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Bolivia and the Program to Support Employment: an Impact Evaluation of its Conditional Cash Transfer Component

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Abstract: The Bolivian Program to Support Employment provides subsidized training to the unemployed and helps comparatively untrained and inexperienced people improve their employability. Albeit this programme was discontinued in 2017, a second version is currently being implemented to continue its work. This impact evaluation assesses the impact of the PSE on employment, labor income and the quality of employment for adult Bolivians. Through a difference-in-differences methodology, it appears that the programme has a positive and significant impact on each of these three variables. Supplemental regressions are conducted and it appears that the impact of the PSE on the employment of several population categories follows labor market expectations. Furthermore the PSE also has a positive and significant impact on employment formality for its beneficiaries, an especially important issue in Bolivia, where 85 percent of all employment is informal. Even if there are important issues with the data used in this analysis, dampening the conclusions, it is fairly safe to state that the PSE has fulfilled its goals and that its successor should not only continue this impact but also go further.

Key words: conditional cash transfer, employment, labor income, employment benefit

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SECTION 1. INTRODUCTION

Poverty and unemployment are among the biggest concerns for policy makers in Latin America and the Caribbean[1] (LAC). Furthermore, with economic growth slowing down from 2.8 percent in 2013 to -0.7 percent in 2016, unemployment in Latin America and the Caribbean has reached more than 26 million people (ILO Blog, 2017; World Bank, 2018a). To counter these changes, governments in LAC have been implementing policies with specific goals of improving employment, employability or income poverty. Such policies include Conditional Cash Transfer programmes, of which the Bolivian case of the Programme to Support Employment (PSE) is one example. Conditional Cash Transfer programmes are not new and yet they managed to change social policy in LAC within a few years.

A Conditional Cash Transfer (CCT) programme or co-responsibility transfer programme is a system whereby a certain number of people or households receive a money transfer conditional on their fulfillment of specific conditions intended to reduce the incidence of income poverty and break the poverty cycle. Considering these programmes have the potential to bring a supplemental source of income for poor families and ultimately break the inter-generational cycle of poverty through human capital investments, they are considered crucial for social policies in LAC (Das, Do and Özler, 2005). Indeed, since their first implementation in 1995, CCTs have covered 132 million people in the region through 30 different programmes in 20 countries (Cecchini & Atuesta, 2017). Globally in LAC, CCT programmes are successful at reducing income poverty and income inequality, and improving employment (de Janvry, Finan, Sadoulet & Vakis, 2006; Fiszbein & Schady, 2009; Rinehart & McGuire, 2017; World Bank, 2014).

The Programme to Support Employment (PSE) aims at improving the employability and lead to employment for adult Bolivians, with specific mandates for the unemployed lacking experience or training. The programme was active between 2012 and 2017 with anyone registered to the national employment services being eligible to it. It provided the unemployed with subsidized training to improve their employment conditions. Furthermore, the programme also improved the range of employment services provided to all unemployed (IDB, 2016b, 2016c). Although this programme was discontinued in 2017, there has been no impact evaluation performed as of yet. It is crucial that policy makers know its impact in order to implement the most effective policies. This research will thus, not only investigate the impact of the PSE on employment but also on labor income and the access to better jobs. This thesis aims at filling the impact evaluation gap for this programme and may also be instructive to the development of new policies for poverty reduction and employment, not only in LAC but in any developing economy.

[1] The region of Latin America and the Caribbean will henceforth refer to these 33 countries and dependent territories: Antigua and Barbuda, Argentina, Bahamas, Barbados, Belize, Bolivia (Plurinational State of), Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, and Venezuela (Bolivarian Republic of) (United Nations Economic Commission for Latin America and the Caribbean, 2018a).

It will appear that the PSE has a positive and statistically significant impact on the employment situation, labor income and the quality of employment for adult Bolivians. However, the analysis incurred several important data limitations that may require the conclusions to be taken cautiously as there is a possible upward bias in the results. Consequently, the PSE appears to have a positive and significant impact on the variables of interest outlined here, but considering the data, there can be no absolute certainty if the bias is large. Without access to better data on the programme, I conclude that the PSE has met its objectives.

The rest of this research will be organized as follows: in section 2, the PSE will be presented in details, the theoretical framework of the programme as well as the literature on the topic will be examined in Section 3. The data used in this impact analysis will be presented in Section 4, followed by the methodology of the analysis will be dealt with in Section 5. All leading to the results in Section 6 and a conclusion in Section 7 with a summary of the findings and a way forward for the programme.

SECTION 2. THE PROGRAM TO SUPPORT EMPLOYMENT (PSE)

The programme was implemented by the Bolivian Ministry of Labor, Employment, and Social Security (MTEPS) with the support of the Inter-American Development Bank in 2012 (IDB, 2010; MTEPS, 2012). It associates a CCT component with a general expansion of governmental employment services. In this sense, the policy is focused on employment and employability of the population. The programme was in action until the end of 2017 when it was discontinued for evaluation and impact analysis as scheduled since its implementation (IDB, c). The first aim of this programme was to provide a better incorporation of adult job seekers into the labor market through three different components (IDB, 2010, 2016a, b):

(I) Expanding the Plurinational Employment Services of Bolivia (SPEBO) to help for labor intermediation and labor insertion. The national employment services are referred to as the Bolsa de Empleo.

(II) A pilot project supporting the employment and employability of adults through subsidized training

(III) Data collection and monitoring for evaluation and future analyses.

1. Component of Interest

Component II of the programme, which is the focus of this thesis, concentrated primarily on adults that have graduated from technical schools and/or universities but do not have enough experience, on-the-job training or skills to be hired for a permanent position (IDB, 2010). This component was organized as a pilot project destined to benefit 20,000 job seekers but also 5,000 employers in finding qualified personnel. Incidentally, the programme was targeted to adults that fit real job descriptions but needed a training period to be able to obtain a permanent position (MTEPS, 2012). Consequently, the programme did not necessarily put all its focus on the poorest part of the population but rather, any unemployed adult Bolivian was eligible to it. It is however more likely that the more educated unemployed obtained training opportunities since their knowledge is valued by companies. The PSE was limited to the urban areas with offices of employment services, thus the following cities: Cobija, Cochabamba, El Alto, La Paz, Montero, Oruro, Potosí, Santa Cruz, Sucre, Tarija and Trinidad (IDB, a).

This part of the programme is designed as a Conditional Cash Transfer which refers to social policy programmes generally understood to grant benefits (whether in cash or in-kind) if and when a specific course of action is completed (Das, et al, 2005). This specific component focuses on redistributing income to unemployed adults to help cover the costs linked with their training opportunity. The need for such a programme was illustrated in 2015 with a labor demand survey in Bolivia showing that 56 percent of the surveyed companies had difficulties finding qualified personnel because the candidates lack either experience or skills (IDB, b). The beneficiaries of the programme, adults encountering problems with insertion into the labor market, are eligible to benefits which represent a given percentage of the minimum wage, depending on several criteria (MTEPS, 2012). Problems with insertion into the labor market encompass certain aspects of the process such as access to information about job offers or the possibilities to gain experience through training and on-the-job learning (MTEPS, 2012).

2. Requirements, Application and Training

The pilot project was directed at unemployed adults in Bolivia and the specific requirements of the programme only involved being at least 18 years old, actively looking for a job, and not receiving benefits from another programme linked with employment (IDB, a). For the companies offering the positions, eligibility requirements only took into account their geographical location, whether the company was located near in a city covered by the programme (IDB, a).

To this end, Component II was organized in six different steps:

(1) Creation of a platform with a registration system for both labor demand and supply to give them the means to follow their entire process within the programme.
(2) Establishment of a reliable record of job opportunities offered by companies and introduction of a link between labor demand and supply.
(3) Preselection of the job seekers to benefit from the training period. This step leads to a list of candidates fulfilling the requirements of the job offer, given for the company to make a choice.
(4) Selection of the beneficiaries. The preliminary list was examined by the company and after candidates were selected to be beneficiaries, documents were drafted to establish their contract.
(5) Training of the beneficiaries on the job for a maximum of three months.
(6) Follow-up with the process of labor insertion if applicable.

Unlike several other programmes in Latin America and the Caribbean, the PSE was available even in remote communities surrounding the main cities where the programme was implemented. Job seekers could register through the internet, phone or go to a regional or local office capacitated with the programme (MTEPS, 2012). In order to finalize the application, job seekers needed to go to one of the offices but having started the application previously, several lengthy and sometimes costly journeys could be avoided. Companies had similar arrangements to register and list their job offers. Considering information is one of the major deterrent in the take-up of social policy programmes, public announcements through the radio or television were made to promote the pilot project (IDB, a). The programme thus covered a large part of the country for the potential registration but training was only available in the companies offering an opportunity, which were likely to be near the designated urban areas.

As for the period of training itself, its length was regulated by the programme, with an introductory course of 12 hours given to the beneficiaries, training that could not exceed 8 hours per day, 48 hours per week and could not go over 3 months (MTEPS, 2012). The overall benefits were calculated individually on the basis of the contract between the company and the beneficiary to take into account the number of hours and days of training (MTEPS, 2012). Other criteria such as education level, type of job opportunity or potential remuneration for a similar permanent position were also taken into account in the calculation. The benefits could thus range between 100% and 150% of the national minimum salary. Indexing the benefits on the national minimum salary instead of having a fixed amount helped the benefits follow the high level of inflation in Bolivia. Between 2012 and 2016, the average inflation as a yearly percentage change in consumer prices was 4.76% (World Bank, 2018b). At the end of the training period, an evaluation of the beneficiary was performed to warrant the labor insertion or explain the reasons why the beneficiary was not retained in the company (MTEPS, 2012).

3. Programme Goals

Component II of the PSE followed a specific timeline with its implementation and preliminary evaluations. The programme was put in action in 6 urban areas in 2012 and later expanded to 5 other urban areas. A mid-project evaluation was performed in 2015 with the comparison of preliminary expectations and actual achievements of the programme. Finally, the programme was discontinued at the end of 2017 and the overall evaluation process started.

While the Program to Support Employment had a general aim of improving the employment and employability of adults in Bolivia with a set of components to reach this goal, more specific results were set at its inception as preliminary expectations (IDB, 2016a).

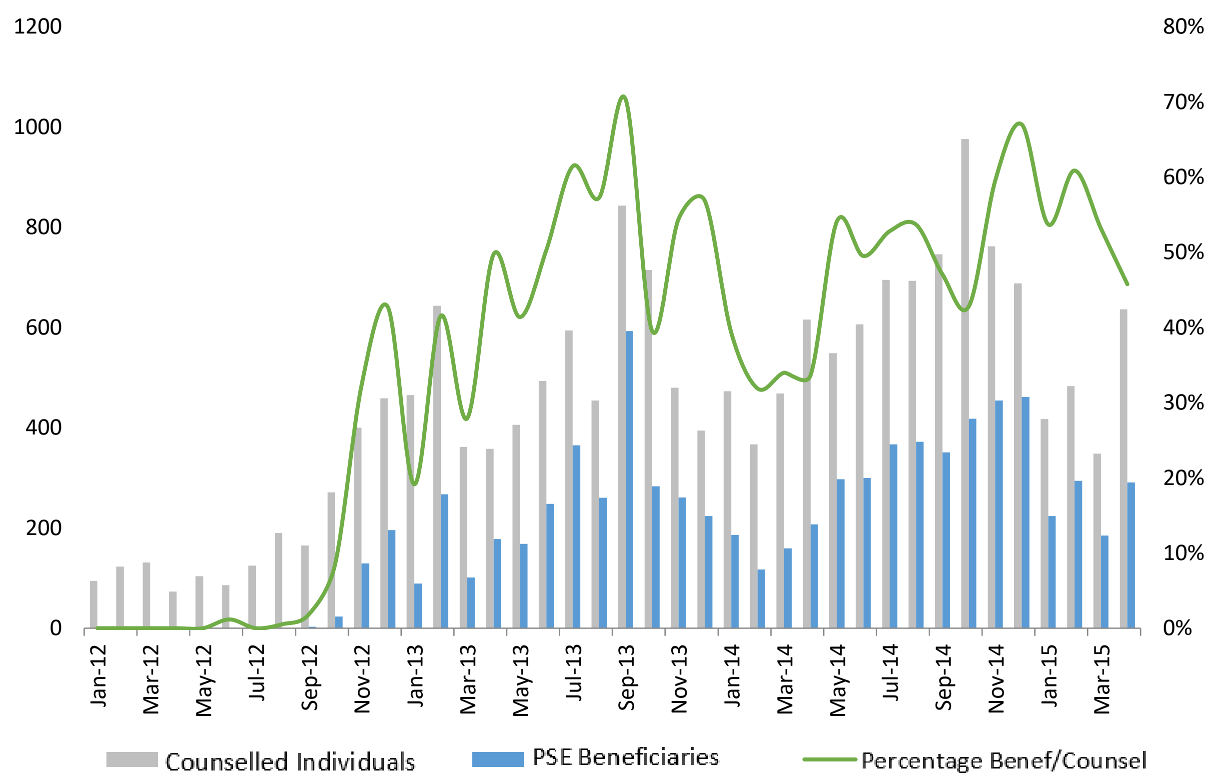
(a) 17,000 adults were expected to receive job training subsidies
(b) At least 8,500 beneficiaries of training were expected to be hired by the firm conducting it
(c) 75,000 job seekers were to receive intermediation and orientation services
(d) 22,500 job vacancies were expected to be put through the public employment services
(e) 1,000 new employers were expected to register their vacancies through the programme

Data for the mid-project evaluation was collected between 2012 and mid-2015 (IDB, c). The results give a snapshot of the strengths and weaknesses of the programme. Moreover, these results went on to be used in planning and implementing its successor PSE II.

(a) 8,076 beneficiaries received benefits for their three months training period in a company between January 2012 and March 2015.
(b) 60 percent of these beneficiaries obtained a permanent position within the firm that conducted their training, before or at the end of said three months training (4,845 beneficiaries) between January 2012 and March 2015.
(c) 44,000 cases of counselling were performed between January 2012 and March 2015.
(d) 41,000 vacancies were registered through the system by March 2015.
(e) 6,158 new companies registered their vacancies in the database between January 2012 and March 2015.

The mid-project evaluation shows that the goals of the PSE were already fulfilled or can be expected to be fulfilled by the end of the programme. For example, after November 2012, there are very few months when the number of beneficiaries was close to or under 200 as shows Figure 1, thus we can expect the programme to fulfill its goal (a) by becoming more common knowledge along the years.

Figure 1. Bolsa de Empleo counselling and PSE beneficiaries (January 2012-March 2015)



Source: IDB, b.

In expanding the PSE to the other urban areas between 2012 and 2017, the programme also expanded the network of the Plurinational Employment Services of Bolivia (SPEBO). Considering individuals registered at the SPEBO or Bolsa de Empleo are the basis for PSE beneficiaries, general employment services have been improved through the expansion of the PSE. During that time, the number of SPEBO offices grew from one to eleven, and the state services have also been expanded to reach out to businesses for vacancies and anyone looking for employment, not solely the untrained unemployed (IDB, 2016b).

