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Active Labor Market Policies in a context of high informality: The effect of PAE in Bolivia[†]

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Abstract

Information asymmetries and limited skills are two main factors affecting jobseekers' chances to access quality jobs in developing countries. This paper evaluates the effectiveness of a job intermediation and wage subsidy program in Bolivia, a country with one of the highest levels of informality in Latin-America. Using administrative and survey, we find that the program substantially increases employment, formality, and earnings. These effects are heterogeneous across different subsamples of interest. Our results suggest that Active Labor Market Policies might be an effective solution for improving access to quality jobs in the context of high informality.

Keywords: intermediation, wage subsidy, informality, Bolivia

JEL Codes: J24, J28

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1. Introduction

Labor markets in Latin American and Caribbean (LAC) and particularly in Bolivia are largely informal (62 and 81 percent of workers, respectively, do not contribute to social security) (Alaimo et al., 2015). From a policy perspective, it is important to reduce informality because it affects individuals' welfare and productivity but also the economy as a whole, through imposing pressure on fiscal balance, social security, poverty, and inequality.

High labor costs, workers' limited skills, and information asymmetries are some of the main factors affecting access to formal jobs. Individuals from vulnerable groups (e.g., youths, women and those with lower levels of education) are more likely to be affected by these restrictions and to work informally (Attanasio et al., 2011).

Active Labor Market Policies (ALMP) represent a potentially effective policy to redress these barriers and to increase individuals' chances of getting good quality jobs (Pignatti, 2016; Kluve, 2016). Evaluations of ALMP in LAC, and particularly of training programs, which is the most commonly implemented policy of this kind in the region, show positive results on employment and formal employment for youth and women (Card et al., 2017; Escudero et al., 2018; McKenzie, 2016). However, evidence about the effectiveness of other ALMP (e.g., wage subsidies, search and matching assistance programs) are still scarce in LAC (Escudero et al., 2018).

This paper evaluates the effectiveness of the *Programa de Apoyo al Empleo* (Program for the Support of Employment, PAE) on workers' employment, formality (i.e., contributing to social security), and earnings in Bolivia. PAE is a public program offering jobseekers registered in the Public Employment Service (PES) information about job vacancies posted by formal firms, which are also registered in PES, and three months of wage subsidy if they are selected for the vacancy. Thus, PAE provides jobseekers information about the labor market, a wage subsidy to reduce firms' hiring costs, and a job experience in a formal firm, which might also help them to signal productivity and to acquire skills for future job searches.

The fact that access to PAE is universal and that firms discretionary select candidates from the list of jobseekers sent by PES make randomization into the program hard to implement. To identify the effect of PAE, we combine propensity score matching and difference-in-difference techniques accounting for differences in observables and time-invariant characteristics that might affect selection into the program and the labor outcomes.

We use three sources of information: administrative records from PES and PAE and an individual survey. Data from PES provides information about jobseekers' socioeconomic characteristics; and, characteristics of the job offers, such as the number of offers, occupational category, and offered salary. Records from PAE allow us to identify the program's beneficiaries. These two administrative datasets are merged with an individual telephone survey applied to jobseekers registered in PES in the period between January 2015 and June 2017. The survey provides information regarding the employment characteristics of jobseekers at the time of their registration in the program and at the time of the survey (between December 2017 and February 2018).

Our results show that PAE increases the probabilities of employment in 9 percentage points (pp) and of formal employment in 4 pp, and earnings in 9 percent. We also find evidence of heterogeneous effects. The effects of PAE on the probabilities of employment and formal employment are larger for adults and for those with tertiary education.[1] Regarding gender differences, we find that relative to men, PAE has larger effects on women's probability of having formal jobs and earnings. The effect of PAE on earnings is also larger for adults than for youths. Moreover, we find evidence that while the effects of PAE on

[1] Following the national regulation of Bolivia (Law 342), we define youth as those younger than 29.

employment and formality seem to be larger in the short-term, the one on earnings seems to increase over time. Finally, a cost-benefit analysis reinforces the positive returns of PAE over future individual labor outcomes.

This paper contributes to the scarce empirical literature about the effectiveness of ALMP different than training in LAC. In their metanalysis, Card et al. (2017) find that, in LAC, no program estimates correspond to intermediation services, only 3 percent to employment subsidies, and 97 percent to training programs.[2] Similarly, Escudero et al. (2018) find only one published evaluation of an employment subsidy program (Galasso et al., 2004) and one of an intermediation service (Dammert et al., 2015) in the region. Thus, our paper is one of the first evaluations of a program combining an intermediation service, a wage subsidy, and a job experience in a formal firm in LAC. This paper is also the first evaluation of an ALMP in Bolivia (Card et al., 2017).

The rest of the document is organized as follows. Section 2 reviews the evidence of similar ALMP effectiveness in LAC and describes the program. Section 3 describes the identification strategy. Section 4 presents the data and summary statistics. Section 5 presents the main results and robustness checks. Section 6 shows a cost-benefit analysis, and Section 7 concludes.

2. ALMP in LAC and PAE

2.1 ALMP effectiveness in LAC

Despite the interest in ALMP in developing countries, evidence about their effectiveness has begun to become available only recently (McKenzie, 2017). In LAC, this expansion has been motivated by the increasing interest in ALMP as a public policy tool aimed at improving not only labor market inefficiencies but also poverty and inequality (Escudero et al., 2018).

