correcting the problems associated with the poor quality of administrative data and obtaining information relevant to the present evaluation. In this context, a survey was designed to obtain information regarding the socioeconomic characteristics and employment status characteristics of job seekers at the first time of its registration in the PES. Also, labor information at the moment of the survey. Out of a total of 37,142 job seeker registrations between 2015 and 2017, 14,881 completed the survey. The collection of surveys was done regressively per year, beginning in 2017 and ending in 2015, through a non-probabilistic sampling.

The collection of information through telephone surveys for this evaluation is explained by the advantages of this method of collection compared to other alternatives such as *face-to-face* surveys or *online* surveys. However, it is compulsory to analyze the possible impact that the collection method had on the information obtained. In this sense, there are two points that must be explored. First, the fact that conducting a telephone survey implicitly excludes those job seekers who do not have this asset (whether mobile or landline), which could imply a selection bias. This fact is particularly relevant in Bolivia, where according to the 2012 Census, 18.21% of households in the urban area indicated that they do not have access to neither landline or mobile. Second, it is required to analyze if the information obtained by this method of collection generates systematic differences in relation to other alternative and if the method affect the decision to participate or not in the survey, called mode effect.

Although the method of collecting face-to-face surveys has been more widely used and has a better reputation, the extension of telephone coverage in the last 60 years along with its lower cost, speed and

⁹ As an example of the relevance of this issue, the education information in PES is registered by the following levels: Without Education; Second grade of high school approved: completed high school: tertiary education, completed elementary; elementary, high school, technician, bachelor and college student. As can be noted there is a superposition of groups hardly identifiable. The reasons behind this issue is explained by the fact that whenever a new program, a policy or a pilot was released that required information from PES, a new category was included in the database. Unfortunately, since there is no clarity about the boundaries of use of these new categories and even the objectives of those policies or pilots, we are not able to identify the groups without making assumptions or loss information by aggregation of the information.

quality have contributed to the expansion and success of the use of the phone surveys (Szolnoki & Hoffmann, 2013)¹⁰. Although, the method suffers from disadvantages related to interviewer bias, lower response rate, the impossibility of visual support through cards and in some cases an overrepresentation of certain population group (Holbrook et al., 2003; & Platt, 2011; Szolnoki & Hoffmann, 2013).

In this context and within the framework of the present evaluation, three points are analyzed, two of them related to problems of coverage bias. The first, associated with the lack of access to telephone for some job seekers and second, the existence of overrepresentation of some group of job seekers. Finally, considering the possibility of existence of systematic differences in the answers, the quality of information obtained in the survey will be analyzed in relation to the data recorded in the administrative database of the PES, for those variables in which it is possible to do this.

Only 229 people in the PES database did not have a register phone number or had a record that did not correspond to the characteristics of the telephone numbers in Bolivia, which represents only 0.62% of the total. This does not imply that phone coverage for job seekers is as high as 99%, but rather that because of the nature of the program and the registration it is possible that some of these records have registered phones from friends or relatives. Nevertheless, the percentage still seems low and we could assume that this lack of coverage would not impose a bias in the estimation made in the framework of the evaluation¹¹.

As a next step, considering that the population of job seekers registered in the PES database reached 37,142 records and that 25,586 were tried to contact, although only 14,881 completed the survey, we next analyze if there are statistical differences between those who completed the survey and those who do not completed the survey. This analysis can be done only using the information available in the PES database.

Table 1 presents the differences between those job seekers who completed the survey in relation to those who did not¹². It is observed that those who completed the survey have a higher level of education, there is a greater presence of women, they are mostly married and have a reserve salary registered in the PES 7% higher, they have less number of registration of offer and a greater representation is observed of job seekers of 2017. There are no statistically significant differences in the fact of being a beneficiary and completing the survey. In this sense, we can affirm that the people who completed the survey are different from those who do not, which generates an overrepresentation of a group that seems to have better perspectives for their participation in the labor market. In this sense, the impacts estimated within this document would be attributable only to those job seekers with better perspectives. We later will analyze the impact of this overrepresentation over the results obtained, for this, we will correct our sample through a Heckman model.

Table 1. Linear probability of having completed the survey

	Completed survey
Age/10	0.01*** (3.4)
Woman	0.02*** (3.8)
Tertiary education	0.10*** (17.7)

¹⁰ Lately, the use of online surveys has been gaining space in the collection of surveys such as opinion surveys, consumption surveys and, to a lesser extent, in social research. The importance of the method regards due to its speed, lower cost, the possibility of have interactive support and flexibility (Szolnoki & Hoffmann, 2013). Although the main criticism over online surveys regards on the problems associated with the lack of representativeness explained by the lack of universal access to internet.

¹¹ Results are presented in the Appendix, where we analyze which socioeconomic variables determine the probability of not having a telephone.

¹² We considered a dummy variable that has the value of 1 for those job seekers that completed the survey and 0 those that were not contacted or those that did not complete it.

Single	-0.03*** (-4.2)
Reservation wage	0.07*** (7.4)
Main city	0.06*** (10.3)
Number of offers in the data	-0.01*** (-6.2)
year 2015	-0.21*** (-27.9)
year 2016	-0.01** (-2.0)
Treated (1 if treated; 0 if control)	0.00 (-0.2)
Constant	-0.17** (-2.3)
<i>Observations</i>	37,132
<i>R²</i>	0.06
<i>F</i>	259.54

t statistics in parentheses
** p < 0.05, *** p < 0.01

Lastly, we explore if the information collected in the survey is consistent with the information provided at the PES database. As mentioned above, the administrative information in the PES registry is scarce and in some cases the level of aggregation does not seem very clear, so we will restrict the analysis only to some variables of interest such as age and education. Table A.X and Graph A.Y in the Appendix shows a high correlation by the information given in both datasets. As can be seen the relation between the completed years of education registered in the survey has a high correlation with the groups of education described in PES.

It is worth mention a difficulty that arises during the collection of information. During the pilot of the survey there was a decrease in the response rate of earning income for those who are salaried, explained by the sensitivity of respondents to answer about that question by telephone. To resolve this, we decided to collect this variable as earnings categories instead of using a continuous variable. In this sense, the current monthly earnings for salaried is collected categorically. Therefore, whenever we estimate the impact of PAE over earnings we will use the average value of the category (i.e. for the category from Bs1,000 to Bs2,000, we use the average value of Bs1,500)¹³.

Evaluation strategy

The empirical strategy for the evaluation of PAE on employment, formal employment and earnings performs a combination of *Propensity Score Matching (PSM)* with a *Difference in Differences model (DD)*. The defined strategy was chosen considering the particularities of the program, which prevent the development of an experimental evaluation.

¹³ We also perform a robustness check estimating the labor income.