However, it is noteworthy that in Bolivia 85 percent of all employment is informal and that the average income is barely equivalent to three times the poverty line (IDB, 2016b, 2016c). Labor informality is defined as the lack of access to health care from employment (IDB, 2016c). Informality is likely to encompass jobs requiring little education or training and that are not the result of a formal employment contract. For this reason, jobs and measures of employment included in the PSE may not represent the Bolivian labor market as a whole because informal employment is not as likely to be promoted by the Bolsa de Empleo and the PSE as is formal employment. Moreover, the SPEBO still remain unknown to most of the population and businesses, thus improvements in the coverage and the diversification of services provided are needed in order to avoid these potential biases.

After establishing the success of the Program to Support Employment with the preliminary evaluation after 2015, the Bolivian Ministry of Labor, Employment and Social Security, with the support of the Inter-American Development Bank launched a second phase of the programme: the PSE II. The project essentially reproduces its initial design but provides further focus on the most vulnerable categories of the working population: women, youth, the disabled and the indigenous population (IDB, 2016b). Learning from the experience of the first programme, the overall objectives of its successor are to diversify and fortify the services provided by the Plurinational Employment Services of Bolivia, increase the coverage of such services and support the vulnerable groups in obtaining employment and increased labor income (IDB, 2016c). The goals of the entire programme are directed at all unemployed individuals, whether they receive on-the-job training or not. The individuals benefitting from training opportunities are expected to reap most of the programme benefits but the non-beneficiaries can also expect improvements in their situations with the expansion of general employment services.

SECTION 3. THEORETICAL FRAMEWORK & LITERATURE REVIEW

As is the case for most programmes destined to improve employment and employability of the untrained and uneducated, several analyses have shown that they improve employment and earnings on the medium to long-term but not necessarily on the short-term (Kaplan, Novella, Rucci & Vazquez, 2015). For the PSE, this would mean that the beneficiaries of the programme do not necessarily see significant changes in their employment situation or labor income immediately after training but rather receive opportunities to improve their situation over the longer term. As a consequence, no matter the results of this evaluation, there may be a larger impact of the PSE over the long-run which cannot be accounted for considering how recently the programme was discontinued. However, as the programme provides training through direct cooperation with companies, the impact of the PSE is likely to be present on the short-term as well, with immediate hiring after the training for example.

1. Human Capital Development

The main goal of any policy with a CCT component such as the PSE is to redistribute income to the most in need, especially in times of crisis, in order to help people that are likely to be credit-constrained make long-term investment in human capital through incentives (Ravallion, 2003; Rawlings & Rubio, 2005). Programmes with a CCT component such as the PSE are based on a human capital model which explains that earnings are a function of skills acquired either at school or through on-the-job training (Polachek & Siebert, 1993). Albeit employment and employability programmes such as the Program to Support Employment in Bolivia are not directly aimed at improving earnings, there is still a secondary effect from the investment in human capital. The main purpose of these programmes is to improve employment through human capital investment but the subsidies given to the beneficiaries are also impacting revenues, albeit temporarily.

However, the new skills and experience obtained by the beneficiaries will be valued on the labor market meaning that labor income will increase on the long-run. Even if the trainee is not hired by the company that conducted the training, the improvements in skills and experience are likely to also have a positive impact on the employment prospects of the newly trained individuals. In this sense, whether or not a worker is hired by the company conducting the training, they are likely to be able to find more employment offers as well as higher salaries or more employment benefits than their previous activity since the new skills and experience make them more valuable to companies. A certain part of those skills can be expected to be company specific while the rest are more general skills, therefore the company conducting the training stands to benefit the most from hiring the trainee. Companies hiring a trainee who was trained at another company, thus only with the general skills that can be applied to the new company still stand to benefit from this hiring as a substantial part of the job training has already been performed. Consequently, human capital investments with the PSE training opportunities are worthwhile for both workers and companies considering the programme oversight and subsidies.

Human capital models also show that in order to invest in one's human capital, one needs to forego potential earnings, which can make the process particularly costly in some cases. As individuals need to be unemployed thus without labor earnings to benefit from the PSE this point is not directly present but these individuals may have to forego temporary sources of income such as odd jobs. The PSE may not be focused on the poorest share of the population as the training opportunities primarily target more educated individuals but even in this situation, human capital investments require capital. Because the poor and the untrained are not likely to have the capital to back loans to invest in themselves, they can be trapped in low productivity sectors because they do not have the capacity to undertake the investments required to be able to reach more productive activities (World Bank, 2014). Furthermore, there are, in most cases, direct costs involved with the training such as a commute to the company. The benefits granted to the PSE beneficiaries during their periods of training are therefore a crucial incentive for the unemployed to undergo training because individuals can then afford such human capital investments. Programmes with a CCT design such as the PSE can thus increase efficiency in the economy by giving access to better positions for the poor or untrained through training and redistribution, ultimately affecting the under-investment in human capital of these individuals (World Bank, 2014).

2. Matching

Employment programmes take their basis on two different conditions: that beneficiaries are actively seeking to participate in the programmes and that such labor market programmes can improve the prospects of the participants (Mourelo & Escudero, 2017). Programmes with a CCT design such as the PSE are based on human capital investment models but the labor market is also characterized by frictions, as encompassed by matching theory. The modelling of this theory shows that inefficiencies make it hard for employers to find employees (and vice versa) while adjustments to demand and/or offer changes are far from simultaneous on the labor market (Cole & Rogerson, 1999; Mortensen & Pissarides, 1994). Matching theory shows that labor market frictions are complicating labor demand and offer relationships. The PSE directly impacts these inefficiencies to make demand and offer relationships more fluid.

The theory of change behind the Program to Support Employment in Bolivia starts from the realization that the unemployed rely mostly on informal ties to find employment and because of this, companies have a hard time finding qualified and/or skilled personnel and workers have a hard time finding employment outside of their relations (IDB, b). These frictions are a major deterrent for employer-employee matching. The PSE was implemented with the goal of formalizing the relationships between the demand and the supply of labor and helping the unemployed obtain training. The programmes thus facilitates the interaction between companies and the unemployed, making it easier for firms to find and/or train personnel and for the unemployed to find a position they are qualified to hold. With companies having access to a larger pool of candidates, they are able to find better matches for their labor demand and train the best candidates. Conversely, with the access to the entire database of labor demand posted by the companies, workers are able to find employment that is more adapted to their experience or skills and find it more easily.

The costs linked with the search for either labor demand or labor supply are also drastically reduced by the PSE which acts as an intermediary on the global level. Ultimately, with much lower search costs and more adapted matches, the labor market inefficiencies or frictions can be reduced and employment conditions improved. The PSE thus directly impacts the employer-employee matching with the global database of vacancies as well as the counseling of unemployed workers. The effect on matching was also a core part of the training opportunity component, as the PSE organized the database of opportunities as well as the workers registration and the pre-selection of suitable candidates. By directly impacting frictions, the PSE is actively making the Bolivian labor market more fluid which can be expected to improve overall employment levels and decrease turnover rates because the matching is less cumbersome and the matches are more efficient.

Furthermore, on top of improving the matching of labor demand and offer, the PSE helps with the current employment needs of the companies through the training part. When simple matches between offer and demand are not sufficient for companies to find workers, training opportunities can be created for skills and experience that are valued on the labor market. As a consequence, this programme is efficient because the investments in human capital are assured to show returns either in the company doing the training or another. Human capital investments thus assure better matches on the labor market while better matches assure the reduction of frictions and create more specialized opportunities for human capital investment.

3. Limitations and Challenges of CCTs

Even though programmes with a CCT design are deemed successful in the majority of cases, it remains that one of the biggest challenges faced by such programmes is the actual take-up by the population. Costs, whether they are linked to information, compliance or psychology, are necessarily involved in CCTs (Moynihan, Herd & Harvey, 2014; Rinehart & McGuire, 2017). It has been shown that each of these costs have a negative impact on the take-up rate of CCT programmes whether it is in developed economies or in Latin America and the Caribbean more specifically (Rinehart & McGuire, 2017). The PSE is not exempt from these costs and the expansion of the national employment services network was one of the first steps in the implementation of the programme. Although the programme has recorded an important increase in registration across time, there is still a large part of the unemployed in Bolivia that did not use the programme. Consequently, it must be taken into account that even if individuals incur costs that reduce their likelihood of take-up, some may have conditions rendering take-up almost impossible. For example, individuals who live far away from any of the eleven urban areas where the programme was present were very unlikely to register to the programme since most of its opportunities are only present within these urban areas.

On a more methodological dimension, the issue of leakage has been arising in the literature considering CCT programmes are covering more than 50 percent of the poor and extreme poor in LAC. Leakage refers to the beneficiaries of CCTs that would have the same behavior even if they did not receive benefits from the government, some other analyses define leakage as the percentage of beneficiaries that are not poor (Robles, Rubio & Stampini, 2015). Leakage is also often referred to as inclusion errors (Soares, Ribas & Osório, 2010). Depending on the specific design of the programme, leakage can be linked with the eligibility requirements. In the case of the PSE, leakage would refer to the training of people that would not need it in order to obtain a better job than the one they previously had. The cooperation of the companies conducting the training with the employment services is likely to diminish the impact of leakage but a much larger programme could have significant leakage. Consequently, it appears that the targeting is a crucial step in implementing a CCT programme that will fulfill its objectives without having a trade-off between efficiency and coverage when implementing it (Soares et al, 2010).

As a comparison, the PSE is a smaller programme than most CCTs in LAC because there have only been 19,544 beneficiaries of training opportunities between 2012 and 2017 compared to an unemployed population of 178,266 in 2017 (World Bank, 2018b). The lack of infrastructures is a significant cause for this fact as well as an issue for the expansion of the programme. The PSE went from covering 6 cities in 2014 to 11 in 2016 but there are still a large number of communities that are shut out of the PSE and employment services in general. Nevertheless, it is noteworthy that the coverage of the programme was expanding and that one of the main goals of its successor is to expand this coverage.

4. Hypotheses

Considering the goals and the design of the PSE and its Component II, the central impact is meant to be the employment and employability of adult Bolivians. The first research question of this thesis deals with the impact of the PSE on employment after the beneficiaries received training. The new on-the-job training and skills obtained by the workers are part of the labor demand put out by the companies therefore the new capabilities will be valued by companies, whether it is the one that conducted the training or not. Furthermore, even if the training is subsidized, companies are spending time and money giving experience to the workers therefore they are likely to hire the former trainees after the three months training period. As a consequence, the PSE is expected to improve the employment prospects of the trainees thanks to more experience and skills that companies are looking for on the labor market. To this effect, the following hypothesis will be examined in this impact evaluation:

H1: Having benefitted from a training period through the PSE has a positive and significant effect on the employment situation of the unemployed registered at the Bolsa de Empleo.

However, the effects of this programme are not expected to be limited to the binary situation of employment. The training provides skills and experience valued on the labor market and the employment services match the profiles with corresponding labor demand. The Programme to Support Employment can be expected to have a positive impact on the earnings of working adults since the training gives beneficiaries more skills and on-the-job experience. Not only are these skills and experience expected to be valued by the company conducting the training but also by other companies looking for workers to fill similar positions, thus the impact of the PSE on labor income can be expected to be present for all beneficiaries. Thus, not only are the beneficiaries of the PSE expected to have more employment prospects but they can also be expected to receive higher salaries compared to their previous employment. The workers completed training for a position that was offered by a company, thus the new skills learned by the workers should impact their value to companies. For this reason, the second research question of this thesis investigates the impact of the PSE on labor income as reflected by the following hypothesis:

H2: Benefitting from a training opportunity through the PSE has a positive and significant effect on the labor income level received by the worker.

Since the former trainees have more value for the companies, their new job prospects can be expected to be of higher quality through other dimensions than solely a higher salary. The quality of employment can be understood as the benefits involved with the contract for this job. Per the Bolivian standards, the potential benefits workers can receive include: an end of year bonus, a second end of year bonus, health care coverage, maternity and/or nursing leave, retirement pension, compensation and five year term. The compensation benefit includes all sums of money workers are eligible to receive when they are laid off for reasons outside of their responsibilities. The five year term reflects the possibility for workers with this benefit to receive five supplemental months of salary after completing five years in the position (one month worth of salary per year). Considering the potential new benefits involved with jobs, the following hypothesis will be examined as showed by the third research question of this thesis directed at the impact of the PSE on employment quality:

H3: Benefitting from a training period through the PSE has a positive and significant impact on the quality of employment (proxied by the access to benefits such as health care or retirement pension).

This impact analysis will be able to uncover the effect of the PSE on the non-employed and thus show whether the programme is actually fulfilling its goals.

SECTION 4. DATA & DESCRIPTIVE STATISTICS

The data used for this impact analysis was provided by the Inter-American Development Bank and consists of a telephone survey to unemployed Bolivians age 18 or older, who were registered at the Bolsa de Empleo (national employment agency). The survey consists of 81 questions on socio-economic conditions and employment history, with the respondents only answering the relevant questions depending on their employment status or current situation. More specifically, the data collected describes the individual's socio-economic situation at the moment of registration with variables such as age, gender or number of children. Then, employment, unemployment or inactivity spells are described before registration and at the moment of the survey. This telephone survey was conducted between December 2017 and March 2018 and resulted in a database of 15,180 Bolivian cases. This database represents the respondents of the telephone survey out of the 46,762 people registered at the Bolsa de Empleo and the 19,544 PSE beneficiaries.

1. Treatment & Control Groups

From the design of the PSE, all individuals answering the survey are registered at the Bolsa de Empleo but only some have obtained a training opportunity. Consequently, the treatment group selected for this impact evaluation will encompass all individuals who received a training opportunity through the PSE. The control group, on the other hand, consists of unemployed individuals who were registered at the Bolsa de Empleo but did not receive a training opportunity. It was impossible to implement an experimental design for this analysis as the programme expanded general employment services and on-the-job opportunities at the same time as the geographical expansion. Furthermore, all the observations making up the dataset are individuals completing a phone survey which directly impeded the implementation of a randomized design considering the small pool of respondents. The final groups include 15,167 individuals with 3,772 PSE beneficiaries (treatment group) and 11,395 non-beneficiary individuals only registered at the Bolsa de Empleo (control group)[2]. It is important to note that the inactive, the unemployed that are not looking for a job either in period 0 or period 1 were kept in the dataset in order to avoid potential complications due to an even smaller sample. Consequently, the study of employment is made as opposed to non-employment and not unemployment since inactivity is included in the possible choices. However, the main analysis is conducted again in supplemental regressions with the inactive dropped from the sample. These supplemental regressions are presented in Appendix B.

This choice of groups also stems from the scarcity of data on unemployed individuals in Bolivia as 85 percent of all jobs are informal and governmental employment services only cover a limited share of the unemployed (IDB, 2016b, 2016c). While a significant number of informal jobs may not be represented in the database used in this research, a large number of individuals included in it do not have access to health care from their jobs and therefore have informal employment. It remains that there might be a bias in the results towards formal employment and that the conclusions reached here may not be applicable to larger datasets. The limited share of the unemployed covered by the Bolsa de Empleo could also create a selection bias in the sample. For example, the unemployed that are not registered in the Bolsa de Empleo could have more training and skills and because of it, feel more confident about finding work. The opposite case could also be possible where the least trained and skilled do not register at the employment agency because they have little hope that they will find a job. Because of these biases, the impact of the PSE may be under or overestimated.