In contrast to developed countries, ALMP in developing countries, and particularly in LAC, generally show positive, nevertheless small, effects on vulnerable groups (Card et al., 2017; Escudero et al., 2018). Recent evidence from LAC shows that ALMP are statistically more effective for women and youth (Escudero et al, 2018). Moreover, the evidence shows that effects from medium-run evaluations are not statistically significantly different from those in the short-run and that long-term evaluations are scarce in the region.

Training programs are the most commonly implemented and evaluated ALMP in LAC (Escudero et al., 2018). Generally, these programs can be categorized into two groups. First, those designed for vulnerable jobseekers (mainly youth), which include classroom and maybe on-the-job training. These programs usually focus on short-term interventions aimed at improving individuals' technical and socioemotional skills as a mechanism to increase their employability in good quality jobs (McKenzie, 2017). The second group of programs focuses more on on-the-job training. In addition to acquiring skills, individuals in these programs are intended to acquire job experience in formal firms, which is expected to reduce information asymmetries and improve their employability in future job searches.

More evidence about training policies that include classroom training is available in the region. Two of the better-known evaluations correspond to *Juventud y Empleo* in the Dominican Republic and *Jóvenes en Acción* in Colombia. 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. In turn, Card et al. (2011) found a positive impact on formal employment conditional on being employed and in wages for a program implemented in 1999 in the Dominican Republic. Long-term evaluations of these programs show that some of the short-term effects hold in the long-term (Attanasio et al., 2015; Ibarraran et al., 2019).

[2] Evidence about intermediation services are more frequent in Nordic and Anglo countries, while evidence about subsidies are more frequent in Germanic and Nordic countries.

In contrast, evidence of programs with an emphasis on on-the-job training is scarce.[3] In LAC, the only existing randomized evaluation corresponds to the *Programa Primeros Pasos* (PPP) in Argentina (Berniell & de la Mata, 2017). PPP offers youths, aged 16 to 25, a 12-months subsidy to acquire on-the-job training in a formal job. PPP increases the probability of formal employment, in the short-run (12 months after finishing the program) and the medium-run (4.5 years after the program started) and reduces the unemployment rate by 10 percent.

Similarly, evidence about the effectiveness of subsidized employment and search assistance programs is scarce in the region (Card et al., 2017; Escudero et al., 2018). Galasso et al. (2004) analyze the impact of a wage subsidy program in Argentina, finding that it improves the probability of employment and does not affect earnings. The effects are larger among women and youth. Regarding search assistance programs, Dammert et al. (2015) find evidence of a positive short-term effect of public labor-market intermediation services in Peru on employment, particularly if the information is delivered through digital channels.

2.2 Background and description of PAE

Partially explained by a favorable commodity price context, Bolivia has experienced high levels of economic growth and poverty reduction since 2005.[4] Nonetheless, the country still has the main challenge of improving productivity and job quality. In 2012, when PAE was designed, Bolivia had one of the lowest unemployment rates in the region (2 percent in 2012) but a high level of informality (81 percent). Youth, women, and people with lower levels of formal education were particularly disadvantaged in these indicators.[5]

In September 2012, the Bolivian Ministry of Work, Employment and Social Security, with the financial support of the Inter-American Development Bank, implemented PAE.[6] The aim of the program is to facilitate the placement of jobseekers who, although accomplishing the job selection requirements, had low chances of accessing formal employment opportunities. For PAE, young workers, particularly those with lower levels of education, and workers without previous formal sector experience are the ones considered as less likely to have access to formal jobs.

In Bolivia, as in other developing countries, labor market conditions, such as high labor costs and restrictive labor regulations, generate disincentives for employers to formally hire workers. Unless employers know in advance the jobseeker's contribution to the firm's productivity or they have perfect control over his future returns (Pallais, 2014), these market conditions might incentivize the use of informal recruitment channels.[7] Thus, jobseekers who are less able to signal productivity are more likely to be trapped in poor quality jobs.

To solve this, PAE offers jobseekers a three-months subsidized job in formal firms. The wage subsidy varies between 1 and 1.5 minimum wages according to the educational level requirement and the

[3] Most of the evidence comes from programs in developed countries. For instance, Gelber et al. (2016) find that an internship program in New York increases earnings and employment in the short-term.
[4] Between 2005 and 2017 the poverty rate in Bolivia reduced from 59.6% to 36.4% and the yearly average GDP was 4.9%.
[5] In 2012 the unemployment rate for youth, women and people with low level of education were 3%, 3% and 1%, respectively. In turn, informality rates were 87%, 83% and 96%, respectively. Informality rate is defined as percentage of employed workers contributing to social security. Inter-American Development Bank, Labor Market and Social Security Information System (SIMS).
[6] In 2017, a second version of PAE was implemented. The new version maintains the same logic and logistic of the original program but includes three specific pilots aim at targeting three vulnerable groups (youths, women, people with disabilities). Our evaluation corresponds to the original program design.
[7] According to Mazza (2017), nearly 80 percent of workers in Bolivia finds jobs through informal channels.

economic sector of the vacancy.[8] During its lifetime, the program has benefited nearly 20 thousand individuals, 55 percent of whom were women and 49 percent had at least some tertiary education.[9]

PAE operates through the PES.[10] Both jobseekers and firms offering vacancies need to be registered at PES to be eligible for PAE. In addition, jobseekers are required to be older than 18 at the moment of registration in PES and to meet the requirements of the vacancy. In turn, firms are required to be formal (i.e., to have an active national tax identification number) and that the vacancy credibly leads to permanent hiring.[11] Firms can only apply for a limited number of PAE beneficiaries depending on their size and can only reapply to the program if at least 50 percent of its previous beneficiaries were hired after graduating from the program.[12]

The process of matching jobseekers and vacancies is made by caseworkers. Whenever a PAE vacancy is posted, a PAE caseworker makes an initial screening of candidates, identifying those accomplishing the selection criteria and preferences, and compiles a shortlist. The intermediation process consists in matching the jobseeker's job offer and the job vacancy's occupation codes. Shortlists typically include at least three jobseekers per vacancy and are provided directly to the employer.[13] After receiving the shortlist, employers contact and interview jobseekers and select one of the candidates. Job interview and offer decisions are discretionary to the firm and the job acceptance decision is discretionary to the jobseeker. Once the firm and the selected jobseeker reach a deal, the firm communicates it to PAE, which after some administrative checks, starts paying the subsidy.