For this, we first estimate a *PSM* running a probit model of the treatment variable (T) on a vector of covariates X . It is important to notice that the variables included in the PSM are those who influence at the same time program participation and outcomes of interest. All the variables included in the estimation are pre-date program participation (i.e. during their registration in the PSE dataset). We include a rich series of personal, educational, household characteristics and some information about previous jobs. The set of covariates includes a dummy variable if the beneficiary defines himself as indigenous, a dummy if the beneficiary is a woman, age in years, a dummy if the person has some type of disability, a dummy if the job seeker is married, a dummy if the job seeker is a head of household, the number of children the job seeker has, a dummy if the job seeker declares that has a diploma of her last level of education achieved, dummies for the year when was registered, dummies for the month in which was registered, a dummy for each family income group, dummies for the city where was registered in the PES, the logarithm of the offer salary in the record of PES database and finally a dummy variable if the job seeker was ever promoted in a previous job.

$$P_i^* = \gamma + \delta X_i + \epsilon_i \quad (1)$$

Where P_i is a latent variable that determines the value of T under the following scheme:

$$T_i = \begin{cases} 0 & \text{if } P_i^* \leq \bar{p} \\ 1 & \text{if } P_i^* \geq \bar{p} \end{cases}$$

The results of the propensity score model (Table A.X in Appendix) shows that being woman decreases the probability of participating in PAE, being indigenous also decreases the probability of participation. The jobseekers with disabilities had a lower probability of participate in PAE. Having dependents increase the probability of participation in PAE. Having more education increase de probability of participation, but having a diploma reduce the probability of participation in the program. Have been registered in the first semester reduce the probability of participation in comparison with being registered in December. Dummies for family income does not affect the probability of participation overall. Compared with being register in El Alto, had been registered in other cities, has a lower participation probability. Analyzing previous career history, had been ever promoted in a previous job has no impact on the probability of participation in the PAE. The logarithm of the offer salary recorded on PES database has a negative impact on the probability of participation in PAE.

Once we calculate the estimated probability of being a beneficiary of the program, we restrict the sample to the common support. The method used to perform the PSM is through Kernel Matching that uses the predefined kernel bandwidth of 0.06¹⁴. This method makes it possible to ensure that the estimates of the impacts are based on comparable differences between beneficiaries and non-beneficiaries. The methodology assumes that the estimated impact is independent once it is controlled by the variables included in the set X of covariates.

Through a DID model, we control for those characteristics that are invariable in time and that could affect the participation in the program and the labor outcomes analyzed. The fundamental identification assumption of DID model is that, in the absence of the program, the difference in the variables of interest between the control group and the treatment group would have remained constant over time (assumption of parallel trends). For this we regress the following equation:

$$\widehat{y}_{it} = \beta_0 + \beta_1 * Post + \beta_2 * PAE + \beta_3 * Post * PAE + \epsilon_{it} \quad (2)$$

Where \widehat{y}_{it} is our variable of interest, includes, the probability of being employed, the probability of having a formal employment, considering formal employment as access to long-term social security contributions

¹⁴ At the end of the document in Appendix, we present the results using different bandwidth alternatives.

and the logarithm of labor income, where for the case of those that are not working, an income of 0 is assumed.

By combining the two methodologies, we created a comparison group for the beneficiaries of the program in terms of observable and unobservable variables.

Results

Table 2 presents descriptive statistics of the variables included as covariates in the PSM estimation, divided for beneficiaries and non-beneficiaries of the program. As can be seen, with baseline information (ie. before entering the program) we can affirm that the people within the control group were statistically different than those who were beneficiaries of the program. There were less indigenous people among the beneficiaries (10 % against 6%), fewer women (58% vs 56%), they were slightly older in age (31.5 versus 31 years), they were less jobseeker with disabilities (3.7% vs. 5.2%), they were more likely to have children (87% for treated against 81% for untreated), were less likely to have a degree of completion of their studies (29% against 33%) and registered a lower level of salary required in the PES records. After having performed the PSM and once we restricted the analysis to the common support, we can see that the statistically significant differences noted above between beneficiaries and non-beneficiaries were eliminated, so we can say that after matching there are no significant differences in observable characteristics between the two groups.

Graph 1 presents the distribution of propensity scores for the treatment group and control group. As can be noted, only a minor part of the distribution is outside the common support.

Graph 1. Distribution of the propensity scores for treatment and control groups

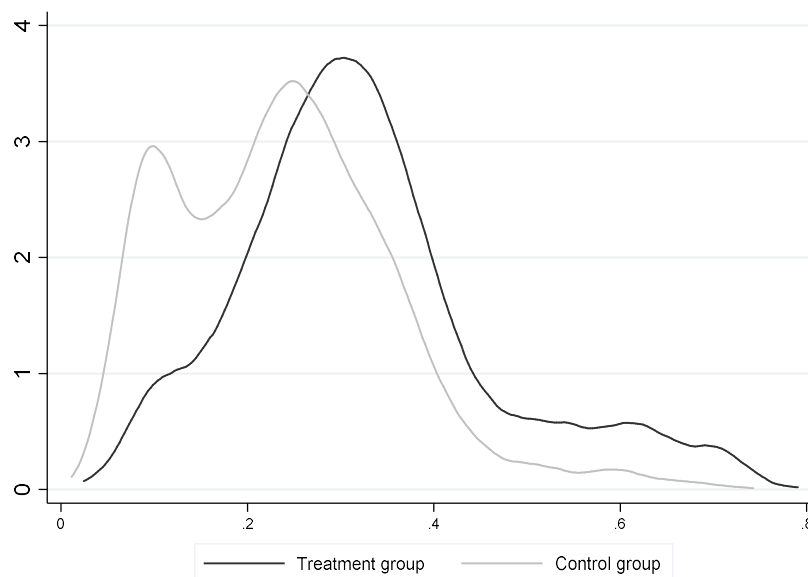


Table 2. Descriptive statistics at baseline between treatment and control group

	Unweighted Variables			Weighted Variables		
	Mean Control	Mean Treated	t	Mean Control	Mean Treated	t
Employment status before registration	0.303	0.295	0.91	0.30	0.30	0.17
Ever received a promotion	0.323	0.310	1.33	0.32	0.31	0.76
Indigenous	0.099	0.067	5.88 ***	0.07	0.07	0.56
Woman	0.583	0.561	2.27 **	0.56	0.56	0.27
Age	31.524	31.091	2.58 ***	31.09	31.09	0.01
Age Squared	1073.241	1040.016	2.61 ***	1038.87	1039.80	0.09
Education	14.333	14.308	0.39	14.31	14.31	0.07
Handicap	0.052	0.037	3.73 ***	0.04	0.04	0.57
Married	0.255	0.264	-1.03	0.26	0.26	0.06
Head of HH	0.346	0.357	-1.30	0.35	0.36	0.59
Dependents	0.815	0.872	-2.34 **	0.87	0.87	0.01
Education degree	0.330	0.294	4.01 ***	0.30	0.30	0.19
Year 2015	0.189	0.239	-6.50 ***	0.23	0.24	1.65 *
Year 2016	0.539	0.653	-12.23 ***	0.66	0.65	0.93
Year 2017	0.272	0.109	20.83 ***	0.11	0.11	0.82
January	0.086	0.050	7.09 ***	0.06	0.05	1.25
February	0.111	0.060	9.09 ***	0.06	0.06	0.25
March	0.111	0.103	1.25	0.10	0.10	0.22
April	0.101	0.068	6.06 ***	0.07	0.07	0.24
May	0.126	0.077	8.19 ***	0.07	0.08	0.79
June	0.075	0.065	2.06 **	0.06	0.07	0.75
July	0.075	0.083	-1.62	0.08	0.08	0.02
August	0.070	0.102	-6.22 ***	0.10	0.10	0.08
September	0.061	0.104	-8.62 ***	0.10	0.10	0.22
October	0.067	0.121	-10.28 ***	0.12	0.12	0.86
November	0.068	0.100	-6.28 ***	0.10	0.10	0.19
Income family 1	0.170	0.126	6.43 ***	0.12	0.13	0.94
Income family 2	0.370	0.400	-3.28 ***	0.40	0.40	0.64
Income family 3	0.298	0.301	-0.41	0.31	0.30	1.19
Income family 4	0.097	0.097	-0.04	0.10	0.10	0.29
Income family 5	0.035	0.035	0.00	0.04	0.04	0.18
Income family 6	0.022	0.027	-2.01 **	0.03	0.03	0.26
Income family 7	0.007	0.011	-2.24 **	0.01	0.01	0.29
Income family 8	0.001	0.002	-1.44	0.00	0.00	0.34
El Alto	0.206	0.180	3.49 ***	0.19	0.18	0.86
Sucre	0.025	0.085	-16.00 ***	0.08	0.08	0.03
La Paz	0.365	0.248	13.06 ***	0.26	0.25	1.45
Cochabamba	0.086	0.092	-1.08	0.09	0.09	0.65
Oruro	0.074	0.088	-2.77 ***	0.09	0.09	0.11
Potosi	0.041	0.043	-0.55	0.04	0.04	0.14