It stands to note that with such a design for the groups, the analysis is not impervious to another source of a self-selection bias in obtaining the answers as the respondents of the survey could be a sample that does not represent the registered unemployed Bolivians as a whole in their socio-economic characteristics. The survey consists of 165 variables ranging from the respondents date of birth to how long they have been looking for employment, therefore completing the survey has to have been a rather long process. For this reason, it is likely that certain categories of the working age population will be more represented in the dataset than in the overall population such as mothers taking care of their children, or the elderly looking for a job to complement their pension if they have one. These categories of the population can be expected to have more time to complete

[2] Out of the initial database of 15,180 individuals, 3 individuals that registered to the Bolsa de Empleo at age 17 were removed since they were not eligible to the PSE from their registration date. Furthermore, 10 individuals registered to the Bolsa de Empleo before 2012 and thus could not be eligible to the PSE. As there is no way to know whether they were active within the Bolsa de Empleo after 2012, they were removed from the database as well, leading to the final groups.

the survey than heads of households that are in dire need of any source of income to survive. Considering these categories as well as youth and the disabled are the most susceptible to unemployment in Bolivia, it is possible that the impact of the PSE be overestimated by misrepresenting the working population in the dataset. Certain population or employment categories may be over or under-represented in this sample compared to the overall individuals registered at the Bolsa de Empleo.

Finally, for the impact analysis in general, there is the concern that the result may not hold as the programme is expanded with PSE II. This impact analysis takes into account individuals registered at the Bolsa de Empleo who are by default eligible to the PSE, but expanding the coverage of the Bolsa de Empleo may bring a share of the population that could respond differently to the same opportunity or have different needs. The Inter-American Development Bank executed a survey on job seekers and their opinion on the employment services (IDB, 2015b). Of the respondents, 88 percent said they did not use the employment services with 42 percent of these individuals saying they did not know about the services and 37 percent saying they did not need it (IDB, 2015b). Expanding the coverage could be done by targeting the share of the population that do not know about the employment services but in this case the results obtained for the PSE in this evaluation can hardly be expected to remain identical for a larger sample. By reaching more uneducated and/or untrained workers through an extended coverage, the results of this impact analysis would certainly prove to be biased either upward or downward depending on the composition of the new larger sample.

Although this impact evaluation will still bring results as to the impact of the PSE for this sample, there is no way to correct for these potential biases considering the data available. Consequently, the internal validity of the conclusions can hold but the external validity of this analysis may be put in question as the generalization of the conclusions may not fit bigger samples of individuals registered at the Bolsa de Empleo.

2. Descriptive Statistics

Table 1 describes the main characteristics of the treatment and control groups before the training opportunities were conducted. For nearly all variables, distribution within the treatment and control groups are almost identical but some variables suggest the presence of selection bias for the PSE beneficiaries. There is a 2 percentage points difference between the treatment and control groups for the disabled as well as 3.5 percentage points difference between the treatment and control groups for indigenous people. These differences show that there are fewer disabled and indigenous in the treatment group compared to the control group thus suggesting a selection bias. Concern of differences between the groups due to selection bias is especially important as companies are independently deciding which candidates they are selecting for the training opportunities, which can be expected to create discrepancies between the groups. Albeit these descriptive statistics cannot remove all suspicions of unobserved differences between the sample and the registered population as a whole, the observed characteristics across the treatment and control groups are relatively similar.

Table 1. Descriptive Statistics

		Treatment Group (Registered at the Bolsa de Empleo + received training through the PSE)	Control Group (Registered at the Bolsa de Empleo)
Observations		3,772	11,395
City of Residence	El Alto	17.58%*	20.25%
	Sucre	7.90%	3.06%
	La Paz	25.64%	35.77%
	Cochabamba	9.20%	8.55%
	Oruro	8.83%	7.31%
	Potosí	4.96%	4.20%
	Tarija	5.91%	5.55%
	Santa Cruz	12.99%	12.15%
	Trinidad	2.17%	1.44%
	Cobija	4.83%	1.72%
Gender	Female	56.31%	57.92%
	Male	43.69%	42.08%
Average Age		31.19	31.53
Average number of interviews obtained since registration		1.29	0.46
Average number of jobs obtained since registration		0.96	0.23
Average number of children at registration		0.84	0.82
Know how to read and write	YES	99.44%	99.20%
	NO	0.56%	0.80%
Disability	YES	5.17%	7.18%
	NO	94.83%	92.82%
Indigenous	YES	6.42%	9.91%
	NO	93.58%	90.09%
Average years of education		14.31	14.32
Average Family Income (in bolivianos)**	<1000	11.77%	17.04%
	1,000-1,999	40.16%	37.17%
	2,000-2,999	31.42%	29.50%
	3,000-3,999	9.33%	9.66%
	4,000-4,999	3.34%	3.50%
	5,000-6,999	2.65%	2.19%
	7,000-9,999	1.09%	0.70%
	10,000+	0.24%	0.23%

Source: Own computations on the dataset provided by the Inter-American Development Bank. The sum of individual percentages within the same variable may not amount to 100 percent due to rounding. *Each percentage represents the share of the category (line) within the total observation of the group (sum of the column for one variable). For example, 17.58 percent of the individuals in the treatment group live in El Alto. **As a comparison, one U.S. dollar was worth 6.91 Bolivian bolivianos and for the entire period of the programme (2012-2017) as given by the average exchange rate (World Bank, 2018c).

Figure 2 shows the different regions of Bolivia and geographical distribution of the offices where the employment services and the PSE are accessible for the unemployed. The time frame of the PSE deployment is also a likely cause for the differences in location of individuals within the groups. The eleven cities with offices providing employment services and access to the PSE were not created all at once, until 2014 there were only 6 offices and 4 more were created in 2014 followed by 1 more in 2015 (IDB, 2015a).

Figure 2. Cities in Bolivia where the Employment Services have an office

Source: IDB, 2015a

An important part of this impact evaluation concerns the effect of the PSE on the labor income of people receiving a training opportunity. As a consequence, the variables dealing with the income received in periods 0 and 1 are crucial to this analysis. Period 0 here refers to the moment the individual registered for the programme while period 1 refers to the moment they completed the survey which is after the programme was discontinued. A major restriction in the data is that the income values in period 1 for the beneficiaries of the PSE were not reported as a continuous variable like all the other income questions but rather as a categorical variable. For issues of comparability, this categorical variable was extrapolated into different continuous variables to give a measure of the impact on labor income. The type of model used for the data analysis of this hypothesis is thus restricted by the data and the conclusions reached for labor income need to be taken cautiously due to this limitation.

Based on the survey, labor income variables were created regardless of the person's occupation, whether an employee or self-employed. Salaries were reported on a scale chosen by the respondent, whether it is daily, weekly, bimonthly or monthly. Furthermore, respondents could choose to report their salaries in bolivianos or dollars. To compare these reported salaries, all income were put on a monthly basis and the 27 salary observations reported in dollars were converted in bolivianos by applying an exchange rate of 1 dollar for 6.91 bolivianos. This exchange rate was identical for all the years the programme was active and thus consists of both a yearly exchange rate and an average (World Bank, 2018c).

To assure comparability in the income reported by the survey, all monthly salaries in bolivianos were corrected for inflation with the Consumer Price Index of Bolivia between 1985 and 2017 and put on the basis of 2010. Period 0 refers to the income they received for their last employment before registering to the Bolsa de Empleo, which can be a long time in some cases. For this reason, controlling for inflation is particularly important to avoid an overestimation of the PSE impact by having inflated income values for period 0. Period 1 refers to the labor income they are receiving at the moment of the survey, and all the individuals were surveyed between November 2017 and March 2018. Consequently the Consumer Price Index of 2017 will be used for all income observations in period 1 as outlined in Table 2.

Table 2. Consumer Price Index for Bolivia with a 2010 basis

Year	Consumer Price Index for Bolivia	Year	Consumer Price Index for Bolivia
1985	3.903125526	**2002**	64.21700979
1986	14.68887	**2003**	66.360108
1987	16.83031058	**2004**	69.30475869
1988	19.5235122	**2005**	73.04252447
1989	22.4859061	**2006**	76.17279784
1990	26.33521768	**2007**	82.80458994
1991	31.98335021	**2008**	94.39757003
1992	35.84064574	**2009**	97.55929376
1993	38.89709191	**2010**	100
1994	41.95986613	**2011**	109.8126898
1995	46.23692204	**2012**	114.8491113
1996	51.9820846	**2013**	121.4134042
1997	54.42963213	**2014**	128.4354258
1998	58.60614242	**2015**	133.6511419
1999	59.8717516	**2016**	138.4963157
2000	62.63077962	**2017**	142.404938718029
2001	63.62639217		

Source: World Bank Databank, 2018b.

As stated earlier, a major limitation in studying the impact of the PSE on labor income is that the survey reports the income of the PSE beneficiaries after treatment as a categorical variable instead of a continuous variable. Ultimately the results of this analysis will give a general direction for the impact of the PSE but no precise influence on labor income can be expected from this data. Considering the survey does not report labor income as a continuous variable for the treatment group in the period after treatment, it is important that the values imputed to this variable take different values in order to assess the impact of the PSE through a sensitivity analysis. Categorical income variables cannot be expected to be as precise as continuous variables to test for the impact of the PSE therefore several regressions will be performed with a continuous variable for the income in categories. Labor income for the variable in categories will take the values outlined in Table 3 in the subsequent regressions.

Table 3. Values replacing the categorical income variable in the dataset

Income Variable in Categories	Minimum Income values	Mean Income values	Maximum Income values	Mean Income values without upper outliers	Maximum Income values without upper outliers
<1000	1	499.5	999	499.5	999
1,000-1,999	1,000	1,499.5	1,999	1,499.5	1,999
2,000-2,999	2,000	2,499.5	2,999	2,499.5	2,999
3,000-3,999	3,000	3,499.5	3,999	3,499.5	3,999
4,000-4,999	4,000	4,499.5	4,999	4,499.5	4,999
5,000-6,999	5,000	5,999.5	6,999	5,999.5	6,999
7,000-9,999	7,000	8,499.5	9,999	8,499.5	9,999
10,000-13,999	10,000	11,999.5	13,999	11,999.5	13,999
14,000+	14,000	52,000	90,000		

Source: Own computations on the IDB dataset.

In the first column of Table 3, for the first category, the value 1 is imputed as a lower bound to the income category because the income variable is later put in log and using the true minimum 0 would only create missing observations. Furthermore the logged value of 1 being 0, this change does not impact the fact that this equation uses the lower bound of the income variable in categories.

Considering there is no upper limit to the final income category, an average income value of 52,000 bolivianos and a maximum of 90,000 bolivianos was deemed acceptable in the second and third column of Table 3. These values were chosen based on the distribution of the income category in period 1 and their counterparts in period 0. The average and maximum income value is thus arbitrary for the final income category. To avoid this issue the final two columns use similar specifications for average and maximum income values but without the upper income outliers.

For the empirical testing of employment quality as proxied by employment benefits, the answers to the related questions were reported individually. Therefore, binary variables were created for each type of benefit taking the value 1 when a benefit was stated to be received. However, to differentiate between missing values and a benefit not received, the binary variables were changed to take the value 0 when the person stated that they were not receiving benefits at all and when the person was receiving at least one other benefit and the concerned benefit was left unanswered. For example, if an individual reports 'None' to the question of benefits received, then the seven binary variables take the value 0 since no benefit is received. If another individual reports only receiving one benefit then it is assumed that all other benefits are not received and therefore the binary variable for this one benefit takes the value 1 while the binary variables for all other benefits take the value 0. It is therefore assumed that not answering any of the questions regarding the benefits leads to missing values while stating a positive answer to at least one question leads to answering them all. Considering the measures of employment quality consist of seven different binary variables, a specification was created for each of the measures in order to differentiate each aspects of the benefits and outline the most important impact of the PSE. However, another binary variable was created to encompass any access to benefits thus taking the value 1 if the individual has access to at least one of all benefits and taking the value 0 when the individual had access to none.

SECTION 5. EMPIRICAL METHODOLOGY

1. Impact Evaluations

Impact analyses not only compare the ex-ante objectives of the programme with its outcomes but also study the counterfactuals. In this sense, these analyses compare the impact of a programme on specific individuals between a situation where they are under the treatment and another situation where they do not receive the treatment. However, it is by definition not possible to study these two different outcomes for the same people but impact evaluations rely on several methods and assumptions to obtain the impact of the treatment unaffected by its environment or exterior causes (Gertler, Martinez, Premand, Rawlings & Vermeersch, 2016). This analysis thus differs from monitoring, which only compare the objectives and outcomes for the individuals under treatment as in the mid-project evaluation of the PSE done in 2015.

As only the programme outcomes were monitored for the PSE, it is important to conduct an impact evaluation in order to isolate and examine the sole impact of the programme. It is only through this evaluation that we can demonstrate whether the programme was successful at improving employment in Bolivia for example.

2. Difference-in-Differences Methodology

The difference-in-differences method is based on the comparison of changes in outcomes between a treatment group and a control group (Gertler et al, 2016). The identifying assumption is that of parallel trends meaning that the different variables are moving simultaneously between the treatment and control groups. More specifically, this implies that both groups need to be very similar in their characteristics before the treatment so that the evaluation analyzes the impact of the programme without being biased by different group characteristics. This assumption outlines that considering very similar treatment and control groups in period 0, outcomes are assumed to be similar in period 1 if the programme were absent altogether therefore differences in outcome between the groups in period 1 with the programme can only be due to this programme. This identifying assumption thus requires suitable treatment and control groups for the analysis. There is, however, no way to prove such an assumption because we do not have access to counterfactual outcomes. This assumption is needed because the methodology can only use a group of individuals under the treatment and a control group not receiving the treatment, with the two groups consisting of different individuals. Thanks to this assumption, the methodology can then compare the outcome of both groups in the presence of the programme and deduce the actual programme's impact. This assumption is the only path to assure that the counterfactual is taken into account without studying the outcome of both situations for the same individuals.

Thus, even after controlling for several characteristics in both groups, there may still be a bias in the programme impact. For example, the unemployed that are not beneficiary of the training programme could have more incentives and motivation to find training of their own when seeing the beneficiaries finding better employment after a training period. Results from this analysis would be affected by these spillovers and likely to show a downward bias in the programme impact as the non-beneficiaries are indirectly and positively impacted by the presence of the programme. However, there might also be an upward bias in the estimates since individuals expressing positive unobserved characteristics such as potential, intelligence, commitment or motivation are more likely to obtain the training opportunities and to find a job even in the absence of training. The programme impact could thus be overestimated because of an over-representation of individuals with positive unobserved characteristics in the treatment group.