PAE combines three main components: job search support, a wage subsidy, and acquiring a formal job experience. First, PAE offers a cost-free job intermediation service aiming to improve jobseekers' (firms') information about the quality and quantity of job vacancies and firms (jobseekers) and to allow more efficient job matchings. Second, the wage subsidy component aims at encouraging firms to hire jobseekers that they would not hire otherwise (e.g., because they do not have experience or are unsuccessfully signaling their skills and productivity) by reducing the cost of hiring and testing a worker (McKenzie, 2017; Pallais, 2014). Third, by offering a formal job experience, PAE improves jobseeker's productivity signaling in future labor market searches. If deficiencies in signaling productivity affect jobseekers' chances of obtaining formal jobs in Bolivia, then formal experience, even if it is of short duration, could act as a better signal of the productivity (Pallais, 2014). In this regard, Berniell & de la Mata (2017) find that the impact of PPP may be due to the gaining in formal experience rather than improvements in human capital. A formal job experience might also help workers to acquire knowledge about and networks in formal firms, which would improve their confidence in approaching employers in further job searches. Galasso et al. (2004) find this particularly relevant for young and female workers in Argentina. Finally, working in a formal setting could help workers to gain the skills needed in similar jobs in the future. The education system in Bolivia fails in providing individuals with the skills set demanded in the labor market, as documented by employer surveys in the country (Bagolle et al., 2019). Short job experiences, like the one supported by PAE, might contribute to the acquisition of these skills.

3. Evaluation strategy

[8] Wage subsidies increases with educational level and by economic sector. For each educational level, subsidies in manufacture are higher than in services, which in turn are higher than in commerce.

[9] Jobseekers could be beneficiaries of PAE only once in their lifetime.

[10] PES works as a single window for different labor programs, such as: *Mi Primer Empleo Digno*, for disadvantaged youths; *Intermediación Directa*, which is a search and intermediation assistance program; and *Plan de Empleo*, which is a platform combining several policies aiming at increasing employability. Unfortunately, due to data restrictions, it is not possible to identify individuals who are beneficiaries of these interventions. Therefore, our estimates correspond to lower bounds estimates of the real effect of PAE.

[11] At registration with the program, firms sign an affidavit stating the intention that the vacancy leads to a permanent hiring.

[12] The maximum number of beneficiaries of a firm could not exceed 50 percent of its current stock of workers. Once a firm achieved its quota of beneficiaries, it could only reapply for more a year after the first beneficiaries graduated from PAE.

[13] For each jobseeker, shortlists provide national identity number, name and surname, date of birth, address, phone number and occupation sought. These shortlists do not rank jobseekers but listed them by the date of registration into PES.

Considering that assignment into PAE is not random, we combine kernel propensity score matching (PSM) and difference-in-difference (DID) methods to estimate the effect of PAE on labor outcomes. PSM allows us to create a comparison group that is similar in terms of observable characteristics to PAE beneficiaries. In addition, DID allows us to control for time-invariant unobservable characteristics that might affect both participation in PAE and labor outcomes. The key identifying assumption is that, in the absence of the treatment, the labor outcomes of individuals in the control and treatment groups would have followed a parallel trend.

We start estimating the propensity scores by running a probit model of the treatment variable T on a vector of covariates X corresponding to a period before the treatment (i.e., at the time of registration in PES). We include a rich set of individual and household characteristics, including a dummy variable for whether the beneficiary was working at the moment of registration at PES; a dummy variable for whether the jobseeker was ever promoted in a previous job; a dummy if the jobseekers defines himself as indigenous; sex; age; age squared; years of education; a dummy for having a disability; civil status; a dummy for being the head of household; number of children; a dummy if the jobseeker holds a tertiary education diploma; household income; dummies for the year, month and city of registration at PES; and the logarithm of the expected salary (i.e., the wage the jobseeker expected to obtain when manifested interest in a job vacancy at registration in the PES).

$$P_i^* = \gamma + \delta X_i + \epsilon_i \tag{1}$$

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

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

After estimating the propensity score, we restrict the sample to the common support.[14] Then, we implement a kernel PSM, where each individual in the treatment group is matched with a weighted average of individuals in the control group. For calculating these weights, we use the Epanechnikov kernel function, where weights are proportional to the proximity of the propensity scores of the treatment and control individuals in a determined neighborhood.

Finally, we estimate a DID regression on the weighted outcomes generated previously:

$$\hat{y}_{it} = \beta_0 + \beta_1 time_t + \beta_2 T_i + \beta_3 (time \cdot T)_{it} + \epsilon_{it} \tag{2}$$

Where $\hat{y}_{it}$ is a labor market outcome (i.e., employment, having a formal job, or the logarithm of labor income); *time* is a dummy variable indicating the time of registration at the PES (pre-treatment) and the time of interview (post-treatment) and T_i is a dummy variable indicating the treatment status.