Tarija	0.055	0.051	1.07		0.05	0.05	0.20
Santa Cruz	0.119	0.135	-2.51	**	0.13	0.14	1.07
Trinidad	0.013	0.023	-4.37	***	0.02	0.02	0.00
(Log) wage offer (PES)	0.015	0.055	9.54	***	7.61	7.61	0.56

Table 3 presents the estimated impacts of the program on the probability of being employed. The evaluation finds a positive and significant impact of 8pp. for those who were beneficiaries of PAE. Before the implementation of the program, treated and controls had similar rate of employment (approximately 29%). After having participated in the program, the employment rate for the beneficiaries was 55%, untreated job seekers also increased their participation in employment up to 47%.

Table 3 also present the impact of the program on access to formal employment, considering formality as access to long-term social security, it is observed that the program has a significant impact in 3pp. It is important to note that only 12% of the beneficiaries of the PAE had access to a formal job, a figure slightly lower than the average formality of the country (which reaches 19%, SIMS), while only 8% of those not treated were able to access a job with these characteristics.

Table 3. Impact of PAE on employment and formal employment

	Employment (1)			Formal Employment (2)		
	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline						
Control	0.296	0.006	53.126	0.022	0.002	12.360
Treated	0.295	0.007	39.603	0.019	0.002	8.628
Diff (T-C)	-0.001	0.009	-0.141	-0.003	0.003	-0.902
Follow up						
Control	0.472	0.006	78.122	0.084	0.003	24.772
Treated	0.555	0.008	68.374	0.119	0.005	22.555
Diff (T-C)	0.083	0.010	8.174	0.036	0.006	5.726
Impact						
Diff-in Diff	0.084	0.014	6.113	0.039	0.007	5.582
Observations			28,872			28,872
R ²			0.05			0.03

Finally, we analyze the impact of the PAE on the monthly logarithm of labor earnings. For this, we analyze four different measures of income: (1) unconditional monthly earnings, in which workers (beneficiaries or not) who do not work are assigned an income of 0 ; (2) labor earnings, conditional on working before and after the program; (3) labor earnings conditional on have been working before the program, in which for those job seekers who did not work after the PAE but worked before the program, an income of 0 is assigned; and finally (4) labor earnings conditional to be working after the program, where job seekers working after the program but not working before are assigned with an income of 0. These different measures allow us to analyze the impact of the program completely across the different profiles of job seekers in the PAE.

Regarding unconditional monthly labor earnings (1), the impact of PAE on labor earnings of the beneficiaries is as high as 87% in relation to the control group. As can be seen in Table 4, the difference in income from beneficiaries and not treated is the same before the program, whereas after the intervention,

the beneficiaries obtained a higher income. The difference observed is mainly explained by a higher associated income of the beneficiaries who were working at the time of registering for the program.

Regarding labor earnings conditional on working before and after the program (2), a positive impact of 7.9%, significant at 10% is observed. It is worth nothing that PAE positively affected the income of job seekers who were beneficiaries of the program. While before the intervention, the labor earnings for both (treated and untreated) was statistically similar, after the program the beneficiaries obtain an earning income 12% higher than untreated ones.

When we analyze the impact of the intervention on the monthly income for those job seekers who report they were working at the time of their registration in the PES database (3), we identified an impact as large as 68% in relation to the control group. When we restrict the analysis conditional to be working at the time of follow-up (4) we observe a positive impact of the program is 11.5% in relation to the control group, although the impact is not statistically significant.

Table 4. Impact of PAE on monthly earnings

	Unconditional (Log) Monthly earnings			(Log) Monthly earnings conditional on working before and after PAE			(Log) Monthly earnings conditional on working before PAE			(Log) Monthly earnings conditional on working after PAE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline												
Control	0.494	0.054	9.219	7.245	0.020	371.058	7.245	0.020	371.081	1.919	0.073	26.154
Treated	0.490	0.072	6.839	7.288	0.025	297.165	7.288	0.025	297.184	1.938	0.097	20.060
<i>Diff (T-C)</i>	-0.004	0.089	-0.042	0.043	0.031	1.365	0.043	0.031	1.365	0.018	0.121	0.151
Follow up												
Control	2.304	0.060	38.463	7.455	0.025	293.574	3.230	0.116	27.950	7.517	0.013	579.388
Treated	3.177	0.082	38.945	7.577	0.027	285.420	3.950	0.146	27.118	7.651	0.014	545.991
<i>Diff (T-C)</i>	0.873	0.101	8.629	0.122	0.037	3.328	0.720	0.186	3.872	0.133	0.019	6.978
Impact												
<i>Diff-in Diff</i>	0.877	0.135	6.494	0.079	0.048	1.646	0.677	0.189	3.591	0.115	0.123	0.936
Observations			28,684			6,690			8,504			15,852
R ²			0.06			0.03			0.22			0.38

As mentioned before in the analysis of the impact of PAE over monthly earnings we use the average value of the defined categories. This use could produce errors as measurement errors, although there is no reason to think that these errors can be systematic different for a treatment or control group or systematic different for some job seekers such those with higher education level or other variable. In this sense, the aggregation could generate larger variance and wider confidence intervals, not biasing the estimation or the consistency.

As an alternative, in Table 5 we estimate the impacts of PAE over labor earnings replacing the average value by an estimation of current labor earning income for salaried¹⁵. As can be seen in Table 7, the results are robust to those found using the midpoint of categories. An average impact of 87% for unconditional

¹⁵ In order to do this we use an extended mincer equation using variables such as age, education, sex, a dummy if the job seeker has an ethnic origin, a dummy if he has a disability, a dummy if he is a head of family, the number of children you have (if any), dummies for family income groups, dummy if the job seeker obtained a diploma of the last level of education attained, dummies by groups of educational level (primary, secondary, tertiary), dummy by city where you registered in the PES, dummy if it is a city of the axis, dummies for the benefits you access in your current job (bonuses, health insurance, social security, if you were promoted, if you raised the salary, etc).

monthly labor income, which is mainly explained by a higher income of the beneficiaries, compared to the control group, who worked before participating in the program.