3. Specifications and Data Checks

All the specifications examined in the empirical testing follow the model of Equation (1) using the difference-in-differences methodology, only the dependent variable will change throughout the subsequent specifications.

$$(1)\ Y_{it} = \beta_0 + \beta_1 time_t + \beta_2 beneficiaries_i + \beta_3 timetreated_{it} + \beta_4 X_i + \varepsilon_{it}$$

Where Y_{it} describes the dependent variable of the specification for individual i at time t, they will include employment, labor income and employment benefits. Following the difference-in-differences methodology, $time_t$ refers to the binary variable of the observation time frame (period 0 or period 1) which will vary by time periods (t). Then $beneficiaries_i$ is another binary variable differentiating the PSE beneficiaries and the individuals only registered at the Bolsa de Empleo which will only vary by individuals (i). These binary variables are followed by $timetreated_{it}$ an interaction variable of the two previous binary variables that will give the impact of the PSE on the dependent variable and will vary by both individuals and time periods (it). Consequently, the results for β_4 is the point of interest of the regressions as it will give the impact of the PSE on the dependent variable. The following variable X_i encompasses the control variables that are used to assure the comparability of the treatment and control groups. These variables will control for age, gender, number of interviews had since registration, number of jobs held since registration, whether the individual is indigenous, whether the individual has a disability, the number of children at registration, the number of people in the household at registration, the level of family income at registration, whether the individual can read and write and the years of education completed at the time of registration, all only varying by individuals (i). Finally ε_{it} is the error term of the regression. All the variables are further explained in Table 4. Each specification will also include a year and location fixed effect to account for the unobserved differences between variables that may depend on year and/or location such as a short and sudden economic growth spurt leading to more employment or a rise in unemployment in one specific city during a short period of time.

For the three variables of interest in this research (employment, labor income and employment quality) empirical testing will be performed first without control variables to estimate a raw specification and then control variables will be added progressively in several specifications in order to check if the initial programme impact is due to certain specific factors. The first column of the outputs will thus show the raw model, followed by a similar specification adding control variables for age, gender, disability, number of children, and indigenousness. The third column examines the specification with the addition of the number of people in the household, whether the individual knew how to read and write at registration, family income and completed years of education at registration as control variables. Then, the fourth column adds the number of interviews had before registration and the last columns examines the full specification with the addition of the control variable for the number of jobs held before registration at the Bolsa de Empleo.

It may not be as straightforward to control for the number of interviews and jobs obtained as they are potential outcome variables but the data for both variables goes until the moment of registration. For this reason, controlling for these two variables only makes the treatment and control groups more similar in period 0 as this holds constant the number of interviews and jobs had before the registration to the Bolsa de Empleo. Furthermore, PSE beneficiaries may show more unobserved positive qualities such as intelligence or potential leading to higher numbers of interviews had before registration because they match more job offers. On the other hand, non-beneficiaries may also have a higher number of interviews because they get to the interview but have a hard time obtaining a job. Including these control variables to the full specification of the model is thus expected to make the estimates more accurate.

Before any regression were performed, the main variables used in the specifications were checked for serial correlation as showed in Appendix A[3]. Even if there are some relatively high coefficients, these results are not unexpected and should not affect the results of this analysis. Most notably, beneficiaries and employment situation have very low correlation coefficients (below 6.37 percent). All the other variables, encompassing the benefits from employment and labor income are highly correlated between each other, but this could be expected from the construction of their respective variable. Furthermore, a job with a higher salary can be assumed to be a better position to hold and therefore is more likely to offer more benefits than a position with a lower salary. Among the highest coefficients is the one between the variable regrouping any type of benefit and

[3] The variables of the linear regressions for labor income were also tested for heteroskedasticity with a White test, and tested for normality through the study of the skewness and kurtosis. These tests show that the data is heteroskedastic and that the independent variables do not follow a normal distribution as showed in Appendix A. In order to correct for heteroskedasticity, all specification will be performed with robust standard errors.

the bonus (96.16 percent) meaning that out of all the individuals receiving benefits from their employment, almost all of them receive a yearly bonus.

Table 4. Variables Specification

Variable	Definition	Variable Source
time	Binary variable, takes the value 1 when the observation concerns the moment the individual completed the survey and takes the value 0 when the observation concerns the moment the individual registered in the programme	IDB
beneficiaries	Binary variable, takes the value 1 when the individual is a beneficiary of the PSE and takes the value 0 when the individual is only registered at the Bolsa de Empleo	IDB
timetreated	Interaction variable of the time and beneficiaries variables	Own computation
emp	Binary variable, takes the value 1 when the individual was employed and takes the value 0 when the individual was unemployed	IDB
benefit	Binary variable, takes the value 1 when the individual has access to at least one benefit from the employment and takes the value 0 when the individual has reported not receiving any benefit.	Own computations
laborincome	Reported monthly income received from employment including employee and independent statuses. The variable is continuous but was reported as a scale of nine categories for the income of PSE beneficiaries in period 1: (1) Less than 1,000 bolivianos per month (2) Between 1,000 and 1,999 bolivianos per month (3) Between 2,000 and 2,999 bolivianos per month (4) Between 3,000 and 3,999 bolivianos per month (5) Between 4,000 and 4,999 bolivianos per month (6) Between 5,000 and 6,999 bolivianos per month (7) Between 7,000 and 9,999 bolivianos per month (8) Between 10,000 and 13,999 bolivianos per month (9) More than 14,000 bolivianos per month	IDB
age	Age when the individual registered	IDB
women	Binary variable for the gender of the individual, takes the value 1 when the individual is a female and takes the value 0 when the individual is male.	IDB
disability	Binary variable for the presence of disability in the individual, can be permanent, transient or absent disability. Takes the value 1 when the individual is disabled and takes the value 0 when the individual is not disabled.	IDB
children	Number of children when registered to the Bolsa de Empleo	IDB
indigenous	Binary variable, takes the value 1 when the individual is indigenous (language learned as a child and considered the native language different than Spanish) and takes the value 0 when the individual is not indigenous	IDB
household	Number of people in the household when registered to the Bolsa de Empleo	IDB
readwrite	Binary variable, takes the value 1 when the individual knew how to read and write when registered to the Bolsa de Empleo and takes the value 0 when the individual did not	IDB
familyincome	Family income when registered to the Bolsa de Empleo, follows a scale	IDB
educ	Years of education completed when registered to the Bolsa de Empleo	IDB
interviews	Number of interviews obtained since the registration at the Bolsa de Empleo	IDB

jobs	Number of jobs obtained since the registration at the Bolsa de Empleo	IDB
categorical	Binary variable for the presence of extrapolated income values within the data. Takes the value 1 when an income value was extrapolated from the categorical variable and takes the value 0 when the income value was originally continuous.	Own computations
bonus	Binary variable, takes the value 1 when the individual receives a yearly bonus from their employment and takes the value 0 when the individual does not receive such a bonus	IDB
secbonus	Binary variable, takes the value 1 when the individual receives a second yearly bonus from their employment and takes the value 0 when this individual does not receive it	IDB
healthcare	Binary variable, takes the value 1 when the individual has access to health care thanks to their employment and takes the value 0 when the individual does not receive access to health care	IDB
maternity	Binary variable, takes the value 1 when the individual receives access to maternity and/or nursing leave from their employment and takes the value 0 when the individual does not receive this benefit	IDB
compensation	Binary variable, takes the value 1 when the individual is entitled to receive money when fired from their employment for reasons other than cause takes the value 0 when the individual does not receive compensation	IDB
fiveyearterm	Binary variable, takes the value 1 when the individual can receive five bonus months of salary after working for five years in the same company and takes the value 0 when the individual is not entitled to this benefit	IDB
pension	Binary variable, takes the value 1 when the individual can receive a retirement pension after finished their career at this job and takes the value 0 when the individual does have not have access to pension from this employment	IDB

Source: Inter-American Development Bank dataset.

4. Employment

The PSE is expected to have a positive effect on employment in Bolivia by providing subsidized training to the unemployed that is likely to result in hiring as showed in Hypothesis 1. Even if the trainee is not hired by the company that conducted the training, the improvements in skills and experience are likely to also have a positive impact on the employment prospects of the newly trained individuals. As the methodology assumes that the differences between the treatment and control groups are parallel in period 0, the regressions will be controlled for a number of variables including the characteristics of the groups. The specification of the impact of the PSE on employment in Bolivia, as expressed in equation (1) and will take EMP_{it} for employment dependent variable.

Considering the dependent variable of this regression is the employment situation which is a binary variable, this regression will be performed through a probit model. Therefore, the results of empirical testing will not be expressed directly by the coefficients of the variables but rather through their marginal effects. These effects then represent changes in estimations of probability that an observation arises.

After conducting empirical testing to assess the impact of the PSE on the full sample of individuals, supplemental specifications will be examined to estimate the effect of the PSE on the probability of employment for individuals belonging to several subgroups. These groups include age, gender, whether the individual is indigenous and years of education completed, all outlined in Table 5. These supplemental specifications will follow the outline of equation (1) with employment as the dependent variable but on the samples of Table 5. These various specifications will give more precise understanding on the impact of the PSE, which could incidentally reveal several points of interest for the implementation of the PSE II.

Table 5. Categories for the specifications of the supplemental employment regressions

CATEGORY	OBSERVATIONS	EQUATION	DEPENDENT VARIABLE
AGE	18-38 years old	(1a)	$EMPage1_{it}$
	39-58 years old	(1b)	$EMPage2_{it}$
	59-78 years old	(1c)	$EMPage3_{it}$
GENDER	men	(1d)	$EMPmen_{it}$
	women	(1e)	$EMPwomen_{it}$
INDIGENOUS	indigenous	(1f)	$EMPindi_{it}$
	non-indigenous	(1g)	$EMPnonindi_{it}$
EDUCATION	under 10 years of education	(1h)	$EMPeduc1_{it}$
	above 10 years of education	(1i)	$EMPeduc2_{it}$

Source: Own computation on the IDB dataset.

5. Labor Iincome

The impact of the PSE on labor income is expected to be positive and significant as outlined in Hypothesis 2. The specification for the impact of the PSE on the labor income received by Bolivians is thus expressed as in equation (1) with $log(LABINC_{it})$ as the dependent variable for logged labor income of individual i in time period t.

As was explained earlier, the income values of treatment group in time period 1 was not reported as a continuous variable thus leading to an extrapolation of continuous values from categorical values. In order to provide robust results with the extrapolated income values, five different specifications are used in this research as outlined in Table 3. The first specification will investigate the impact of the PSE on labor income when the missing continuous income are replaced with the lower bound of their category with $log(LABINmini_{it})$ as the dependent variable. The following specification will examine this impact with the missing continuous income replaced by the average of the category with $log(LABINaver_{it})$ as the dependent variable while the next uses the upper bound of the income categories with $log(LABINmax_{it})$ as the dependent variable of the equation. Then the remaining two specifications will use the average income without the outliers of the last income category with $log(LABINaver2_{it})$ as a dependent variable or the maximum of the categories without the last category with $log(LABINmax2_{it})$ as a dependent variable.

Each of the regressions include income values extrapolated from categorical data, therefore an additional control variable was added for this empirical testing. The binary variable 'categorical' to account for extrapolated income values, this variable is detailed in Table 4.

As the dependent variable labor income is now continuous, these regressions will be performed with an OLS model. This different model was chosen for the specification because labor income is a continuous variable. The labor income measure will therefore estimate the gain in productivity after gaining skills and experience through on-the-job training.

6. Employment Quality

The PSE is not only expected to have a positive effect on whether the trainees gain employment and the income they earn but also on the quality of this employment as demonstrated by Hypothesis 3. By improving their skills and obtaining on-the-job experience in specific occupations, workers can be expected to face better job opportunities than the ones they could obtain before the training. The survey conducted by the IDB did not include whether the individuals considered their new jobs better or not but several other variables relate to certain dimensions of employment's quality. By taking into account the access to health care, retirement pension and maternity leave among others. As previously explained, a supplemental variable was created to encompass the access to any employment benefit.

Employment quality is then investigated as the change in access to any benefit. The impact of the PSE on employment quality in Bolivia is therefore specified in equation (3) with $BENEF_{it}$ as the dependent variable. Similarly to equation (1), the empirical testing of the impact of the PSE on employment quality will be conducted with a probit model since the dependent variable is a binary variable. Since benefits can only be received through employment, this empirical testing only assesses the change in access to benefits between two situations of employment as was the case for labor income.

Further specifications were created to assess the impact of the PSE on the individual benefits workers can be eligible to receive through their employment. All the specifications described here follow the same model as equation (1) except for the dependent variable. Each specification will take one of the following individual employment benefit as dependent variable: a yearly bonus, a second yearly bonus, health care, maternity and/or nursing leave, compensation, a five year term or retirement pension.

Albeit all specifications will give indications on the impact of the PSE on the access to individual employment benefits, the assessment for the access to health care is particularly important. Since formal employment is defined by its access to health care, the impact of the PSE on access to health care can be used as a proxy to conclude on the impact of the PSE on employment formality.

SECTION 6. RESULTS

Following the specifications formulated above, Table 6 through 15 show the results of their empirical testing as given by the outputs obtained through the software Stata 15.1. From this empirical testing, the related hypotheses on the impact of the PSE can be accepted or rejected.

1. The PSE and Employment

The impact of the PSE on employment for Bolivians is showed in Table 6. This empirical testing thus examines the influence of the PSE on whether adults Bolivians go from non-employment to employment after benefitting from a training period in a company. Because this analysis is performed with a probit model, the coefficients obtained in the output of the regression are not directly interpretable as a marginal change but give a direction to the effect. Therefore, average marginal effects were subsequently computed to assess the change in probability of this effect and thus the range of the PSE impact on employment.

The impact for the PSE on employment in Bolivia is given by the marginal effect of the interaction variable between beneficiaries and time. These effects were computed as marginal effects at the mean and average marginal effects for each regression, and showed very similar values in all cases. The marginal effect at the mean expresses the change in probability towards y while considering x=1 and that the individual is at the mean of every other independent variable (Williams, 2018). More specifically, this individual has the average age, had the average number of interviews but is also the "average amount of disabled" or the "average amount of indigenous". These do not necessarily represent the population very well for a relatively small sample like the one used in this evaluation. On the other hand, the average marginal effects compute each possible option within each variable and the average of the outcomes becomes the marginal effect (Williams, 2018). Consequently, average marginal effects are considered a more accurate measure than marginal effects at the mean for this evaluation, therefore only the average marginal effects are reported in the outputs.

Consequently, beneficiaries of a training period with the PSE experience a 0.1440 percentage points increase in their probability to gain employment after benefitting from training compared to their non-beneficiary counterparts as showed by the average marginal effects of the raw model. Comparatively, the full specification including of the control variables shows a 0.1392 percentage points increase in the probability. Considering the mean employment before the treatment (at period 0) was 0.2965 for the sample, we can conclude a 49% change in the probability to gain employment for the raw specification while the full specification shows a 47% change. Considering the full specification is more accurate than the raw model, this number indicates that participation in the programme attributes a 47% increase in employment probability after training. Considering the main goal of the PSE, the empirical testing of this sample shows that there is indeed a positive and significant impact of the PSE on employment for adult Bolivians as given by the marginal effects and their p value. The marginal effects are positive for the programme and the p value of almost all coefficients and marginal effects are below 0.01 meaning that the results are statistically significant at the 99% level of confidence.