Considering that our sample is composed of jobseekers registered in the PES (i.e., receive information about vacancies), the coefficient of interest, β_3, should be interpreted as the marginal effect of the other two PAE components described above: receiving a wage subsidy and the chance of having a formal job experience.

4. Data and descriptive statistics

Data for the present evaluation comes from three sources. First, administrative records from PES contain socioeconomic information and information about the job offer (i.e., interest in a vacancy) of the jobseekers registered in the PES between January 2015 and June 2017. Second, administrative data from PAE allow us to identify the program's beneficiaries. Finally, we use information from a telephone

[14] Graph A1 in the Appendix shows the distribution of propensity scores for the treatment and control groups. Less than 1% of the sample falls outside the common support.

survey, collected between December 2017 and February 2018, to the jobseekers registered in PES during January 2015 and June 2017.

Out of 37 142 jobseekers registered in PES in this period, 66 percent were reached by interviewers, and 39 percent (14 463) completed the survey. To do this a team of interviewers received a list of individuals registered in PES (PAE beneficiaries and non-beneficiaries) divided by years. Interviewers were asked to first contact all individuals registered in 2017; only then, those registered in 2016; and, finally, those registered in 2015.[15] Accordingly, Table A1 in the Appendix shows that the proportion of individuals registered in 2017 who were contacted and completed the survey is larger than in the previous years.

Collecting information through telephone surveys presents advantages over face-to-face (e.g., lower costs and speed) and online surveys (e.g., accessibility) (Szolnoki & Hoffmann, 2013). However, it also introduces some challenges. By conducting a telephone survey, one might introduce a sample selection bias by excluding jobseekers who do not have a telephone. Also, collecting data by phone, in contrast to other alternatives, might affect the quality of the information reported or affect the decision to participate in the survey (i.e., mode effect). The overall response rate might also be lower, or it could change across population groups, making some of them overrepresented (Holbrook et al., 2003; Nandi & Platt, 2011; Szolnoki & Hoffmann, 2013).

We explore the presence of such problems in our data. First, the chances of introducing sample selection bias for not having a telephone are neglectable in our sample. Despite that the 2012 Census Data in Bolivia indicates that 18 percent of households in urban areas do not have access to either landline or mobile phones, only 0.6 percent of jobseekers registered in our PES dataset does not show a valid phone number. Second, we test for whether the quality of the data reported in the telephone survey differs from the administrative records from the PES. As mentioned above, given that the PES registry includes only a few variables, we restrict the analysis to only three variables of interest: age, sex, and education. Correlation coefficients between the information reported in both datasets for these three variables are high and statistically significant (Table A2 in the Appendix). Finally, using the information available in the PES database, we test for systematic differences between those who answer or not the telephone survey (Table A3 in the Appendix). Although we find that the probability of completing the telephone survey is associated with individual socioeconomic characteristics, we find that there is not selective attrition bias (i.e., the conditional probability of completing the survey is not affected by being a PAE beneficiary or not).[16]

Table 1 presents the mean values of the covariates included in the PSM estimation at the baseline (i.e., at registration in PES), for individuals in the control and treatment groups. The first three columns (unweighted variables) show that jobseekers in our sample were 31 years old, mostly women (58 and 57 percent in the control and treatment groups, respectively) and not indigenous (10 and 6 percent in the control and treatment groups, respectively). They also have 14 years of education, no disabilities (5 and 1 percent in the control and treatment groups reported having a disability, respectively) and are less likely to have a tertiary education diploma (33 and 30 percent). Finally, individuals in the treatment group have higher monthly family income (Bs$2,228 or US$320 and Bs$2,095 or US$301, respectively)[17] and lower expected wages than those in the control group. Implementing the PSM allows us to have a balanced sample in the pretreatment covariates, as shown in the last three columns of Table 1.

[15] To consider an interview as "refused" interviewers were required to make at least five communication attempts, at different times.

[16] Table A3 in the Appendix shows the differences between those who completed or not (including the ones who were not contacted) the survey. Those who completed the survey are older, more likely to be women and married, have a higher level of education, higher expected wage and manifested interest in fewer vacancies than those who did not complete the survey. As expected by the data collection protocol, those registered in 2017 are more likely to complete the survey.

[17] Through the paper, income is deflated to 2017 prices and converted to US$ using an exchange rate of 6.96 bolivianos per US$.