Table 5. Impact of PAE on monthly earnings

	Unconditional (Log) Monthly earnings (1)			(Log) Monthly earnings conditional on working before and after PAE (2)			(Log) Monthly earnings conditional on working before PAE (3)			(Log) Monthly earnings conditional on working after PAE (4)		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline												
Control	0.494	0.054	9.219	7.245	0.020	371.058	7.245	0.020	371.081	1.919	0.073	26.154
Treated	0.490	0.072	6.839	7.288	0.025	297.165	7.288	0.025	297.184	1.938	0.097	20.060
Diff (T-C)	-0.004	0.089	-0.042	0.043	0.031	1.365	0.043	0.031	1.365	0.018	0.121	0.151
Follow up												
Control	2.337	0.060	38.819	7.506	0.023	329.747	3.259	0.116	28.208	7.591	0.012	654.367
Treated	3.203	0.082	39.130	7.636	0.022	340.122	3.987	0.146	27.265	7.696	0.012	654.234
Diff (T-C)	0.866	0.102	8.522	0.130	0.032	4.062	0.728	0.186	3.906	0.106	0.017	6.408
Impact												
Diff-in Diff	0.870	0.135	6.425	0.087	0.045	1.945	0.685	0.189	3.626	0.088	0.122	0.715
Observations			28684			6690			8504			15852
R ²			0.06			0.04			0.22			0.39

In the Appendix section, we present the impact of PAE over previously described outcome variables: employment, formal employment, monthly labor income, using different values of the kernel bandwidth. Three additional alternatives of bandwidth are considered: i) 0.09; ii) 0.03; y) 0.01. The results shown, in Tables A4, A5 and A6 show consistency with the predefined kernel bandwidth of 0.06.

Finally, to analyze the consistency of our estimations, in the Appendix, we present an additional analysis of the impacts of the program replacing the standard errors by a Bootstrap estimation with 500 replications, the results are also consistent with this change.

Heterogeneous impacts

The present section presents a heterogeneity analysis, to do this, we use the following estimation:

$$\widehat{y}_{it} = \beta_0 + \beta_1 * Post + \beta_2 * PAE + \beta_3 * Post * PAE + \beta_4 * Post * PAE * di + \epsilon_{it} \quad (3)$$

Where di is our labor market variable of interest. Having in mind that vulnerable groups faces additional barriers we restrin our analysis to females, youths and job seekers with low level of education.

We first perform the analysis by gender, where di is equal to a dummy variable that is 1 if the job seeker is a female.

Table 6. Heterogeneous Impact of PAE for females

	Employment (1)				Formal Employment (2)				Unconditional (Log) monthly earnings (3)			
	Coef.	Std. Error	t		Coef.	Std. Error	t		Coef.	Std. Error	t	
Diff-in-Diff	0.086	0.021	4.09	***	0.033	0.011	2.96	***	0.892	0.208	4.28	***

Woman	-0.058	0.011	-5.16	***	-0.006	0.004	-1.55	-0.664	0.109	-6.09	***
Woman*Treated	0.001	0.019	0.04		-0.001	0.006	-0.15	0.033	0.182	0.18	
Woman*Post	-0.063	0.017	-3.78	***	-0.034	0.008	-4.28	-0.619	0.163	-3.81	***
Woman*Treated*Post	-0.003	0.028	-0.10		0.009	0.014	0.65	-0.023	0.272	-0.08	

Table 6 presents the marginal impacts of being female. There are no different effects of the PAE program for women. Even though that there is a negative impact of being a female on employment and labor earnings, these are not statistically significant. On the other hand, the differential impact of access to formal employment for women is positive, but again not significant.

Later we first perform the analysis for youths, where di is equal to a dummy variable that is 1 for those job seekers who were 28 years old or younger at the time of registering in the PES. We use the 28 years threshold because in Bolivia a person can be considered a youth if has between 16 and 28 years¹⁶.

Table 7. Heterogeneous Impact of PAE for Youths

	Employment (1)				Formal Employment (2)				Unconditional (Log) monthly earnings (3)			
	Coef.	Std. Error	t		Coef.	Std. Error	t		Coef.	Std. Error	t	
Diff-in-Diff	0.128	0.02	6.52	***	0.052	0.01	5.23	***	1.279	0.193	6.64	***
Youth	-0.118	0.011	-10.63	***	-0.021	0.004	-5.94	***	-1.146	0.106	-10.79	***
Youth*Treated	0.081	0.019	4.37	***	0.006	0.006	1.05		0.802	0.178	4.50	***
Youth*Post	0.080	0.016	4.86	***	0.037	0.008	4.86	***	0.819	0.16	5.12	***
Youth*Treated*Post	-0.087	0.027	-3.19	***	-0.027	0.014	-1.98	**	-0.801	0.27	-2.97	***

Table 8 presents the impact of PAE over youths, there are statistical differences in the impact. While middle aged beneficiaries (those older than 28 years) have a positive impact of 13 pp on employment, youths have an impact of just 4,1 pp. (9.6 pp. lower). Regarding formality, youths only have an impact of 3 pp, while beneficiaries older than 28 have an impact of 5,2 pp. and statistically significant. Youths also perceive a lower impact over earnings, that is 80% lower than for middle-agers. The results are consistent with the idea that the formal labor experience could boost the labor success for those who are more productive, but who cannot screen their productivity. It is also possible that the differences could be explained by the fact that youth have a better performance in the market in comparison with middle agers, however these results are not the case, since as can be noted in Table 8, youths have a worst performance in the market.

Lastly, we analyze the impact of having a lower educational level has a heterogenous impact. Table 9 shows the impact of the program for people with low levels of education (LLE). As expected, and under the hypothesis that the program gives a way to screen productivity but not improve technical skills, we observe a lower impact over employment and over labor earnings. While the impact on employment for those with high level of education (HLE) is as big as 10 pp., for LLE job seekers the impact is only 3 pp. Regarding labor earnings, the impact for HLE jobseekers is 112% while for LLE job seekers is just 36%. We do not observe differences statistically significant over the access to formal employment by educational level. Is worth noting that the level of employment for LLE job seekers is higher and statistically relevant in comparison with job seekers with HLE. This is consistent with higher unconditional monthly earnings. This

¹⁶ Law No 342. The “Law of Youth” has the objective to guarantee the exercise of rights and duties for youths, the institutional framework, the instances of representation and the establishment of public policies.

is documented in the region since most of unemployed are those with high level of education, since their reservation wage is bigger.