The specifications with different sets of control variables between the raw and full models show comparable results with an average marginal effect of the PSE on employment ranging between 0.1392 and 0.1397, all significant at the 99% level of confidence. These different specifications show that control variables are important in obtaining an accurate estimate of the PSE impact because the socio-economic controls in column (2) change the estimate by roughly half a percentage point. The results are thus robust to different specifications and statistically significant.

Albeit the conclusions from this testing are clear-cut and show a positive and significant impact of the PSE on employment, there are issues to be considered. The pseudo R-squared which a measure of "goodness of fit" for the model is only between 2.73% and 4.14% for this model. However, it is important to note that McFadden's pseudo R-squared for a probit model are considerably lower than for OLS regressions and that values between 20 and 40% are often considered an excellent fit for the model depending on its purpose (Hensher & Stopher, 1979; Louviere, Hensher & Swait, 2000). However, "good" values for a pseudo R-squared are subject to much debate thus a low value may not necessarily indicate that the model does not fit the data very well. Even when considering this lower metric, the pseudo R-squared values of this model show a rather low level of fitness for the model. This indicators implies that the predictive ability of the specification modelled is not very good, which limits the internal validity of the results. It is still noteworthy that specification adding control variables to the model increases the predictive ability of the model as is demonstrated by increasing pseudo R-squared coefficients between the raw and full specification.

As a consequence, Hypothesis 1 is accepted following this empirical testing with the results proving that the Program to Support Employment has had a positive and significant impact on the employment situation of the individuals benefitting from a training opportunity. Further analysis of different categories in the sample is conducted in Table 7 with comparable probit regressions for different sample subcategories.

The results for the regressions of the impact of the PSE on different population subcategories are presented in Table 7 and 8. Considering the regressions with different sets of control variables for the main specification of Table 6 showed very similar coefficients and average marginal effects, only the specification with the full set of control variables will be reported in the output of these supplemental employment regressions.

Table 6. Impact of the PSE on Employment

	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
Dependent Variable	(1) EMP_{it}	(2) EMP_{it}	(3) EMP_{it}	(4) EMP_{it}	(5) EMP_{it}
time	0.1803*** (0.0060)	0.1817*** (0.0060)	0.1817*** (0.0060)	0.1819*** (0.0060)	0.1818*** (0.0060)
beneficiaries	-0.0390*** (0.0094)	-0.0363*** (0.0094)	-0.0364*** (0.0094)	-0.0531*** (0.0096)	-0.0629*** (0.0100)
timetreated	0.1440*** (0.0127)	0.1397*** (0.0127)	0.1397*** (0.0164)	0.1392*** (0.0126)	0.1392*** (0.0126)
age		0.0018*** (0.0004)	0.0015*** (0.0004)	0.0016*** (0.0004)	0.0016*** (0.0004)
women		-0.0880*** (0.0055)	-0.0861*** (0.0055)	-0.0850*** (0.0055)	-0.0841*** (0.0055)
disability		-0.0756*** (0.0125)	-0.0736*** (0.0125)	-0.0714*** (0.0124)	-0.0702*** (0.0124)
children		0.0172*** (0.0029)	0.0196*** (0.0029)	0.0195*** (0.0029)	0.0196*** (0.0029)
indigenous		0.0672*** (0.0110)	0.0686*** (0.0109)	0.0680*** (0.0109)	0.0676*** (0.0109)
household			-0.0083*** (0.0014)	-0.0084*** (0.0014)	-0.0085*** (0.0013)
readwrite			0.0694** (0.0332)	0.0671** (0.0330)	0.0681** (0.0330)
familyincome			0.0049** (0.0023)	0.0047** (0.0023)	0.0047** (0.0023)
educ			0.0011 (0.0009)	0.0010 (0.0009)	0.0011 (0.0009)
interviews				0.0212*** (0.0025)	0.0176*** (0.0027)
jobs					0.0177*** (0.0050)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	30,334	30,110	30,110	30,110	30,110
Mean	0.2965	0.2965	0.2965	0.2965	0.2965
Pseudo R^2	0.0440	0.0551	0.0562	0.0585	0.0593
Correctly Classified	62.49%	63.68%	63.65%	60.28%	63.89%

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

The first set of supplemental regressions in Table 7 reports the results from different age categories and it is noteworthy that the different samples are of very unequal sizes. The first sample, encompassing the individuals 18 to 38 years old has 24,742 observations while the sample of 39 to 58 years old only has 4,994 observations and the last sample for the 59 to 78 years old individuals is even smaller with 476 observations. Results reflect this trend with lower statistical significance as the sample size diminishes. However, between these samples it stands to say that the first and last subcategories are experiencing roughly similar effects on employment as the complete sample. The complete sample experiences an average marginal effect of an increase of the probability to gain employment after the training period of 0.1392 percentage points while the first age subcategory experiences an increase in this probability of 0.1180 percentage points and the last sample an increase of 0.1559 percentage points, slightly higher. From the results, it seems that the individuals between 39 and 58 years old are the ones benefitting the most from the programme as the impact of the PSE for this category is a 0.2260 percentage points increase in the probability of gaining employment. Coefficients and average marginal effects remain very similar for the other variables, whether it is in the complete sample or the age subcategories. Considering the mean employment for each age group, the beneficiaries between 18 and 38 years old had a 42% increase in employment probability while individuals between 39 and 58 years old experienced a 59% increase in their own employment probability and the beneficiaries between 59 and 78 years old had a 43% increase. The largest impact of the PSE was indeed for the beneficiaries between 39 and 58 years old. The very low pseudo R-squared also remain a concern for the age samples as they are between 3.89 and 7.95 percent, proving a rather low fitness of the model. This concern will remain for every sample categories studied, the predictive ability of the different specification remain relatively low with pseudo R-squared below 10%. Consequently the estimates may not be very good predictors for the impact of the PSE on the different variables. As a consequence, albeit the PSE has an equally positive and significant effect on employment across age categories (except for the third sample which is not statistically significant) individuals between 39 and 58 years old are the ones benefitting the most. From an efficiency point of view, special provisions for the youngest age groups could be introduced in PSE II in order to bring a higher impact of the programme on employment considering the first age group is five times bigger than the second age group.

Then, the impact of the PSE was investigated depending on gender and samples appeared to be relatively equivalent with 17,348 observations for women and 12,762 observations for men. The average marginal effects of interest appeared to be surprisingly close between the two samples. Both groups have a positive and significant effect of the PSE, with men gaining 0.1454 percentage points in the probability to obtain employment following the training while women gained 0.1335 percentage points in their own probability. Participation in a training opportunity led to a 44% increase in the employment probability for men while the probability for women increased by 49%, hence a relatively greater impact for women. This reversal in the difference of the PSE impact can be accounted by lower mean employment for women before the treatment, compared to men leading to a larger relative impact. As a consequence, the PSE has a positive and significant impact on the employment of both men and women with a relative impact that benefits women the most.

Although these results are robust to different specifications and different samples, it is likely that the sample studied here does not represent the Bolivian working population as a whole. This sample is 56.31% female for the treatment group and 57.92% female in the control group, proportion that are unlikely considering women are usually the ones caring for children meaning that men are likely to represent a larger share of the working population. In this case, women would be more available to answer the telephone survey than men, which could account for the sample distribution. However, it is noteworthy that even if the sample distribution is not representative of the entire working population in Bolivia, the relative impact of the PSE on women may not change with a different sample.

Next, the impact on indigenous and non-indigenous people was studied, and the differences are larger between these two groups. Results for the impact of the PSE on the employment of indigenous people are based on a sample of only 2,706 observations compared to 27,404 for the non-indigenous. Furthermore, this study avoids the potential labor discriminations altogether as the groups are only compared on the impact of the PSE for them to gain employment after the training. Consequently, there is no way to account for the potential discrimination to obtain the training opportunity, which was also the case for the differences between genders. The results show that indigenous people have a positive but non-significant average marginal effect of 0.0232 percentage points increase in their employment probability while the non-indigenous have a positive and significant increase of 0.1445 percentage points. Although the PSE still has a positive impact on whether indigenous people gain employment after training, it is a considerably smaller increase in the probability than for their non-indigenous counterparts. In terms of actual impact, the indigenous beneficiaries experienced a 6% increase in their employment probability compared to their indigenous non-beneficiaries counterparts while the non-indigenous beneficiaries experienced a 50% increase in their own employment probability. Consequently, the PSE is much more beneficial to the non-indigenous part of the population. This relatively large difference in relative impact could be due to the fact that indigenous people are likely to live in communities in specific locations and therefore have access to fewer employment opportunities. It is also possible that language remains a barrier for the employment of indigenous people if they are not fully capable in Spanish. In that sense, PSE II being implemented with special provisions for indigenous people is going in the right direction to correct this impact differential.

Finally, the impact of the PSE was tested on education categories which again have very different samples. The individuals having completed at most 10 years of education make up a sample of 2,764 while the individuals having completed more than 10 years of education make up a sample of 27,346. As was the case before, the smaller sample does not give significant results but the differences still give an indication of the action of the PSE. Individuals with up to 10 years of education thus have a positive average marginal effect of 0.0461 percentage point increase while the individuals with more than 10 years of education have a positive and significant effect of 0.1479 percentage point increase for their average marginal effect. These average marginal effects translate into beneficiary individuals with up to ten years of completed education having experienced a

13% increase in employment probability than their non-beneficiary counterparts while the beneficiaries with more than ten years of education had a 51% increase in their own employment probability. Even without taking into account the differences in obtaining the training opportunities, the difference in the impact of the PSE remains important. The PSE thus has a much larger impact on the employment of people with more than ten years of completed education. This effect may be accounted for by the fact that jobs requiring less than ten years of education are most likely informal and thus, the PSE can be expected to have a smaller impact on employment for such jobs because of low training requirements. Consequently, provisions for the individuals with few years of completed education should be added to PSE II in order to correct for such a difference.

Even if some population categories are concentrating the positive impact of the PSE on employment, it stands to note that every regression shows positive average marginal effects no matter the category or control variables involved. As a consequence, it appears as though the PSE is beneficial to employment in any circumstances.

2. The PSE and Labor Income

Even if the PSE has a positive and significant impact on the employment situation of its beneficiaries, this does not mean that a comparable effect will be found in the characteristics of this employment. Therefore, Table 9 to 13 show the results of the empirical testing of the impact of the PSE on the income received from employment. Compared to the previous regressions, the specifications for labor income were conducted with an OLS model, thus, the coefficients obtained can be directly interpreted as marginal effects of the programme. As presented earlier, the lack of comparable data for the income of the entire sample led to severe limitations in the possible ways to conduct this empirical testing. Income values for the treatment group in the period after treatment were extrapolated from the categorical variable present in the dataset. Regressions in Table 9 use the lower bound of the categories while the regressions in Table 10 use their mean values, and Table 11 shows the regressions with the income values at their upper bound. Table 12 examines the regressions using the mean income values without the upper outliers and finally Table 13 shows the regressions using the maximum income values without the upper outliers. The results of these five different regressions show relatively comparable results even if the range of the impact are different. For example, the impact of the programme on labor income is positive and significant across all regressions, whether the significance is at the 90%, 95% or 99% level of confidence.

The output of the regressions in Table 9 using minimum income values after treatment show that individuals going from employment as a non-beneficiary to employment as a PSE beneficiary experience a 8.33% higher income than non-beneficiary individuals for the raw specification and a 6.02% higher income for the full model. This means that using the minimum income possible, individuals earn higher salaries in the job they obtained after a training opportunity compared to the job they held before this training. This 6% increase in labor income can be accounted by the new skills and experience the worker has obtained and in the case of workers being hired in the firm that has conducted the training, the firm-specific skills may play an important role as they are particularly important for the integration of the worker in the company.

Table 7. Impact of the PSE on Employment by Population Categories

Dependent Variable	(1) $EMPage1_{it}$	(2) $EMPage2_{it}$	(3) $EMPage3_{it}$	(4) $EMPmen_{it}$	(5) $EMPwomen_{it}$
	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
time	0.2036*** (0.0065)	0.0893*** (0.0154)	0.0184 (0.0466)	0.2060*** (0.0092)	0.1640*** (0.0079)
beneficiaries	-0.0440*** (0.0110)	-0.1478*** (0.0252)	-0.1333 (0.0944)	-0.0696*** (0.0148)	-0.0603*** (0.0131)
timetreated	0.1180*** (0.0137)	0.2260*** (0.0326)	0.1559 (0.1056)	0.1454*** (0.0194)	0.1335*** (0.0166)
age				0.0003 (0.0006)	0.0026*** (0.0005)
women	-0.0895*** (0.0060)	-0.0834*** (0.0140)	-0.0887* (0.0497)		
disability	-0.0626*** (0.0159)	-0.0667*** (0.0214)	-0.1887*** (0.0670)	-0.1002*** (0.0180)	-0.0416** (0.0173)
children	0.0332*** (0.0035)	0.0127** (0.0051)	0.0165 (0.0122)	0.0315*** (0.0046)	0.0112*** (0.0038)
indigenous	0.0725*** (0.0135)	0.0543*** (0.0202)	0.0123 (0.0586)	0.0848*** (0.0166)	0.0510*** (0.0145)
household	-0.0088*** (0.0014)	-0.0039 (0.0040)	0.0033 (0.0122)	-0.0094*** (0.0020)	-0.0078*** (0.0017)
readwrite	0.1016** (0.0418)	0.0128 (0.0593)	0.0318 (0.1432)	0.0747 (0.0587)	0.0639 (0.0397)
familyincome	0.0031 (0.0025)	0.0108* (0.0063)	0.0272 (0.0202)	0.0004 (0.0035)	0.0083*** (0.0031)
educ	0.0019 (0.0012)	0.0011 (0.0017)	-0.0114** (0.0047)	0.0015 (0.0015)	0.0004 (0.0012)
interviews	0.0155*** (0.0030)	0.0248*** (0.0071)	0.0617* (0.0375)	0.0193*** (0.0040)	0.0160*** (0.0033)
jobs	0.0202*** (0.0062)	-0.0053 (0.0100)	0.0311 (0.0729)	0.0116** (0.0057)	0.0272*** (0.0054)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	24,742	4,994	476	12,762	17,348
Mean	0.2783	0.3804	0.3589	0.3315	0.2706
Pseudo R^2	0.0665	0.0389	0.0795	0.0647	0.0491
Correctly Classified	64.87%	59.85%	64.92%	63.23%	64.54%

Robust standard errors are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.