Table 1. Descriptive statistics at baseline

	Unweighted Variables				Weighted Variables		
	Mean Control	**Mean Treated**	**t**		**Mean Control**	**Mean Treated**	**t**
Employment status at the time of registration	0.303	0.299	0.40		0.298	0.299	0.05
Ever received a promotion	0.323	0.315	0.79		0.319	0.314	0.57
Indigenous	0.099	0.063	6.34	***	0.065	0.064	0.42
Woman	0.583	0.569	1.36		0.569	0.57	0.1
Age	31.524	30.886	3.68	***	30.901	30.888	0.09
Age squared	1073.241	1024.010	3.74	***	1024.794	1024.262	0.05
Education	14.333	14.416	-1.24		14.41	14.419	0.17
Have a disability	0.052	0.018	8.54	***	0.020	0.018	0.85
Married	0.255	0.258	-0.26		0.257	0.258	0.16
Head of household	0.346	0.349	-0.41		0.344	0.349	0.54
# of children	0.815	0.845	-1.22		0.843	0.841	0.11
Tertiary education diploma	0.330	0.302	3.04	***	0.304	0.303	0.19
Monthly Family Income	2095.525	2228.142	-4.87	***	2231.780	2217.115	0.61
Year of registration in the PES							
Year 2015	0.189	0.242	-6.69	***	0.232	0.242	1.44
Year 2016	0.539	0.648	-11.22	***	0.655	0.647	0.96
Year 2017	0.272	0.110	19.70	***	0.113	0.111	0.48
Month of registration in the PES							
January	0.086	0.051	6.67	***	0.057	0.051	1.59
February	0.111	0.060	8.57	***	0.062	0.061	0.25
March	0.111	0.106	0.85		0.106	0.105	0.12
April	0.101	0.071	5.20	***	0.071	0.072	0.17
May	0.126	0.072	8.67	***	0.068	0.072	0.85
June	0.075	0.061	2.83	***	0.058	0.061	0.69
July	0.075	0.080	-1.00		0.082	0.08	0.35
August	0.070	0.103	-6.22	***	0.104	0.104	0.12
September	0.061	0.107	-8.97	***	0.104	0.107	0.55
October	0.067	0.123	-10.34	***	0.124	0.121	0.48
November	0.068	0.100	-6.14	***	0.101	0.101	0.02
December	0.049	0.066	-3.95	***	0.064	0.066	0.65
PES office of registration							
El Alto	0.206	0.181	3.17	***	0.188	0.182	0.91
Sucre	0.025	0.084	-15.52	***	0.085	0.083	0.27
La Paz	0.365	0.248	12.55	***	0.261	0.249	1.54
Cochabamba	0.086	0.094	-13.23	***	0.09	0.094	0.82
Oruro	0.074	0.092	-3.38	***	0.091	0.092	0.26
Potosi	0.041	0.042	-0.35		0.042	0.043	0.13
Tarija	0.055	0.054	0.21		0.055	0.055	0.03
Santa Cruz	0.119	0.132	-2.01	**	0.127	0.133	1.08

Trinidad	0.013	0.019	8.41	***	0.019	0.02	0.15
(Log) wage offer (PES)	7.656	7.608	8.73	***	7.610	7.608	0.46

Note: *Significant at 10%; **significant at 5%; *** significant at 1%

5. Results

Table 2 presents the estimated effect of PAE on the probabilities of being employed and having a formal job, and on the logarithm of monthly labor income.[18] PAE increases the probability of being employed in 9 pp and the probability of having a formal job in 4 pp. Moreover, PAE increases labor income, conditional on working, in 9 percent.[19] While the probabilities of employment and having a formal job and labor income of the treatment and control groups were statistically similar before the intervention, beneficiaries' labor outcomes were improved after treatment.

Table 2. PAE effects on employment, formal employment and (log) labor income

	Employment				Formal Employment				(Log) Monthly earnings conditional on working before and after PAE			
	Coef.	**Std. Error**	**t**		**Coef.**	**Std. Error**	**t**		**Coef.**	**Std. Error**	**t**	
Baseline												
Control	0.298	0.006			0.023	0.002			7.236	0.019		
Treated	0.299	0.008			0.020	0.002			7.290	0.025		
Diff (T-C)	0.000	0.010	0.042		-0.003	0.003	-0.964		0.055	0.032	1.731	*
Follow up												
Control	0.476	0.006			0.085	0.003			7.441	0.026		
Treated	0.567	0.009			0.124	0.006			7.588	0.027		
Diff (T-C)	0.091	0.010	8.695	***	0.039	0.007	5.873	***	0.146	0.037	3.951	***
Impact												
Diff-in-diff	0.090	0.014	6.359	***	0.042	0.007	5.742	***	0.091	0.049	1.880	*
Observations				28134				28134				6511
R2				0.06				0.03				0.03

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

Heterogeneous effects

We explore the heterogeneous effects of PAE by gender, age and level of education. First, while the effect of PAE for males and females is positive, the effects on formal employment and earnings for women are larger than for men. Similarly, PAE has positive effects on adults (older than 28) and youths (between 18 and 28), but the effects are larger for adults in the three outcomes analyzed. Finally, we find that the effect of PAE on employment and formality is larger for those with a higher level of education (i.e., having some tertiary education) than for those with a lower level of education (i.e., those having completed high school at most).

[18] Table A4 in the Appendix shows that the effect of PAE on employment, formal employment and log labor income presented in this Section hold when different kernel bandwidths (0.09, 0.03 and 0.01, rather than the 0.06 default) are used. Similarly, results hold when standard errors are calculated by a bootstrap with 500 replications (Table A5).

[19] Table A6 in the Appendix shows the effect of PAE on labor income, unconditional on working. For this, we calculate an inverse hyperbolic sine transformation (IHS).

Table 3. PAE heterogeneous effects

	Employment					Formal Employment					(Log) Monthly earnings conditional on working before and after PAE				
	Diff-in-diff	Std. Error	t		N	Diff-in-diff	Std. Error	t		N	Diff-in-diff	Std. Error	t		N
Men	0.088	0.022	4.001	***	11816	0.034	0.012	2.875	**	11816	0.074	0.065	1.127		3116
Women	0.092	0.019	4.967	***	16300	0.048	0.009	5.280	***	16300	0.129	0.074	1.741	*	3320
Difference (Men-Women)	-0.005	0.010	-0.500			-0.013	0.006	-2.015	**		-0.056	0.024	-2.270	**	
Adults (>28 years)	0.105	0.020	5.171	***	14344	0.055	0.010	5.213	***	14344	0.145	0.068	2.127	**	3841
Youths (18-28 years)	0.077	0.020	3.825	***	13772	0.028	0.010	2.694	***	13772	0.002	0.073	0.026		2611
Difference (Adults-Youth)	0.027	0.001	22.851	***		0.027	0.001	20.77	***		0.144	0.022	6.492	***	
High education (HE)	0.111	0.016	6.755	***	7136	0.044	0.009	4.849	***	7136	0.099	0.059	1.670	*	1782
Low education (LE)	0.043	0.030	1.440		20972	0.033	0.012	2.863	***	20972	0.041	0.086	0.480		4576
Difference (HE-LE)	0.068	0.019	3.549	***		0.011	0.006	1.787	*		0.058	0.052	1.113		