Table 8. Heterogeneous Impact of PAE for job seekers with Low Level of Education (LLE)

	Employment (1)				Formal Employment (2)				Unconditional (Log) monthly earnings (3)			
	Coef.	Std. Error	t		Coef.	Std. Error	t		Coef.	Std. Error	t	
Diff-in-Diff	0.107	0.016	6.72	***	0.044	0.009	5.06	***	1.116	0.157	7.12	***
LLE	0.056	0.014	4.15	***	-0.002	0.004	-0.51		0.464	0.128	3.61	***
LLE*Treated	-0.001	0.022	-0.04		0.000	0.006	0.00		0.007	0.207	0.04	
LLE*Post	-0.056	0.02	-2.83	***	-0.053	0.007	-7.28	***	-0.602	0.19	-3.17	***
LLE*Treated*Post	-0.076	0.032	-2.40	**	-0.013	0.014	-0.96		-0.799	0.308	-2.60	***

Robustness Check

As a final step, to analyze the sensitivity of our results, we perform several robustness checks. We will verify the robustness of the results following: (i) performing two placebo test and (iii) finally, we perform an exercise to randomize the sample ex post, in order to verify if the results maintain if the sample had been collected by a random probabilistic sampling.

Placebo Test

One way to check the validity of our identification strategy is through a placebo test. For this, this section presents two placebo tests. This document assumes that the impacts found in the labor variables in the beneficiaries of the program PAE, corresponds to having obtained the treatment (PAE) and the consequences that this entails.

The first placebo test eliminated all the beneficiaries of the program from our sample and randomly assigned a placebo variable of treatment among the controls. We expect that, for the program controls, if there are no other variables that are explaining the improvement over the analyzed labor variables, when performing the identification of equation (2), we should not find significant differences in the labor variables.

In the second placebo test, we eliminated the treatment variable (PAE) that corresponds to actually received the treatment and created a random fictitious variable between the treatment and controls that assigns a "treatment" that does not depend on any variable. We hope again, that in this test we will not find significant differences between "placebo treatments" and "placebo controls".

As can be seen in Table A12, the results of the estimates made according to equation (2) for the two-placebo test are not statistically significant. This result gives us confidence to think that what is determining the improvements in the labor variables observed in Tables 3,4 and 5 corresponds to actually received the treatment of the PAE and its positive implications and not to other factors. Figure 2a presents the Distribution of the propensity scores for treatment and control groups.

Ex post randomization of the sample.

One concern of the PAE evaluation refers to the characteristic of the sampling method, since the data collection was done regressively and not through a probabilistic sample, there is a chance that the sample is not representative of the population. In this case it is possible to randomize the sample ex post and analyze

if the results of the evaluation are robust, which would give us an indication that the sample is representative of the population.

For this, we generate an ex post probabilistic sampling with the total population of beneficiaries and controls and check if the impacts maintain when we use those who answered the survey and were in the ex post sample.

Table 9 present the result of the exercise. The results are consistent with the impacts previously found. It is observed that after having carried out the ex post randomization of the sample, the impact on employment is 7 pp. and that the impact on access to formal employment is 3 pp., similar to what was previously observed (8 pp. y 4pp; Table 3). In relation to the impact on income, this reaches 72%, which is very similar to the 87% increase previously found.

Table 9. Impact of PAE on labor variables for the ex-post randomization sample

	Employment (1)			Formal Employment (2)			Unconditional (Log) Monthly earnings (3)		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline									
Control	0.290	0.007	38.96	0.019	0.002	8.80	0.431	0.072	6.01
Treated	0.298	0.011	28.32	0.020	0.003	6.14	0.527	0.101	5.19
<i>Diff (T-C)</i>	<i>0.008</i>	<i>0.013</i>	<i>0.63</i>	<i>0.001</i>	<i>0.004</i>	<i>0.14</i>	<i>0.096</i>	<i>0.124</i>	<i>0.77</i>
Follow up									
Control	0.476	0.008	57.47	0.087	0.005	18.64	2.352	0.083	28.49
Treated	0.555	0.011	48.49	0.117	0.007	15.78	3.172	0.115	27.47
<i>Diff (T-C)</i>	<i>0.079</i>	<i>0.014</i>	<i>5.59</i>	<i>0.030</i>	<i>0.009</i>	<i>3.40</i>	<i>0.819</i>	<i>0.142</i>	<i>5.77</i>
Impact									
<i>Diff-in Diff</i>	<i>0.071</i>	<i>0.019</i>	<i>3.70</i>	<i>0.029</i>	<i>0.010</i>	<i>3.06</i>	<i>0.723</i>	<i>0.189</i>	<i>3.84</i>
Observations	14,562			14562			14461		
R ²	0.05			0.03			0.06		

Conclusions

The present document aims to support the understanding of the impact of having access to a formal work experience over the access to an employment and the quality of them. Answering this question is relevant considering the little evidence about the impact of these type of ALMPs in the literature, particularly in the region. Is particularly important to understand the impact of these type of ALMPs in a context of high informality, in order to do this, we analyze the case of Bolivia, a small and open economy in LAC.

The document uses three sources of information: administrative data from PES, administrative data from the Program itself and data from a telephone survey. The telephone survey was designed to capture information regarding the employment characteristics of workers at the time of their registration in the program and the time of the survey.

The results show that the program has a positive impact on access to employment of 8 pp. in relation to the control group. A positive impact of 4 pp. over access to formal employment (understanding formal employment as access to social security) and an impact of 8% on labor income. These results are consistent with the impacts found in different ALMPs in the region. We were able to identify that the improvement of

the earnings is explained by those who already had working experience. We also identified that the impact of the PAE is higher for those with higher education (tertiary education) and those older than 28 years. We perform several robustness checks in order to verify the validity of the assumptions. The results are consistent with the hypothesis that information barriers, particularly in a context of high informality economy, are a major barrier for access to formal employment.

Appendix

Table A1: PSM

Table A2: Educational level reported in the PES and in the telephonic survey

Years of Education (survey)	Educational level achieved (PES)				
	None	Incomplete high school	Complete high school	Incomplete Tertiary	Complete Tertiary
0	1	59	36	2	8
1	0	23	6	1	0
2	0	39	10	0	0
3	0	82	21	0	3
4	0	69	13	0	0
5	0	160	60	2	5
6	0	57	62	3	5
7	0	34	43	0	2
8	0	49	80	1	4
9	0	32	97	1	2
10	0	47	170	1	7
11	0	48	141	1	7
12	0	159	1644	101	221
13	0	32	449	78	158
14	0	58	537	159	413
15	0	74	699	261	1487
16	0	17	124	188	184
17	0	110	482	970	3711
18	0	11	17	40	311
19	0	4	1	4	55
20	0	1	0	0	1
22	0	0	0	0	1
Total	1	1165	4692	1813	6585