Table 8. Impact of the PSE on Employment by Population Categories

Dependent Variable	(1) $EMPindi_{it}$	(2) $EMPnonindi_{it}$	(3) $EMPeduc1_{it}$	(4) $EMPeduc2_{it}$
	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
time	0.1279***	0.1874***	0.1534***	0.1846***
	(0.0200)	(0.0063)	(0.0202)	(0.0062)
beneficiaries	-0.0100	-0.0657***	-0.0162	-0.0680***
	(0.0366)	(0.0103)	(0.0329)	(0.0105)
timetreated	0.0232	0.1445***	0.0461	0.1479***
	(0.0485)	(0.0131)	(0.0429)	(0.0132)
age	0.0007	0.0021***	0.0007	0.0020***
	(0.0012)	(0.0004)	(0.0009)	(0.0004)
women	-0.1000***	-0.0821***	-0.0942***	-0.0820***
	(0.0190)	(0.0057)	(0.0192)	(0.0057)
disability	-0.0820***	-0.0967***	-0.0861***	-0.0694***
	(0.0257)	(0.0165)	(0.0260)	(0.0145)
children	0.0301***	0.0168***	0.0172***	0.0204***
	(0.0072)	(0.0032)	(0.0066)	(0.0033)
indigenous			0.0724***	0.0716***
			(0.0214)	(0.0128)
household	-0.0083**	-0.0089***	-0.0098*	-0.0082***
	(0.0038)	(0.0014)	(0.0058)	(0.0014)
readwrite	0.1303*	0.0436	0.0564	0.0673
	(0.0682)	(0.0376)	(0.0516)	(0.0434)
familyincome	-0.0012	0.0052**	0.0023	0.0047**
	(0.0091)	(0.0024)	(0.0101)	(0.0024)
educ	0.0024	0.0001		
	(0.0023)	(0.0010)		
interviews	0.0157*	0.0177***	0.0244***	0.0170***
	(0.0090)	(0.0028)	(0.0095)	(0.0028)
jobs	0.0357***	0.0160***	0.0162	0.0179***
	(0.0134)	(0.0050)	(0.0114)	(0.0055)
Year FE	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Observations	2,706	27,404	2,764	27,346
Mean	0.3844	0.2878	0.3493	0.2910
Pseudo R^2	0.0427	0.0622	0.0474	0.0616
Correctly Classified	60.57%	64.31%	61.90%	64.17%

Robust standard errors are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.

However, this effect may also be accounted by a selection bias from unobserved characteristics such as potential. If firms choose workers with the most potential for their training opportunities and then hire them, the treatment and control groups would appear comparable when it is in fact not. The two percentage points difference between the raw and full models demonstrates some of the variation in labor income can be accounted by the socio-economic characteristics included in the control variables. This difference was expected as labor income are usually increasing with completed years of education or lower for women compared to men.

On the other hand, the regressions in Table 10 using average income values after treatment indicate a 12.31% increase in labor income for the raw specification and a 9.60% increase in labor income for the specification with the full set of control variables. Similarly to the regressions in Table 9, the full specification demonstrates a lower PSE impact than the raw specification but logically, using average income values instead of minimum ones for the extrapolated values gives a higher positive impact of the PSE on labor income.

Finally, regressions in Table 11 using extrapolated income values at the maximum of their category show a PSE impact of an 11.12% increase in income for the raw specification while the full specification shows an 8.15% increase in labor income. It appears that assuming higher income values for PSE beneficiaries in the period after the treatment gives a comparatively lower positive impact of the PSE on labor income but all results remain positive and statistically significant. These results are robust to different specifications as the other regressions performed with different sets of control variables are showing very similar coefficients. This effect may be due to the relative distributions of individuals within each income category used in the extrapolations. However, outliers may also drive the estimates, therefore Table 12 and 13 report similar specifications as Table 10 and 11 but without the upper outliers.

When removing the outliers at the top of the income distribution to avoid the arbitrary setting of the upper income values, the impact of the PSE appears relatively similar to previous regressions. Table 12 estimating the impact of the PSE using mean income values without outliers for beneficiaries after the treatment shows a 13.36% increase in labor income the raw specification while the full specification shows a 10.67% increase.

Then, Table 13 examining the regressions using maximum income values without the outliers indicates a 12.17% increase in labor income for PSE beneficiaries when using the raw specification whereas the full specification indicates a 9.63% increase in labor income. As both the coefficients for Table 12 and 13 are higher than their counterparts including the upper income outliers, it is probable that the top income values experience a comparatively smaller increase driving down the coefficients of Table 10 and 11. This effect can be understood as individuals previously holding relatively good jobs involving high salaries are unlikely to be positively affected by a training opportunity. Jobs with high salaries can be expected to require high levels of skills and experience, therefore a training opportunity from the PSE are unlikely to be present for these types of jobs. Furthermore, even in the case that these individuals do receive a salary increase after a training period, this increase is likely to be smaller in relative terms when compared with workers having a much lower salary in the first place.

Nevertheless, the positive and significant impact of the PSE on labor income may also be put into question as the adjusted R-squared of these different regressions are low with coefficients going up to 20%. However it is noteworthy that all adjusted R-squared are increasing with the number of control variables included in the model as for previous specifications, meaning that the fitness of the model increases by adding variables to explain more of the variations in labor income. As a consequence, the predictive ability of the model is low throughout the different specifications even if it does increase as the control variables are added.

Considering the data limitations and the potential lack of comparability to other samples, the PSE appears to have a positive and significant impact on the labor income earned by beneficiaries of the programme when compared to non-beneficiaries. There can be no precise estimate as to the impact of the PSE on labor income but considering the data at hand, a 6 to 10% salary increase may be expected. As a consequence, Hypothesis 2 is also accepted following its empirical testing.

3. The PSE and Employment Quality

Finally, regarding Hypothesis 3, Table 14 examines the results of the empirical testing of the impact of the PSE on employment quality as proxied by the access to employment benefits. The dependent variable of the main regression encompasses the access to any of the following benefits: a yearly bonus, a second yearly bonus, health care, maternity and/or nursing leave, compensation when laid off, a five year term and retirement pension. However, considering the correlation coefficients present in Appendix A, we can assume that most of the impact on employment benefits is encompassed by the yearly bonus (96.16% correlation) and health care (76.41% correlation).

As in the previous probit regressions, the interaction variable between the beneficiaries and time gives the difference-in-differences impact of the PSE on employment quality. With a positive coefficient from the regression output, individuals who receive training through the PSE are more likely to go from not receiving benefits to start receiving at least one. The range of this effect is then given by the average marginal effect which indicates that being a PSE beneficiary increases the probability of receiving employment benefits by 0.1703 percentage points for the raw specification and by 0.1627 percentage points for the full model. More specifically, considering the mean access to employment benefits, there is a 49% increase in the probability to start having access to any employment benefit when individuals have gone through a training period with the PSE as given by the raw model. Comparatively, the full specification shows a 47% increase in this probability.

Table 9. Impact of the PSE on labor income using minimum extrapolated income

Dependent Variable	(1) Log(LABINmini$_{it}$)	(2) Log(LABINmini$_{it}$)	(3) Log(LABINmini$_{it}$)	(4) Log(LABINmini$_{it}$)	(5) Log(LABINmini$_{it}$)
time	0.0389** (0.0183)	0.0436** (0.0179)	0.0506*** (0.0175)	0.0497*** (0.0176)	0.0506*** (0.0176)
beneficiaries	0.0142 (0.0260)	0.0177 (0.0254)	0.0197 (0.0249)	0.0223 (0.0251)	0.0157 (0.0253)
timetreated	0.0833*** (0.0307)	0.0684** (0.0303)	0.0604** (0.0297)	0.0608** (0.0297)	0.0602** (0.0297)
categorical	-0.0169*** (0.0173)	-0.0113 (0.0170)	-0.0349** (0.0166)	-0.0346** (0.0166)	-0.0353** (0.0166)
age		0.0068*** (0.0010)	0.0068*** (0.0010)	0.0068*** (0.0010)	0.0068*** (0.0010)
women		-0.2289*** (0.0121)	-0.2188*** (0.0118)	-0.2189*** (0.0118)	-0.2183*** (0.0118)
disability		-0.1680*** (0.0339)	-0.1228*** (0.0324)	-0.1229*** (0.0324)	-0.1224*** (0.0324)
children		-0.0097 (0.0067)	0.0258*** (0.0068)	0.0258*** (0.0068)	0.0260*** (0.0068)
indigenous		-0.0611** (0.0257)	0.0155 (0.0253)	0.0153 (0.0253)	0.0149 (0.0253)
household			-0.0179*** (0.0032)	-0.0179*** (0.0032)	-0.0181*** (0.0031)
readwrite			-0.0339 (0.0727)	-0.0346 (0.0729)	-0.0349 (0.0728)
familyincome			0.0886*** (0.0052)	0.0887*** (0.0052)	0.0887*** (0.0052)
educ			0.0263*** (0.0022)	0.0263*** (0.0022)	0.0264*** (0.0022)
interviews				-0.0037 (0.0047)	-0.0062 (0.0049)
jobs					0.0122** (0.0061)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	10,391	10,326	10,326	10,326	10,326
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0178	0.0614	0.1104	0.1105	0.1108

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 10. Impact of the PSE on labor income using average extrapolated income

Dependent Variable	(1) Log(LA-BINaver$_{it}$)	(2) Log(LA-BINaver$_{it}$)	(3) Log(LA-BINaver$_{it}$)	(4) Log(LA-BINaver$_{it}$)	(5) Log(LA-BINaver$_{it}$)
time	0.1072***	0.1146***	0.1248***	0.1237***	0.1247***
	(0.0185)	(0.0181)	(0.0177)	(0.0178)	(0.0178)
beneficiaries	0.0070	0.0106	0.0124	0.0160	0.0092
	(0.0260)	(0.0255)	(0.0250)	(0.0252)	(0.0254)
timetreated	0.1231***	0.1057***	0.0961***	0.0966***	0.0960***
	(0.0310)	(0.0305)	(0.0299)	(0.0299)	(0.0299)
categorical	0.0587***	0.0654***	0.0427**	0.0431***	0.0424**
	(0.0175)	(0.0172)	(0.0167)	(0.0167)	(0.0167)
age		0.0070***	0.0070***	0.0069***	0.0070***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
women		-0.2403***	-0.2283***	-0.2285***	-0.2279***
		(0.0123)	(0.0120)	(0.0120)	(0.0120)
disability		-0.1659***	-0.1154***	-0.1155***	-0.1151***
		(0.0344)	(0.0328)	(0.0328)	(0.0328)
children		-0.0138**	0.0239***	0.0239***	0.0241***
		(0.0068)	(0.0069)	(0.0069)	(0.0069)
indigenous		-0.0715***	0.0062	0.0060	0.0056
		(0.0261)	(0.0259)	(0.0259)	(0.0259)
household			-0.0172***	-0.0172***	-0.0175***
			(0.0033)	(0.0033)	(0.0032)
readwrite			-0.0671	-0.0681	-0.0684
			(0.0723)	(0.0726)	(0.0725)
familyincome			0.0954***	0.0955***	0.0955***
			(0.0053)	(0.0053)	(0.0053)
educ			0.0275***	0.0275***	0.0276***
			(0.0023)	(0.0023)	(0.0023)
interviews				-0.0051	-0.0075
				(0.0050)	(0.0051)
jobs					0.0124**
					(0.0062)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	10,695	10,627	10,627	10,627	10,627
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0379	0.0811	0.1311	0.1312	0.1315

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 11. Impact of the PSE on labor income using maximum extrapolated income

Dependent Variable	(1) Log(LABIN-max$_{it}$)	(2) Log(LABIN-max$_{it}$)	(3) Log(LABIN-max$_{it}$)	(4) Log(LABIN-max$_{it}$)	(5) Log(LABIN-max$_{it}$)
time	0.2326***	0.2399***	0.2495***	0.2487***	0.2497***
	(0.0184)	(0.0181)	(0.0176)	(0.0177)	(0.0177)
beneficiaries	0.0018	0.0057	0.0070	0.0094	0.0027
	(0.0262)	(0.0256)	(0.0252)	(0.0253)	(0.0255)
timetreated	0.1112***	0.0945***	0.0859***	0.0862***	0.0855***
	(0.0302)	(0.0298)	(0.0292)	(0.0292)	(0.0292)
categorical	0.1755***	0.1823***	0.1614***	0.1616***	0.1610***
	(0.0174)	(0.0172)	(0.0167)	(0.0167)	(0.0167)
age		0.0068***	0.0068***	0.0067***	0.0068***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
women		-0.2200***	-0.2086***	-0.2088***	-0.2082***
		(0.0117)	(0.0114)	(0.0114)	(0.0114)
disability		-0.1619***	-0.1150***	-0.1151***	-0.1147***
		(0.0331)	(0.0316)	(0.0316)	(0.0316)
children		-0.0123*	-0.0223***	0.0223***	0.0225***
		(0.0066)	(0.0067)	(0.0067)	(0.0067)
indigenous		-0.0633**	0.0078	0.0077	0.0072
		(0.0248)	(0.0244)	(0.0244)	(0.0244)
household			-0.0161***	-0.0161***	-0.0164***
			(0.0031)	(0.0031)	(0.0030)
readwrite			-0.0437	-0.0443	-0.0447
			(0.0680)	(0.0682)	(0.0681)
familyincome			0.0896***	0.0897***	0.0897***
			(0.0052)	(0.0052)	(0.0051)
educ			0.0248***	0.0248***	0.0250***
			(0.0021)	(0.0022)	(0.0022)
interviews				-0.0034	-0.0057
				(0.0046)	(0.0047)
jobs					0.0123**
					(0.0058)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	10,695	10,627	10,627	10,627	10,627
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.1020	0.1404	0.1851	0.1852	0.1854

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 12. Impact of the PSE on labor income using average extrapolated income without upper outliers

Dependent Variable	(1) Log(LABINaver2$_{it}$)	(2) Log(LABINaver2$_{it}$)	(3) Log(LABINaver2$_{it}$)	(4) Log(LABINaver2$_{it}$)	(5) Log(LABINaver2$_{it}$)
time	0.1250***	0.1324***	0.1423***	0.1412***	0.1422***
	(0.0180)	(0.0176)	(0.0172)	(0.0172)	(0.0172)
beneficiaries	0.0002	0.0042	0.0062	0.0100	0.0029
	(0.0244)	(0.0238)	(0.0233)	(0.0234)	(0.0236)
timetreated	0.1336***	0.1167***	0.1068***	0.1073***	0.1067***
	(0.0296)	(0.0291)	(0.0284)	(0.0284)	(0.0284)
categorical	0.0593***	0.0657***	0.0440***	0.0444***	0.0437***
	(0.0171)	(0.0168)	(0.0163)	(0.0163)	(0.0163)
age		0.0066***	0.0067***	0.0067***	0.0068***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
women		-0.2450***	-0.2332***	-0.2334***	-0.2328***
		(0.0119)	(0.0116)	(0.0116)	(0.0116)
disability		-0.1551***	-0.1051***	-0.1052***	-0.1048***
		(0.0342)	(0.0326)	(0.0326)	(0.0326)
children		-0.0138**	0.0228***	0.0229***	0.0230***
		(0.0065)	(0.0066)	(0.0066)	(0.0065)
indigenous		-0.0632**	0.0124	0.0122	0.0117
		(0.0257)	(0.0255)	(0.0255)	(0.0255)
household			-0.0163***	-0.0163***	-0.0166***
			(0.0032)	(0.0032)	(0.0031)
readwrite			-0.0782	-0.0793	-0.0796
			(0.0720)	(0.0723)	(0.0723)
familyincome			0.0943***	0.0943***	0.0943***
			(0.0052)	(0.0052)	(0.0051)
educ			0.0272***	0.0272***	0.0274***
			(0.0022)	(0.0022)	(0.0022)
interviews				-0.0055	-0.0080
				(0.0049)	(0.0051)
jobs					0.0131**
					(0.0061)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	10,647	10,579	10,579	10,579	10,579
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0449	0.0907	0.1426	0.1427	0.1430