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

Effects over time

To explore whether PAE has differentiated effects over time, Table 4 shows the effects of PAE for the cohorts registered in 2015, 2016 and 2017. Table 4 shows that PAE has positive effects on employment for the three cohorts of applicants. In contrast, the effect on formality is larger in the short-term (i.e., for the most recent cohorts of 2017 and 2016) and the one on earnings is larger in the long-term (i.e., for those applying in 2015).[20] The fact that the PAE effect on formality seems to vanish over time suggests that the program requires additional interventions to help workers to stay in formality.

Table 4. Impact of PAE disaggregated by year

	Employment					Formal Employment					(Log) Monthly earnings conditional on working before and after PAE				
	Diff-in-diff	Std. Error	t		N	Diff-in-diff	Std. Error	t		N	Diff-in-diff	Std. Error	t		N
Year															
2015	0.107	0.037	2.895	***	6398	0.025	0.026	0.971		6398	0.209	0.106	1.965	**	1802
2016	0.061	0.018	3.427	***	15748	0.027	0.009	3.111	***	15748	0.038	0.068	0.564		3385
2017	0.144	0.041	3.521	***	5596	0.093	0.024	3.835	***	5596	0.175	0.119	1.471		1183

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

Robustness check

The fact that our evaluation sample does come from a random selection of jobseekers registered in PES in the period of interest might raise concerns the external validity of our estimated effects. In this section, we perform two robustness checks and analyze whether our results hold: first, we recalculate our estimates using an ex-post randomized sample; and second, we estimate the impacts of PAE using inverse probability weighting (IPW).

For the ex-post randomization, we generate an ex-post probabilistic sampling from the total population of beneficiaries and controls registered in PES in 2015-2017, in which a 50 percent chance of ending in the

[20] These results need to be taken carefully because differences in the composition of applicants to the different cohorts might confound with the effects of PAE over time.

sample is assigned to everyone. Given that in our case answering the telephone survey is independent of the chosen sampling selection procedure, we assume that the individuals who did not reply to the survey would have done it neither if a random sample was originally implemented. Therefore, individuals who ended up being selected for the ex-post random sample and for whom we do not have information from the telephone survey are treated as a regular refusal. Table 5 shows the results of estimating the previous effects for individuals randomly assigned to the ex-post sample who answered the telephone survey.

Results are consistent with the effects presented above. The effects on employment and on formal employment are 9 pp and 3 pp, respectively, and similar to the ones for the original sample (9 pp and 4pp; Table 2). The effect on labor income is 8 percent, which is similar to the 9 percent previously found, however, it is not significant. We also find similar heterogeneous effects, qualitatively favoring adults, those with a higher level of education and women.

Table 5. Impact of PAE on labor variables for the ex-post randomization sample

	Employment					**Formal Employment**					**(Log) Monthly earnings conditional on working before and after PAE**				
	Coef.	**Std. Error**	**t**		**N**	**Coef.**	**Std. Error**	**t**		**N**	**Coef.**	**Std. Error**	**t**		**N**
Full Sample	0.085	0.020	4.285	***	14244	0.029	0.010	2.888	***	14244	0.079	0.073	1.076		3261
2015	0.079	0.046	1.730	*	2852	0.008	0.030	0.266		2852	0.045	0.161	0.277		583
2016	0.071	0.025	2.816	***	7930	0.020	0.012	1.651	*	7930	0.017	0.090	0.195		1663
2017	0.137	0.057	2.389	**	3084	0.116	0.035	3.324	***	3084	0.212	0.192	1.101		648
Men	0.076	0.031	2.452	**	5942	0.004	0.017	0.218		5942	0.029	0.093	0.311		1598
Women	0.094	0.026	3.640	***	8288	0.048	0.012	3.898	***	8288	0.125	0.105	1.193		1555
Adults (>28 years)	0.101	0.028	3.568	***	7080	0.040	0.014	2.787	***	7080	0.108	0.110	0.985		1896
Youths (18 – 28 years)	0.085	0.028	3.012	***	7092	0.023	0.014	1.595		7092	-0.069	0.101	-0.681		1315
High education	0.111	0.023	4.841	***	10624	0.039	0.012	3.195	***	10624	0.042	0.087	0.480		2354
Low education	0.034	0.041	0.844		3594	0.002	0.016	0.129		3594	0.020	0.135	0.151		791

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

The second robustness check deals with the potential sample selection due to survey non-response. For this, we use IPW to estimate the effects of PAE. First, we estimate a logistic model for the probability of completing the survey, conditional on been reached by interviewers, and using information from the PES administrative records. Then, we proceed to calculate the probability of completing the survey and calculate the inverse of the probability to estimate the impact of PAE. Table 6 shows that the IPW results are similar in magnitude and significance to the ones presented in Tables 2, 3 and 4.