Graph A1: Age when jobseeker first registered at the PES

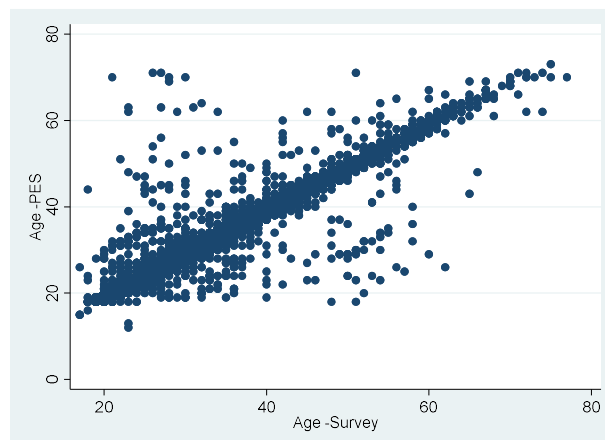


Table A4. Impact of PAE on employment using different Bandwidths in the PSM

	Employment											
	Bandwidth=0.01 (1)			Bandwidth=0.03 (2)			Bandwidth=0.06 (3)			Bandwidth=0.09 (4)		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline												
Control	0.298	0.006	50.172	0.297	0.006	51.895	0.296	0.006	53.126	0.296	0.005	54.359
Treated	0.295	0.007	39.603	0.295	0.007	39.603	0.295	0.007	39.603	0.295	0.007	39.603
Diff (T-C)	-0.003	0.010	-0.341	-0.002	0.009	-0.169	-0.001	0.009	-0.141	-0.001	0.009	-0.066
Follow up												
Control	0.470	0.006	74.446	0.471	0.006	76.368	0.472	0.006	78.122	0.473	0.006	79.849
Treated	0.555	0.008	68.374	0.555	0.008	68.374	0.555	0.008	68.374	0.555	0.008	68.374
Diff (T-C)	0.085	0.010	8.237	0.084	0.010	8.245	0.083	0.010	8.174	0.082	0.010	8.160
Impact												
<i>Diff-in Diff</i>	0.088	0.014	6.274	0.086	0.014	6.179	0.084	0.014	6.113	0.083	0.014	6.057
<i>Observations</i>			28,872			28,872			28,872			28,872
<i>R2</i>			0.05			0.05			0.05			0.05

Table A5. Impact of PAE on formality using different Bandwidths in the PSM

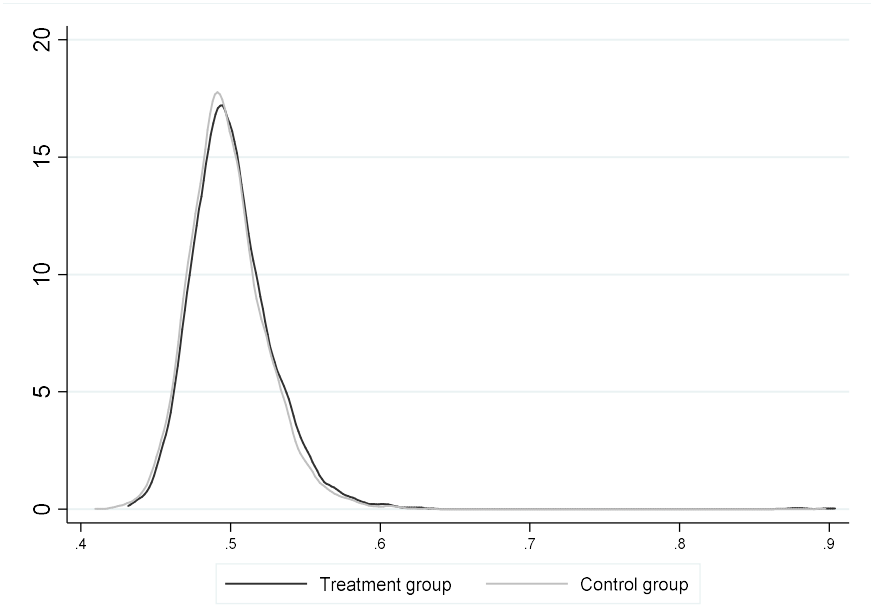
	Formal Employment											
	Bandwidth=0.01 (1)			Bandwidth=0.03 (2)			Bandwidth=0.06 (3)			Bandwidth=0.09 (4)		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline												
Control	0.022	0.002	12.513	0.022	0.002	12.407	0.022	0.002	12.360	0.022	0.002	12.442
Treated	0.019	0.002	8.628	0.019	0.002	8.628	0.019	0.002	8.628	0.019	0.002	8.628
Diff (T-C)	-0.002	0.003	-0.786	-0.002	0.003	-0.857	-0.003	0.003	-0.902	-0.003	0.003	-0.888
Follow up												
Control	0.083	0.003	24.613	0.084	0.003	24.541	0.084	0.003	24.772	0.083	0.003	25.181
Treated	0.119	0.005	22.555	0.119	0.005	22.555	0.119	0.005	22.555	0.119	0.005	22.555
Diff (T-C)	0.036	0.006	5.799	0.036	0.006	5.679	0.036	0.006	5.726	0.036	0.006	5.806
Impact												
<i>Diff-in Diff</i>	0.039	0.007	5.606	0.038	0.007	5.524	0.039	0.007	5.582	0.039	0.007	5.647
<i>Observations</i>			28,872			28,872			28,872			28,872
<i>R2</i>			0.03			0.03			0.03			0.03

Table A6. Impact of PAE on formality using different Bandwidths in the PSM

	Unconditional (Log) Monthly earnings											
	Bandwidth=0.01 (1)			Bandwidth=0.03 (2)			Bandwidth=0.06 (3)			Bandwidth=0.09 (4)		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline												
Control	0.511	0.057	8.933	0.496	0.055	9.038	0.494	0.054	9.219	0.486	0.052	9.324
Treated	0.490	0.072	6.839	0.490	0.072	6.839	0.490	0.072	6.839	0.490	0.072	6.839
Diff (T-C)	-0.021	0.092	-0.225	-0.006	0.090	-0.068	-0.004	0.089	-0.042	0.004	0.089	0.040
Follow up												
Control	2.280	0.063	36.465	2.292	0.061	37.478	2.304	0.060	38.463	2.310	0.059	39.400
Treated	3.177	0.082	38.945	3.177	0.082	38.945	3.177	0.082	38.945	3.177	0.082	38.945
Diff (T-C)	0.898	0.103	8.735	0.886	0.102	8.687	0.873	0.101	8.629	0.867	0.100	8.633
Impact												
Diff-in Diff	0.918	0.138	6.669	0.892	0.136	6.550	0.877	0.135	6.494	0.864	0.134	6.448
Observations	28,684			28,684			28,684			28,684		
R2	0.06			0.06			0.06			0.06		

Graph A2. Placebo Test. Distribution of the propensity scores for treatment and control groups.