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 13. Impact of the PSE on labor income using maximum extrapolated income without upper outliers

Dependent Variable	(1) Log(LABINmax2$_{it}$)	(2) Log(LABINmax2$_{it}$)	(3) Log(LABINmax2$_{it}$)	(4) Log(LABINmax2$_{it}$)	(5) Log(LABINmax2$_{it}$)
time	0.2502***	0.2575***	0.2667***	0.2659***	0.2669***
	(0.0179)	(0.0175)	(0.0171)	(0.0171)	(0.0171)
beneficiaries	-0.0050	-0.0008	0.0007	0.0034	-0.0036
	(0.0246)	(0.0240)	(0.0235)	(0.0236)	(0.0237)
timetreated	0.1217***	0.1056***	0.0966***	0.0970***	0.0963***
	(0.0288)	(0.0283)	(0.0277)	(0.0277)	(0.0277)
categorical	0.1764***	0.1828***	0.1628***	0.1631***	0.1624***
	(0.0170)	(0.0167)	(0.0163)	(0.0163)	(0.0163)
age		0.0063***	0.0065***	0.0065***	0.0065***
		(0.0009)	(0.0009)	(0.0009)	(0.0009)
women		-0.2244***	-0.2133***	-0.2135***	-0.2128***
		(0.0113)	(0.0110)	(0.0110)	(0.0110)
disability		-0.1508***	-0.1045***	-0.1046***	-0.1042***
		(0.0329)	(0.0314)	(0.0314)	(0.0314)
children		-0.0123**	0.0212***	0.0213***	0.0214***
		(0.0062)	(0.0063)	(0.0063)	(0.0063)
indigenous		-0.0549**	0.0141	0.0140	0.0135
		(0.0243)	(0.0240)	(0.0240)	(0.0240)
household			-0.0152***	-0.0152***	-0.0154***
			(0.0030)	(0.0030)	(0.0029)
readwrite			-0.0550	-0.0557	-0.0560
			(0.0677)	(0.0679)	(0.0679)
familyincome			0.0882***	0.0883***	0.0883***
			(0.0049)	(0.0049)	(0.0049)
educ			0.0246***	0.0246***	0.0247***
			(0.0021)	(0.0021)	(0.0021)
interviews				-0.0038	-0.0063
				(0.0045)	(0.0046)
jobs					0.0129**
					(0.0056)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	10,647	10,579	10,579	10,579	10,579
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.1176	0.1583	0.2044	0.2044	0.2047

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Considering the different specifications of Table 14 all give relatively similar estimates, statistically significant at the 99% level of confidence, this impact is robust to different specifications. Nonetheless, even if the results from the previous regressions needed to be taken cautiously because of low R-squared coefficient, this is all the more applicable for this empirical testing as the R-squared only reach 3.69%. Even for pseudo R-squared coefficients of probit regressions, these values demonstrate that the fitness of the model and thus its predictive ability is not very good.

Finally, following this empirical testing, the estimates indicate that the PSE has a positive and significant effect on employment quality for adult Bolivians registered in the programme as there is a positive and significant effect on the access to employment benefits. As a consequence, Hypothesis 3 is accepted after empirical testing even if again, both the internal and external validity of the results can be put in question by the data limitations exposed earlier.

The results of the supplemental regressions for the impact on individual employment benefits are showed in Table 15. Throughout the regression output, it appears that the regressions have very similar number of observations even if the correlation coefficients of the individual variables with the overall variable are very different. This comes from the construction of the variable and does not reflect whether the same number of individuals are receiving the employment benefit. As was the case for the supplemental regressions on employment with population categories, only the main specification with the full set of control variable was utilized since average marginal effect remain very close throughout all the specifications.

As could be expected from the correlation ratios in Appendix A, the average marginal affect for the yearly bonus in column (a) are very close to the results of the main specification in Table 14. The PSE then has a positive and significant average marginal effect of a 0.1713 percentage points increase in access to the yearly bonus while it is a 0.1627 percentage point increase for the overall estimation with the full specification. More specifically, this means that between two situations of employment before and after training, PSE beneficiaries experience a 52% increase in the probability of having access to a yearly bonus compared to their non-beneficiary counterparts.

A high correlation coefficient and close average marginal effect between the individual benefit and the overall variable can also be found for the access to health care as presented by column (c). The average marginal effect of this equation is a statistically significant 0.1500 percentage point increase in the probability to gain access to health care from employment after a training opportunity. PSE beneficiaries gaining employment after the training therefore experience a 71% increase in the probability to have access to health care compared to non-beneficiaries.

Table 14. Impact of the PSE on Employment Quality

	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
Dependent Variable	(1) $BENEFIT_{it}$	(2) $BENEFIT_{it}$	(3) $BENEFIT_{it}$	(4) $BENEFIT_{it}$	(5) $BENEFIT_{it}$
time	0.1100*** (0.0122)	0.1088*** (0.0123)	0.1089*** (0.0123)	0.1091*** (0.0123)	0.1092*** (0.0123)
beneficiaries	-0.0588*** (0.0205)	-0.0542*** (0.0206)	-0.0551*** (0.0206)	-0.0557*** (0.0208)	-0.0569*** (0.0210)
timetreated	0.1703*** (0.0253)	0.1629*** (0.0254)	0.1629*** (0.0254)	0.1628*** (0.0254)	0.1627*** (0.0254)
age		0.0022*** (0.0008)	0.0022*** (0.0008)	0.0022*** (0.0008)	0.0022*** (0.0008)
women		-0.0039 (0.0107)	-0.0029 (0.0107)	-0.0029 (0.0107)	-0.0027 (0.0107)
disability		0.0103 (0.0262)	0.0124 (0.0262)	0.0124 (0.0262)	0.0125 (0.0262)
children		0.0006 (0.0058)	0.0011 (0.0059)	0.0010 (0.0059)	0.0011 (0.0059)
indigenous		-0.0309 (0.0216)	-0.0296 (0.0217)	-0.0296 (0.0217)	-0.0297 (0.0217)
household			-0.0005 (0.0025)	-0.0005 (0.0025)	-0.0006 (0.0025)
readwrite			-0.0960 (0.0726)	-0.0958 (0.0726)	-0.0959 (0.0727)
familyincome			0.0086* (0.0044)	0.0086* (0.0044)	0.0086** (0.0044)
educ			0.0100*** (0.0019)	0.0100*** (0.0019)	0.0100*** (0.0019)
interviews				0.0009 (0.0038)	0.0005 (0.0040)
jobs					0.0021 (0.0057)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	8,462	8,410	8,410	8,410	8,410
Mean	0.3493	0.3493	0.3493	0.3493	0.3493
Pseudo R^2	0.0329	0.0364	0.0369	0.0369	0.0369
Correctly Classified	60.07%	60.73%	60.57%	60.58%	60.55%

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

As employment formality is defined by providing health care access to the worker, this impact is all the more important because the PSE is positively and significantly impacting employment formality. As a consequence, after benefitting from a training opportunity, workers are likely to gain employment that is considered formal when they had been working at informal jobs in the past. Considering the high average marginal effect and its actual impact, the PSE has a great deal of influence on formality. This point of interest, although likely to be continued by the new PSE II, deserves to be highlighted as a legitimate achievement in a country where 85 percent of all employment is informal. Formal employment can then be considered another dimension of the programme impact on employment quality with a positive and statistically significant impact of the PSE on access to health care. As explained earlier, these results still need to be taken cautiously as there may be a selection bias in the sample towards formal jobs or workers more inclined to search for formal employment, leading to a potential upward bias.

However, when it comes to all the other benefits individually the results are much lower with the second yearly bonus having an average marginal effect of 0.0476 percentage point increase, maternity and/or nursing leave having 0.0414 percentage point increase or compensation having 0.0637 percentage point increase. The same impact goes for the five year term with an average marginal effect of 0.0485 percentage point and for the access to retirement pension with an average marginal effect of 0.0398 percentage point. Nevertheless, even if the average marginal effects of the individual employment benefits are low, their pre-treatment mean access level are low as well, meaning that the relative impact of the PSE on each of these benefits may be high. Their respective relative PSE impact are therefore a 61% increase in the probability to have access to a second yearly bonus, a 99% increase in the probability to have access to maternity and/or nursing leave, a 63% increase in the probability to have access to compensation, a 83% increase in the probability to have access to a five year term and a 49% increase in the probability to have access to a retirement pension.

The overall benefits variable may be highly correlated to the yearly bonus and health care but the relative impact of the PSE is just as strong if not stronger for other employment benefits. Albeit the absolute number of individuals having gained access to the individual benefits is low, it is noteworthy that the programme has managed such important increases. This trend can be explained by the overall lack of employment benefits in the Bolivian labor market. Consequently, the PSE has a positive and significant effect on the access to any of these benefits individually, showing that the programme has a positive effect on each dimension of employment quality.

As is the case for every regression in this impact evaluation, the fitness of the models is low with pseudo R^2 coefficient below 6.6% for all these supplemental regressions. Nevertheless, it remains that the PSE has a positive and significant impact on the access to every employment benefit individually, further proving Hypothesis 3.

Table 15. Impact of the PSE on Individual Employment Benefits

Dependent Variable	(a) $bonus_{it}$	(b) $secbonus_{it}$	(c) $healthcare_{it}$	(d) $maternity_{it}$	(e) $compensation_{it}$	(f) $fiveyearterm_{it}$	(g) $pension_{it}$
	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
time	0.1049***	-0.0230***	0.1316***	0.0482***	0.0586***	0.0389***	0.1157***
	(0.0123)	(0.0063)	(0.0114)	(0.0070)	(0.0089)	(0.0072)	(0.0093)
beneficiaries	-0.0600***	-0.0368***	-0.0535***	-0.0210	-0.0598***	-0.0551***	-0.0197
	(0.0210)	(0.0112)	(0.0208)	(0.0143)	(0.0169)	(0.0148)	(0.0177)
timetreated	0.1713***	0.0476***	0.1500***	0.0414***	0.0637***	0.0485***	0.0398**
	(0.0252)	(0.0131)	(0.0242)	(0.0157)	(0.0194)	(0.0165)	(0.0200)
age	0.0021**	0.0005	0.0020***	0.0007	0.0020***	0.0012**	0.0016***
	(0.0008)	(0.0004)	(0.0008)	(0.0004)	(0.0006)	(0.0005)	(0.0006)
women	-0.0015	-0.0033	-0.0509***	-0.0001	-0.0149**	-0.0153**	-0.0204***
	(0.0106)	(0.0055)	(0.0098)	(0.0057)	(0.0076)	(0.0061)	(0.0077)
disability	0.0178	-0.0170	0.0259	0.0060	-0.0111	0.0222	0.0201
	(0.0261)	(0.0151)	(0.0247)	(0.0148)	(0.0199)	(0.0155)	(0.0196)
children	0.0028	0.0052*	0.0098*	0.0101***	0.0053	0.0069**	0.0096**
	(0.0058)	(0.0030)	(0.0055)	(0.0032)	(0.0042)	(0.0034)	(0.0043)
indigenous	-0.0242	-0.0051	-0.0408*	-0.0181	-0.0292*	-0.0245*	-0.0426**
	(0.0215)	(0.0117)	(0.0209)	(0.0132)	(0.0166)	(0.0141)	(0.0173)
household	-0.0010	-0.0067***	-0.0044*	-0.0033*	-0.0085***	-0.0038**	-0.0081***
	(0.0025)	(0.0020)	(0.0024)	(0.0018)	(0.0023)	(0.0018)	(0.0023)
readwrite	-0.1079	0.0542	-0.0918	-0.0498	-0.0053	-0.0164	-0.0768
	(0.0720)	(0.0534)	(0.0690)	(0.0350)	(0.0508)	(0.0395)	(0.0495)
familyincome	0.0072	0.0241***	0.0208***	0.0127***	0.0137***	0.0155***	0.0241***
	(0.0044)	(0.0021)	(0.0040)	(0.0022)	(0.0030)	(0.0023)	(0.0030)
educ	0.0091***	0.0011	0.0182***	0.0065***	0.0062***	0.0055***	0.0082***
	(0.0019)	(0.0010)	(0.0019)	(0.0011)	(0.0014)	(0.0011)	(0.0015)
interviews	-0.0018	0.0045**	-0.0012	-0.0047*	0.0022	0.0024	0.0016
	(0.0039)	(0.0018)	(0.0037)	(0.0028)	(0.0024)	(0.0020)	(0.0028)
jobs	0.0034	0.0097**	0.0040	-0.0118**	0.0117***	0.0070**	-0.0073
	(0.0055)	(0.0043)	(0.0051)	(0.0054)	(0.0034)	(0.0033)	(0.0053)
Year FE	YES	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES	YES
Observations	8,410	8,410	8,410	8,400	8,410	8,400	8,400
Mean	0.3312	0.0775	0.2118	0.0419	0.1004	0.0583	0.0812
Pseudo R^2	0.0382	0.0593	0.0653	0.0660	0.0401	0.0559	0.0619
Correctly Classified	61.57%	92.83%	69.20%	92.32%	85.67%	91.21%	84.73%

Robust standard errors are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.

SECTION 7. CONCLUSION

As was explained in the theoretical framework and literature review, a major challenge for any social policy is that information, compliance and psychological costs are important deterrents for the poor to actually take part in the programmes (Moynihan et al, 2014; Rinehart & McGuire, 2017). Taking into account the low coverage of the PSE and the multiple data limitations that restricted this analysis, we can assess the impact of the programme on several crucial variables.

The Program to Support Employment in Bolivia is showed to have a positive and significant impact on the employment situation, labor income and quality of this employment for adult Bolivians. These results validate all the hypotheses formulated in this research and in the initial expectations of the programme. The PSE is also shown to have a positive and statistically significant impact on employment formality, which is a major success for a country with a majority of informal jobs. However, this impact remains uncertain due to data limitations. As this programme is aimed at the long-term improvements in human capital of the population with potentially low levels of training and education, the results of this analysis reflect the primary objectives set out at its implementation. While the training component of the programme studied here can be expected to be the most beneficial to the population, it remains that even the unemployed that do not obtain a training through the programme stand to benefit from it. As explained earlier, the programme also provides a unique database to match job demand and supply, and counseling for job seekers to better find employment. As the labor market frictions are severely reduced thanks to more efficient matching of demand and supply, there may be long-term gains to the economy that simply could not be taken into account in this evaluation. The conditions of the unemployed, whether they receive training or not, may thus be improved by the very presence of the programme.

This impact evaluation provides the first look at the impact of the PSE through a difference-in-differences methodology which comes out to support the implementation of the second version of the programme, PSE II. With an increasing number of people registered at the Bolsa de Empleo and increasing numbers of counseling and training throughout the five years of the programme as showed in Figure 1, there could be even stronger results for PSE II. Considering the data limitations present in this study and the likelihood of upward bias for the results examined here, PSE II may instead experience a lower impact through the reduction of the biases with a larger sample. Expanded coverage and special provisions for certain categories such as indigenous people and youth are all demonstrated to be needed as these categories experience lower gains from the programme.