Table 6. Impact of PAE on labor variables correcting sample selection with Inverse Probability Weighted Estimators

	Employment					**Formal Employment**					**(Log) Monthly earnings conditional on working before and after PAE**				
	Coef.	**Std. Error**	**t**		**N**	**Coef.**	**Std. Error**	**t**		**N**	**Coef.**	**Std. Error**	**t**		**N**
Full Sample	0.091	0.014	6.400	***	28568	0.043	0.007	5.930	***	28568	0.099	0.049	2.030	**	6604
2015	0.124	0.034	3.590	***	5662	0.033	0.022	1.470		5662	0.232	0.103	2.250	**	1207
2016	0.056	0.018	3.110	***	15996	0.028	0.009	3.250	***	15996	0.057	0.068	0.830		3401
2017	0.140	0.041	3.420	***	6602	0.092	0.024	3.850	***	6602	0.178	0.117	1.530		1819
Men	0.095	0.022	4.310	***	12010	0.037	0.012	3.090	***	12010	0.075	0.065	1.140		3149

Women	0.089	0.019	4.810	***	16574	0.048	0.009	5.400	***	16574	0.137	0.075	1.830	*	3360
Adults (>28 years)	0.109	0.016	6.640	***	21278	0.045	0.009	4.960	***	21278	0.098	0.059	1.650	*	4629
Youths (18 – 28 years)	0.048	0.030	1.600		7288	0.034	0.011	3.010	***	7288	0.019	0.083	0.220		1849
High education	0.110	0.020	5.480	***	14566	0.057	0.010	5.520	***	14566	0.154	0.067	2.300	**	3888
Low education	0.076	0.020	3.750	***	13988	0.030	0.010	2.940	***	13988	0.010	0.074	0.130		2650

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%. A logistic regression is estimating using available information at the PES such as age; gender; a dummy if the jobseeker complete tertiary education; a dummy for being single; the logarithm of the expected salary; dummies for main cities (La Paz, El Alto, Cochabamba, and Santa Cruz); dummies for the year of registration; number of offers registered in the SPE; and a dummy that takes the value of 1 if the job seeker ended up being a beneficiary of PAE (as in Table A3).

6. Cost-Benefit Analysis

We present a simple and conservative calculation of a cost-benefit analysis for PAE. For this, we consider the effects of PAE on labor income and the probability of employment and use a discount rate of 5 percent per year to estimate the Net Present Value. Regarding labor income, as reported in Table 3, the estimated effect of PAE on labor income is 9 percent. Using the labor income at baseline reported for individuals in the control group (Bs$1,388 or US$199), we estimate a benefit attributable to PAE of US$18 (Bs$126) per month, which implies an annual benefit of US$218 (Bs$1,516).

Following Attanasio et al. (2011), we estimate the impact on labor income for 34 years, which is the time the average individual (who is 31 years in the sample) would need to retire at 65 years. The calculation considers two scenarios: one, where gains are permanent; and the other, where gains depreciate at an annual rate of 10 percent. We also assume that the program does not affect the growth rate of labor income.

Regarding the impact on employment, we use the average unemployment duration at the time of registration in PES reported by jobseekers. On average, jobseekers were unemployed for 13.5 months. To estimate the benefits of the PAE on employment, we use the labor income obtained by the treatment group after PAE and only for 13.5 months, which implies a monthly benefit of US$25.6 (Bs$178) and a total benefit for the 13.5 months period of US$343 (Bs$2,392).

Costs associated with the program operation are calculated based on the 2017 minimum salary and the highest stipend payment that can be granted, which is 1.5 minimum salaries for the 3 months. Thus, the cost of subsidizing employment reaches US$1,293 per beneficiary. The opportunity cost incurred by beneficiaries for participating in the program and not receiving another income is not considered.

In the first scenario, the net lifecycle gain of PAE is US$2,771, while in the most conservative scenario the gain is US$2,420. The internal rate of return (IRR) is 17 and 15 percent, respectively, a figure slightly lower to the impact that Attanasio et al. (2011) found for *Jóvenes en Acción*, an ALMP for vulnerable youth in Colombia (they found an IRR between 35 and 21 percent). In a sensitivity analysis, we restricted the sample to jobseekers registered only in 2015 and 2017 and considered the estimated 9 percent PAE effect on labor income. In this case, we still find a positive IRR between 3 and 2 percent.[21]

The cost-benefit analysis shows the effectiveness of PAE even under conservative assumptions and without considering the benefits associated to access to formal employment (e.g., retirement savings, health insurance, vacations). Also, the analysis does not consider that beneficiaries can improve their labor income and job prospects due to the program and the screening provided by it. The analysis also assumes that individuals would permanently earn labor income for 34 years, which could not be the case if they stop participating in the labor market for personal (e.g., maternity) or professional reasons.

[21] In another sensitivity analysis, we restrict the sample to only the 2015 registered jobseekers and consider the 20 percent PAE effect on labor income for this group (as reported in Table 4). In this case, the IRR is between 6 and 5 percent.

A relevant fact that we do not consider in the present cost-benefit analysis is that the benefits in the PAE beneficiaries could be explained at the expense of other jobseekers in the market, which would diminish the impact through a general equilibrium effect. However, evidence in the literature on this regard is not conclusive yet. For instance, Crepon et al. (2013) found that a labor intermediation program in France obtains the benefits at the expense of a decrease in the employment rate of non-beneficiaries. In contrast, Berniell & de la Mata (2018) found no evidence of displacement effect for PPP in Argentina.