Placebo 1



Placebo 2

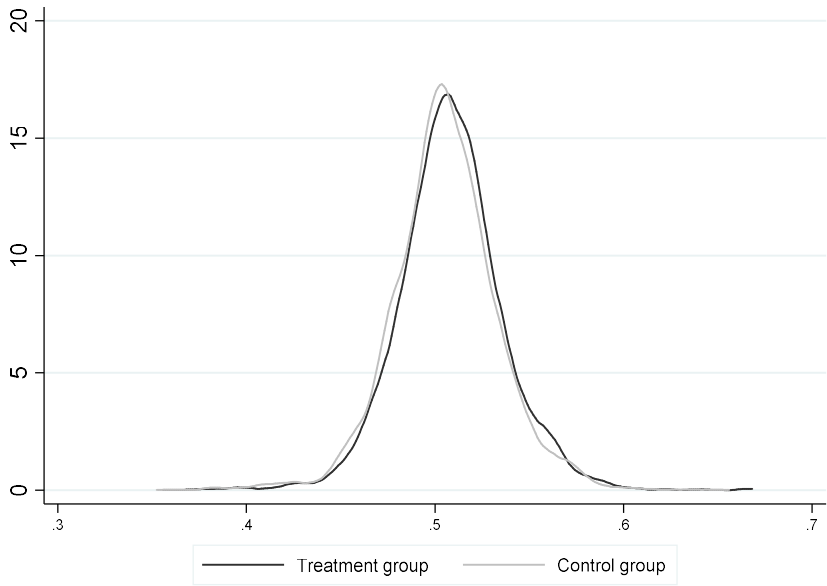


Table A7. Impact of PAE on employment disaggregated by year

	Employment																
	Total			2017			2016			2015			2016 & 2015				
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t		
Baseline																	
Control	0.296	0.006	53.126	0.412	0.014	28.641	0.272	0.007	38.630	0.267	0.016	16.230	0.277	0.006	44.652		
Treated	0.295	0.007	39.603	0.418	0.024	17.081	0.280	0.009	30.868	0.274	0.015	18.094	0.280	0.008	36.048		
Diff (T-C)	-0.001	0.009	-0.141	0.006	0.028	0.213	0.009	0.011	0.748	0.007	0.022	0.300	0.003	0.010	0.324		
Follow up																	
Control	0.472	0.006	78.122	0.446	0.014	31.638	0.458	0.008	57.963	0.511	0.021	23.821	0.475	0.007	69.435		
Treated	0.555	0.008	68.374	0.590	0.024	24.178	0.522	0.010	51.662	0.633	0.016	38.751	0.551	0.009	64.021		
Diff (T-C)	0.083	0.010	8.174	0.144	0.028	5.111	0.064	0.013	4.984	0.123	0.027	4.554	0.075	0.011	6.869		
Impact																	
Diff-in Diff	0.084	0.014	6.113	0.138	0.040	3.450	0.055	0.017	3.214	0.116	0.035	3.315	0.072	0.015	4.879		
Observations	28,872			6,524			16,402			5,682			22,156				
R2	0.05			0.02			0.05			0.10			0.06				

Table A8. Impact of PAE on formal employment disaggregated by year

	Formal Employment														
	Total			2017			2016			2015			2016 & 2015		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline															
Control	0.022	0.002	12.360	0.031	0.005	6.161	0.021	0.002	9.542	0.018	0.004	4.868	0.020	0.002	11.132
Treated	0.019	0.002	8.628	0.052	0.011	4.704	0.013	0.002	5.693	0.022	0.005	4.406	0.016	0.002	7.267
Diff (T-C)	-0.003	0.003	-0.902	0.021	0.012	1.708	-0.008	0.003	-2.464	0.003	0.006	0.541	-0.004	0.003	-1.598
Follow up															
Control	0.084	0.003	24.772	0.066	0.008	8.298	0.086	0.004	19.403	0.114	0.019	6.088	0.088	0.004	22.826
Treated	0.119	0.005	22.555	0.167	0.018	9.033	0.104	0.006	16.833	0.141	0.012	11.965	0.114	0.005	20.703
Diff (T-C)	0.036	0.006	5.726	0.101	0.020	4.993	0.017	0.008	2.275	0.027	0.022	1.238	0.026	0.007	3.831
Impact															
Diff-in Diff	0.039	0.007	5.582	0.080	0.023	3.407	0.025	0.008	3.048	0.024	0.023	1.045	0.030	0.007	4.151
Observations	28,872			6,524			16,402			5,682			22,156		
R2	0.03			0.04			0.03			0.04			0.03		

Table A9. Impact of PAE on unconditional monthly earnings disaggregated by year

	Unconditional (Log) Monthly earnings														
	Total			2017			2016			2015			2016 & 2015		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline															
Control	0.494	0.054	9.219	1.520	0.137	11.094	0.267	0.067	3.961	0.230	0.160	1.435	0.311	0.059	5.259
Treated	0.490	0.072	6.839	1.658	0.238	6.962	0.363	0.088	4.136	0.270	0.143	1.886	0.348	0.075	4.672
Diff (T-C)	-0.004	0.089	-0.042	0.138	0.275	0.503	0.096	0.111	0.864	0.040	0.215	0.188	0.037	0.095	0.390
Follow up															
Control	2.304	0.060	38.463	1.993	0.137	14.510	2.159	0.078	27.643	2.727	0.214	12.734	2.342	0.068	34.568
Treated	3.177	0.082	38.945	3.547	0.245	14.474	2.836	0.101	27.969	3.989	0.165	24.218	3.132	0.086	36.216
Diff (T-C)	0.873	0.101	8.629	1.554	0.281	5.532	0.677	0.128	5.291	1.263	0.270	4.674	0.791	0.110	7.198
Impact															
Diff-in Diff	0.877	0.135	6.494	1.416	0.393	3.603	0.582	0.169	3.439	1.222	0.345	3.540	0.754	0.145	5.184
Observations	28,684			6,481			16,276			5,666			22,013		
R2	0.06			0.03			0.05			0.11			0.07		

Table A10. Impact of PAE on monthly earnings

	Employment						Formal Employment						Unconditional (Log) Monthly earnings					
	Female			Male			Female			Male			Female			Male		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline																		
Control	0.275	0.008	36.26	0.322	0.009	37.59	0.020	0.002	8.39	0.025	0.003	9.05	0.244	0.071	3.43	0.788	0.083	9.47
Treated	0.270	0.010	27.89	0.327	0.012	28.27	0.017	0.003	5.97	0.023	0.004	6.24	0.213	0.092	2.32	0.846	0.113	7.49
<i>Diff (T-C)</i>	<i>-0.005</i>	<i>0.012</i>	<i>-0.38</i>	<i>0.005</i>	<i>0.014</i>	<i>0.36</i>	<i>-0.004</i>	<i>0.004</i>	<i>-1.01</i>	<i>-0.002</i>	<i>0.005</i>	<i>-0.34</i>	<i>-0.031</i>	<i>0.116</i>	<i>-0.27</i>	<i>0.059</i>	<i>0.140</i>	<i>0.42</i>
Follow up																		
Control	0.421	0.008	52.29	0.539	0.009	57.88	0.066	0.004	17.09	0.107	0.006	18.24	1.761	0.078	22.45	3.011	0.093	32.31
Treated	0.501	0.011	45.95	0.624	0.012	52.23	0.106	0.007	15.79	0.136	0.008	16.10	2.619	0.109	24.08	3.897	0.121	32.14
<i>Diff (T-C)</i>	<i>0.080</i>	<i>0.014</i>	<i>5.87</i>	<i>0.085</i>	<i>0.015</i>	<i>5.62</i>	<i>0.040</i>	<i>0.008</i>	<i>5.21</i>	<i>0.029</i>	<i>0.010</i>	<i>2.81</i>	<i>0.857</i>	<i>0.134</i>	<i>6.39</i>	<i>0.886</i>	<i>0.153</i>	<i>5.79</i>
<i>Diff-in Diff</i>	<i>0.084</i>	<i>0.018</i>	<i>4.60</i>	<i>0.080</i>	<i>0.021</i>	<i>3.83</i>	<i>0.044</i>	<i>0.009</i>	<i>5.14</i>	<i>0.031</i>	<i>0.011</i>	<i>2.70</i>	<i>0.888</i>	<i>0.177</i>	<i>5.01</i>	<i>0.827</i>	<i>0.208</i>	<i>3.98</i>