7. Conclusions

This paper offers evidence about the effectiveness of PAE, an ALMP combining labor intermediation, a wage subsidy and the chance of having a formal job experience in a high-informality context. This evidence is particularly relevant given that such ALMP, in contrast to training programs, have received almost no attention in the empirical literature in LAC. From a policy perspective, we contribute to the literature showing evidence about a cost-effective policy that contributes to improving individuals' labor market outcomes.

Our results show that PAE substantially improves the probabilities of employment and formality and labor income. These results are particularly larger among women, adults and those with a higher level of education. Moreover, while the effects of PAE on employment seem to decrease over time, the one on earnings seems to increase. The magnitude of the effects of PAE on employment, formality and labor income is larger than the ones for wage subsidies (Galasso et al., 2004), labor intermediation (Dammert et al., 2015) and well-known training programs (Attanasio et al., 2011; Card et al., 2010) in LAC.

It is important to remind that the restriction to identify individuals in the control group who benefit from the other programs offered by PES provokes that our results potentially represent a lower bound of the real effect of PAE. Additionally, the non-experimental setting of this evaluation requires that the assumptions discussed above hold. However, recent meta-analyses of the effectiveness of ALMP show that average program effects from randomized experiments are not very different from the average effects from non-experimental designs (Escudero et al., 2018; Card et al., 2017).

PAE proves to be effective in the context of high informality as the one in Bolivia. Providing jobseekers information about job vacancies and a subsidy to work in a formal firm improves their chances of employment, formality, and earnings. These results are particularly important for groups that are usually marginalized in formal labor markets, such as women. However, the program has the challenge of improving the access of other marginalized workers and of making their effects more durable over time. The program could benefit from introducing a component of skills training, where jobseekers gain the skills required in the classroom and on-the-job training.

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Appendix

Table A1: Distribution of individuals registered in PES surveyed, by year

	2015	2016	2017	Total
Registered	11 922	18 308	6 912	37 142
	100.0%	100.0%	100.0%	100.0%
Reached	5 941	13 623	5 090	24 654
	49.8%	74.4%	73.6%	66.4%
Completed	2 922	8 219	3 322	14 463
	24.5%	44.9%	48.1%	38.9%

Note: Percentages are relative to the total number of registered individuals in each period.

Table A2: Correlation between information reported in the PES and in the telephonic survey

	Pairwise correlation coefficients	
Age	0.5328	***
Gender	0.9176	***
Education	0.9604	***

Note: Significant at 10%; **significant at 5%; *** significant at 1%.

Table A3. Linear probability of having completed the survey

	Completed survey
Age/10	0.01**
	(0.003)
Woman (yes=1)	0.02***
	(0.005)
Tertiary education (yes=1)	0.09***
	(0.006)
Single (yes=1)	-0.02***
	(0.007)
Expected wage	0.07***
	(0.011)
La Paz	0.08***
	(0.007)
El Alto	0.03***
	(0.007)
Cochabamba	0.07***
	(0.010)
Santa Cruz	0.04***
	(0.008)

Number of offers in the data	-0.01***
	(0.002)
year 2015 (yes=1)	-0.21***
	(0.007)
year 2016 (yes=1)	-0.01
	(0.007)
Treated (1 if treated; 0 if control)	0.00
	(0.006)
Constant	-0.16
	(0.081)
Observations	37132
R^2	0.06
F	204.59

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

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

	Employment				Formal Employment				(Log) Monthly earnings conditional on working before and after PAE			
	Coef.	**Std. Error**	**t**		**Coef.**	**Std. Error**	**t**		**Coef.**	**Std. Error**	**t**	
Bandwidth												
DID - BW01	0.091	0.014	6.357	***	0.040	0.007	5.433	***	0.088	0.049	1.803	*
DID - BW03	0.092	0.014	6.430	***	0.041	0.007	5.635	***	0.091	0.050	1.829	*
DID - BW06	0.090	0.014	6.359	***	0.042	0.007	5.742	***	0.091	0.049	1.880	*
DID - BW09	0.089	0.014	6.280	***	0.042	0.007	5.788	***	0.095	0.048	1.967	**

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

Table A5. Impact of PAE with bootstrap

	Employment				Formal Employment				(Log) Monthly earnings conditional on working before and after PAE			
	Coef.	**Std. Error**	**t**		**Coef.**	**Std. Error**	**t**		**Coef.**	**Std. Error**	**t**	
Robust Variance	0.090	0.014	6.359	***	0.042	0.007	5.742	***	0.091	0.049	1.880	*
Bootstrap	0.090	0.014	6.653	***	0.042	0.007	5.719	***	0.091	0.049	1.869	*

Note: Robust Standard errors are reported. *Significant at 10%; **significant at 5%; *** significant at 1%.

Table A6. PAE effects on labor income, unconditional on working, using an inverse hyperbolic sine transformation (IHS)

	Coef.	Std. Error	t		N
Full Sample	0.794	0.116	6.830	***	28134
Year 2015	0.107	0.037	2.890	***	5596
Year 2016	0.535	0.147	3.640	***	15748
Year 2017	1.334	0.336	3.980	***	6398
Men	0.769	0.182	4.230	***	11816
Women	0.816	0.151	5.420	***	16300
Difference (Men-Women)	-0.047	0.085	-0.547		
Adults (>28 years)	0.900	0.166	5.430	***	14344
Youths (18-28 years)	0.695	0.166	4.190	***	13772
Difference (Adults- Youth)	0.205	0.005	42.314	***	
High education (HE)	0.966	0.135	7.140	***	20972
Low education (LE)	0.395	0.240	1.650	*	7136
Difference (HE-LE)	0.572	0.151	3.776	***	

Graph A1. Distribution of the propensity scores for treatment and control groups