Table A11. Impact of PAE on monthly earnings

	Employment						Formal Employment						Unconditional (Log) Monthly earnings					
	LLE			HLE			LLE			HLE			LLE			HLE		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Control	0.336	0.013	26.09	0.281	0.006	44.18	0.019	0.003	6.21	0.023	0.002	9.70	0.820	0.121	6.77	0.367	0.062	5.93
Treated	0.334	0.015	22.99	0.279	0.009	32.37	0.018	0.004	4.40	0.020	0.003	7.42	0.828	0.139	5.97	0.358	0.083	4.29
<i>Diff (T-C)</i>	<i>-0.001</i>	<i>0.019</i>	<i>-0.07</i>	<i>-0.001</i>	<i>0.011</i>	<i>-0.13</i>	<i>-0.001</i>	<i>0.005</i>	<i>-0.19</i>	<i>-0.003</i>	<i>0.004</i>	<i>-0.72</i>	<i>0.008</i>	<i>0.184</i>	<i>0.04</i>	<i>-0.009</i>	<i>0.104</i>	<i>-0.09</i>
Control	0.466	0.013	35.18	0.471	0.007	67.02	0.045	0.005	8.76	0.098	0.004	22.66	2.131	0.129	16.54	2.334	0.070	33.29
Treated	0.500	0.015	32.47	0.577	0.010	60.66	0.070	0.008	8.92	0.138	0.007	20.83	2.516	0.152	16.54	3.440	0.096	35.80
<i>Diff (T-C)</i>	<i>0.035</i>	<i>0.020</i>	<i>1.70</i>	<i>0.105</i>	<i>0.012</i>	<i>8.92</i>	<i>0.026</i>	<i>0.009</i>	<i>2.72</i>	<i>0.040</i>	<i>0.008</i>	<i>5.03</i>	<i>0.385</i>	<i>0.199</i>	<i>1.93</i>	<i>1.106</i>	<i>0.119</i>	<i>9.30</i>
<i>Diff-in Diff</i>	<i>0.036</i>	<i>0.028</i>	<i>1.28</i>	<i>0.107</i>	<i>0.016</i>	<i>6.70</i>	<i>0.027</i>	<i>0.011</i>	<i>2.48</i>	<i>0.042</i>	<i>0.009</i>	<i>4.88</i>	<i>0.377</i>	<i>0.271</i>	<i>1.39</i>	<i>1.115</i>	<i>0.158</i>	<i>7.07</i>

Table A12. Impact of PAE on monthly earnings

	Employment						Formal Employment						Unconditional (Log) Monthly earnings					
	Youth			Middle-Ager			Youth			Middle-Ager			Youth			Middle-Ager		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Control	0.272	0.008	33.09	0.318	0.008	40.55	0.015	0.002	5.96	0.028	0.003	10.52	0.268	0.079	3.38	0.698	0.075	9.31
Treated	0.276	0.010	26.65	0.315	0.011	29.44	0.012	0.003	4.72	0.027	0.004	7.24	0.316	0.099	3.19	0.681	0.104	6.57
<i>Diff (T-C)</i>	<i>0.004</i>	<i>0.013</i>	<i>0.30</i>	<i>-0.004</i>	<i>0.013</i>	<i>-0.27</i>	<i>-0.003</i>	<i>0.004</i>	<i>-0.79</i>	<i>-0.001</i>	<i>0.005</i>	<i>-0.29</i>	<i>0.048</i>	<i>0.127</i>	<i>0.38</i>	<i>-0.017</i>	<i>0.128</i>	<i>-0.13</i>
Control	0.464	0.009	52.89	0.481	0.009	55.77	0.095	0.005	18.02	0.073	0.004	16.54	2.251	0.087	25.84	2.366	0.085	27.79
Treated	0.533	0.012	46.05	0.578	0.011	50.83	0.116	0.007	15.63	0.122	0.008	16.22	3.016	0.116	25.97	3.359	0.115	29.30
<i>Diff (T-C)</i>	<i>0.069</i>	<i>0.015</i>	<i>4.74</i>	<i>0.097</i>	<i>0.014</i>	<i>6.80</i>	<i>0.021</i>	<i>0.009</i>	<i>2.29</i>	<i>0.050</i>	<i>0.009</i>	<i>5.69</i>	<i>0.765</i>	<i>0.145</i>	<i>5.27</i>	<i>0.993</i>	<i>0.143</i>	<i>6.95</i>
<i>Diff-in Diff</i>	<i>0.065</i>	<i>0.020</i>	<i>3.30</i>	<i>0.101</i>	<i>0.019</i>	<i>5.16</i>	<i>0.024</i>	<i>0.010</i>	<i>2.42</i>	<i>0.051</i>	<i>0.010</i>	<i>5.17</i>	<i>0.717</i>	<i>0.193</i>	<i>3.72</i>	<i>1.009</i>	<i>0.192</i>	<i>5.27</i>

Table A13. Placebo Tests

	Employment						Formal Employment						Unconditional (Log) Monthly earnings					
	Placebo 1			Placebo 2			Placebo 1			Placebo 2			Placebo 1			Placebo 2		
	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t	Coef.	Std. Error	t
Baseline																		
Control	0.299	0.005	54.691	0.298	0.006	46.632	0.020	0.002	12.089	0.021	0.002	10.658	0.511	0.052	9.749	0.513	0.061	8.360
Treated	0.302	0.005	55.876	0.304	0.006	48.658	0.020	0.002	12.249	0.019	0.002	10.195	0.555	0.052	10.696	0.551	0.060	9.212
Diff (T-C)	0.003	0.008	0.413	0.006	0.009	0.686	0.000	0.002	0.023	-0.002	0.003	-0.661	0.044	0.074	0.595	0.038	0.086	0.447
Follow up																		
Control	0.484	0.006	81.256	0.472	0.007	67.525	0.091	0.003	26.527	0.078	0.004	20.752	2.451	0.060	41.174	2.291	0.069	33.153
Treated	0.498	0.006	84.601	0.468	0.007	69.055	0.086	0.003	26.133	0.078	0.004	21.390	2.599	0.059	44.222	2.240	0.067	33.450
Diff (T-C)	0.014	0.008	1.626	-0.004	0.010	-0.395	-0.004	0.005	-0.864	0.000	0.005	0.017	0.149	0.084	1.780	-0.051	0.096	-0.529
Impact																		
<i>Diff-in Diff</i>	0.010	0.011	0.919	-0.010	0.013	-0.755	-0.004	0.005	-0.783	0.002	0.006	0.317	0.105	0.112	0.942	-0.089	0.129	-0.693
Observations	28,884			21,390			28,884			21,390			28,698			21,252		
R2	0.04			0.03			0.02			0.02			0.04			0.03		

Graph A3. Ex post probabilistic sampling. Distribution of the propensity scores for treatment and control groups.