Nevertheless, even with positive and statistically significant results for this impact analysis, it remains that limitations of different kinds are crippling the results described above. The data is a major source of concern as issues are potentially leaving this analysis with doubtful internal and external validity. As was previously examined, the dataset used for this analysis may be biased for several reasons and the conclusions obtained here may not be adaptable to a different and/or larger sample. Selection for the sample remains one the biggest concern as certain characteristics may be over-represented in the sample compared to the overall Bolivian labor market. These biases towards more formal employment or more female survey respondents for example may be compromising the generalization of the results obtaining in this evaluation. Following the potential ways for the results to be biased, the most likely direction of this overall bias is upward which would not only compromise the external validity of the results but also the conclusions of this evaluation. With a significant upward bias, there is no way to conclude with certainty that the impact of the PSE on the several variables of interest is indeed positive and significant. Making the survey a mandatory part of PSE II would certainly circumvent a number of these issues in the future as the data would be more complete and accurate.

Although with caution due to the several data issues, I conclude that the PSE appears to have fulfilled its objectives, with a positive and significant impact on employment, labor income and employment quality for this sample. In some cases, the programme even performed beyond expectations as the mid-programme evaluation has shown. The Program to Support Employment is therefore another success story for policies involving improvements of human capital and the reduction of market inefficiencies. The full implementation of PSE II then seems like a natural step to continue improving the employment and employability of adult Bolivians.

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APPENDIX A. TESTS ON MAIN VARIABLES BEFORE REGRESSIONS

e(V)	beneficiaries	emp	lnlaborincomemini	lnlaborincomemean	lnlaborincomemax	bonus	secbonus	healthcare	maternity	compensation	fiveyearterm	pension	benefit
beneficiaries	1.0000												
emp	0.0328	1.0000											
lnlaborincomemini	0.0529	.	1.0000										
Lnlaborincomemean	0.0699	.	0.9727	1.0000									
lnlaborincomemax	0.0708	.	0.9178	0.9740	1.0000								
Bonus	0.0636	-0.0121	0.2005	0.2576	0.2630	1.0000							
secbonus	0.0119	0.0105	0.1152	0.1177	0.1065	0.3129	1.0000						
healthcare	0.0639	0.0055	0.2571	0.3055	0.3161	0.7300	0.3229	1.0000					
maternity	0.0173	0.0108	0.0935	0.1233	0.1335	0.3311	0.3668	0.3992	1.0000				
compensation	0.0105	0.0064	0.1258	0.1599	0.1653	0.4656	0.3926	0.5640	0.6400	1.0000			
fiveyearterm	-0.0005	0.0117	0.1025	0.1299	0.1362	0.3525	0.4640	0.4280	0.7847	0.7257	1.0000		
pension	0.0245	-0.0103	0.1681	0.2074	0.2209	0.4589	0.2715	0.5757	0.5070	0.5317	0.5408	1.0000	
benefit	0.0583	-0.0106	0.2103	0.2694	0.2742	0.9616	0.3106	0.7641	0.3218	0.4575	0.3462	0.4739	1.0000

Source: Computations on the dataset provided by the IDB, made with the software Stata 15.1.

Test (Test Used)	**P-value (2a)**	**P-value (2b)**	**P-value (2c)**	**Conclusion**
Heteroskedasticity (White test)	0.000	0.000	0.000	With a p value lower than 0.05, the data is considered heteroskedastic by the rejection of the null hypothesis.
Skewness (Normality test)	0.000	0.001	0.014	As for the heteroskedasticity test, the p value is below 0.05 and therefore the null hypothesis is rejected and conclude that the data does not follow a normal distribution.
Kurtosis (Normality test)	0.000	0.000	0.000	This test, confirms the skewness test with a p value meaning that the null hypothesis of is rejected and that the data does not follow a normal distribution.

Source: Computations on the dataset provided by the IDB, made with the software Stata 15.1.

APPENDIX B. SUPPLEMENTAL REGRESSIONS WITHOUT INACTIVE

The regressions in the main analysis examined the impact of the PSE on employment as opposed to non-employment. In this appendix however, the sample does not include the inactive meaning the unemployed that are not looking for a job either in period 0 or period 1. As a consequence, the estimates assess the impact of the PSE on employment as opposed to unemployment.

The new sample essentially dropped 3,254 individuals reporting being inactive meaning unemployed and not looking for a job either in period 0 or period 1. The treatment group then consists of 2,756 PSE beneficiary individuals while the control group consists of 9,157 non-beneficiary individuals. Table 16 gives the descriptive statistics of the new sample and it appears that the distributions of the main and secondary samples are relatively similar. Removing the inactive thus does not drastically change the construction of the secondary sample as compared to the main one.

Table 16. Descriptive Statistics of the Secondary Sample

		Treatment Group (Registered at the Bolsa de Empleo + received training through the PSE)	**Control Group (Registered at the Bolsa de Empleo)**
Observations		2,756	9,157
City of Residence	El Alto	17.63%*	20.05%
	Sucre	8.49%	3.08%
	La Paz	25.15%	36.34%
	Cochabamba	9.11%	8.38%
	Oruro	9.69%	7.15%
	Potosí	5.12%	4.00%
	Tarija	6.39%	5.39%
	Santa Cruz	11.72%	12.32%
	Trinidad	2.03%	1.44%
	Cobija	4.68%	1.85%
Gender	Female	55.41%	56.47%
	Male	44.59%	43.53%
Average Age		31.19	32.14
Average number of interviews obtained since registration		1.32	0.48
Average number of jobs obtained since registration		0.98	0.23
Average number of children at registration		0.88	0.89
Know how to read and write	YES	99.60%	99.28%
	NO	0.40%	0.72%
Disability	YES	5.40%	7.81%
	NO	94.60%	92.19%
Indigenous	YES	6.93%	10.86%
	NO	93.58%	89.14%
Average years of education		14.36	14.26

Average Family Income (in bolivianos)**	<1000	10.41%	17.55%
	1,000-1,999	40.20%	35.70%
	2,000-2,999	31.39%	29.56%
	3,000-3,999	10.01%	10.10%
	4,000-4,999	3.63%	3.73%
	5,000-6,999	2.87%	2.29%
	7,000-9,999	1.23%	0.78%
	10,000+	0.26%	0.29%

Source: Own computations on the dataset provided by the Inter-American Development Bank. The sum of individual percentages within the same variable may not amount to 100 percent due to rounding. *Each percentage represents the share of the category (line) within the total observation of the group (sum of the column for one variable). For example, 17.63 percent of the individuals in the treatment group live in El Alto. **As a comparison, one U.S. dollar was worth 6.91 Bolivian bolivianos and for the entire period of the programme (2012-2017) as given by the average exchange rate (World Bank, 2018c).

All the regressions of the main analysis except the impact of the PSE on the employment of population subcategories because of data limitations were reproduced here with the new sample as a robustness check. The population subcategories showed very few observations in their regressions leading to inconclusive results.

Removing the inactive from the sample in the empirical testing of the PSE impact on employment in Table 17 shows lower estimates with a 0.1327 percentage point increase in the probability to find employment after training for the full model while its counterpart in the main analysis is 0.1392 percentage point. Considering their respective mean, the relative impact of the PSE is a 35% increase in the probability of employment after training for the supplemental specification while it is a 47% increase in the main analysis. The different specifications of the supplemental regressions all show very similar coefficients and statistical significance at the 99% level of confidence in most cases. The change in effect can be accounted by the difference between unemployment and non-employment with the exclusion of the inactive in the supplemental regressions. The inactive are then likely to account for some of the variation in the impact of the PSE on employment. This effect can be understood as discouraged workers stopping their search for a job and becoming inactive in period 0 and gain hope to find a job again thanks to the PSE leading to them going from inactive to unemployed or employed in the best case scenario.

What transpires from the other supplemental regressions in Table 18 through 24 is that the impact of the PSE on labor income and employment benefit, both globally and individually, is still positive in all instances but somewhat larger than in the main analysis. This change can also be accounted by the difference in samples as removing the inactive gives more relative weight for the individual with employment (hence labor income and potential employment benefits) which incidentally increases the relative impact of the PSE on these variables. The raw specifications however, show lower estimates than their counterparts in the main analysis, an effect that is completely reversed with the addition of control variables. The relative impact of the PSE on labor income is directly given by the coefficient estimates and are thus lower than in the main analysis but in the case of employment benefits, they are surprisingly close. In the main analysis, the PSE increased the probability of having access to any benefit by 47% while it is a 48% increase without the inactive. Furthermore, individual employment benefits such as the impact of the PSE on the probability to have access to a yearly bonus was a 52% increase in the main analysis and it is a 53% increase in these supplemental regressions. Access to health care also showed a 71% increase of the probability to have access to it thanks to a training period with the PSE in the main analysis while it is a 70% without the inactive. The impact on formality is thus still positive and significant as the main analysis demonstrated.

As a consequence, when using the full specifications, it appears that the conclusions for the impact of the PSE on employment, labor income and employment quality are robust to specifications with a different sample removing the inactive. The estimates of such regressions appear to be different as the terminology of their interpretation is different, but the overall results all remain positive and statistically significant, further proving the conclusions in the main analysis.

Table 17. Impact of the PSE on Employment (Secondary Sample)

	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
Dependent Variable	(1) EMP_{it}	(2) EMP_{it}	(3) EMP_{it}	(4) EMP_{it}	(5) EMP_{it}
time	0.1329*** (0.0070)	0.1344*** (0.0070)	0.1344*** (0.0070)	0.1344*** (0.0070)	0.1343*** (0.0070)
beneficiaries	-0.0150 (0.0109)	-0.0129 (0.0109)	-0.0133 (0.0109)	-0.0322*** (0.0111)	-0.0437*** (0.0118)
timetreated	0.1364*** (0.0150)	0.1331*** (0.0150)	0.1332*** (0.0150)	0.1327*** (0.0150)	0.1327*** (0.0149)
age		0.0008* (0.0005)	0.0005 (0.0005)	0.0006 (0.0005)	0.0006 (0.0005)
women		-0.0858*** (0.0063)	-0.0839*** (0.0063)	-0.0824*** (0.0063)	-0.0814*** (0.0063)
disability		-0.0800*** (0.0138)	-0.0789*** (0.0139)	-0.0766*** (0.0138)	-0.0755*** (0.0138)
children		0.0161*** (0.0033)	0.0191*** (0.0033)	0.0190*** (0.0033)	0.0191*** (0.0033)
indigenous		0.0652*** (0.0121)	0.0636*** (0.0121)	0.0635*** (0.0121)	0.0630*** (0.0121)
household			-0.0097*** (0.0016)	-0.0098*** (0.0016)	-0.0100*** (0.0015)
readwrite			0.0443 (0.0404)	0.0416 (0.0401)	0.0406 (0.0400)
familyincome			0.0036 (0.0027)	0.0036 (0.0027)	0.0036 (0.0026)
educ			-0.0006 (0.0010)	-0.0007 (0.0011)	-0.0006 (0.0010)
interviews				0.0236*** (0.0030)	0.0195*** (0.0032)
jobs					0.0201*** (0.0066)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	23,826	23,648	23,648	23,648	23,648
Mean	0.3775	0.3775	0.3775	0.3775	0.3775
Pseudo R^2	0.0273	0.0364	0.0377	0.0404	0.0412
Correctly Classified	58.84%	60.11%	60.04%	60.28%	60.41%

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 18. Impact of the PSE on labor income using minimum continuous variables (Secondary Sample)

Dependent Variable	(1) Log(LABINmini$_{it}$)	(2) Log(LABINmini$_{it}$)	(3) Log(LABINmini$_{it}$)	(4) Log(LABINmini$_{it}$)	(5) Log(LABINmini$_{it}$)
time	0.0252 (0.0258)	0.0206 (0.0251)	0.0153 (0.0242)	0.0152 (0.0242)	0.0152 (0.0242)
beneficiaries	0.0201 (0.0388)	0.0173 (0.0373)	0.0222 (0.0369)	0.0268 (0.0372)	0.0275 (0.0373)
timetreated	0.0908* (0.0504)	0.0950* (0.0486)	0.0967** (0.0476)	0.0967** (0.0476)	0.0967** (0.0476)
categorical	0.0668** (0.0298)	0.0650** (0.2736)	0.0373 (0.0283)	0.0385 (0.0284)	0.0386 (0.0283)
age		0.0066*** (0.0017)	0.0065*** (0.0016)	0.0064*** (0.0016)	0.0064*** (0.0016)
women		-0.3047*** (0.0217)	-0.2840*** (0.0212)	-0.2840*** (0.0212)	-0.2841*** (0.0212)
disability		-0.1747*** (0.0552)	-0.1350** (0.0529)	-0.1345** (0.0529)	-0.1346** (0.0530)
children		-0.0269** (0.0109)	0.0122 (0.0109)	0.0123 (0.0108)	0.0123 (0.0108)
indigenous		-0.0246 (0.0410)	0.0537 (0.0388)	0.0522 (0.0389)	0.0522 (0.0389)
household			-0.0250*** (0.0049)	-0.0251*** (0.0049)	-0.0251*** (0.0049)
readwrite			-0.0998 (0.1258)	-0.1044 (0.1274)	-0.1045 (0.1275)
familyincome			0.0979*** (0.0090)	0.0980*** (0.0090)	0.0980*** (0.0090)
educ			0.0261*** (0.0037)	0.0260*** (0.0037)	0.0260*** (0.0038)
interviews				-0.0072 (0.0078)	-0.0070 (0.0083)
jobs					-0.0012 (0.0107)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	3,466	3,446	3,446	3,446	3,446
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0211	0.0856	0.1389	0.1391	0.1391

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 19. Impact of the PSE on labor income using average continuous variables (Secondary Sample)

Dependent Variable	(1) Log(LABINaver$_{it}$)	(2) Log(LABINaver$_{it}$)	(3) Log(LABINaver$_{it}$)	(4) Log(LABINaver$_{it}$)	(5) Log(LABINaver$_{it}$)
time	0.1113***	0.1133***	0.1130***	0.1130***	0.1130***
	(0.0267)	(0.0259)	(0.0250)	(0.0250)	(0.0250)
beneficiaries	0.0130	0.0113	0.0161	0.0216	0.0242
	(0.0390)	(0.0375)	(0.0371)	(0.0374)	(0.0376)
timetreated	0.1220**	0.1224**	0.1229**	0.1229**	0.1229**
	(0.0515)	(0.0496)	(0.0485)	(0.0484)	(0.0485)
categorical	0.1277***	0.1322***	0.1064***	0.1077***	0.1082***
	(0.0301)	(0.0293)	(0.0286)	(0.0286)	(0.0286)
age		0.0073***	0.0072***	0.0071***	0.0071***
		(0.0018)	(0.0017)	(0.0017)	(0.0017)
women		-0.3265***	-0.3024***	-0.3024***	-0.3026***
		(0.0221)	(0.0215)	(0.0215)	(0.0216)
disability		-0.1409**	-0.0975*	-0.0971	-0.0974*
		(0.0554)	(0.0532)	(0.0532)	(0.0533)
children		-0.0276**	0.0135	0.0137	0.0137
		(0.0112)	(0.0110)	(0.0110)	(0.0110)
indigenous		-0.0376	0.0427	0.0410	0.0411
		(0.0419)	(0.0403)	(0.0404)	(0.0404)
household			-0.0248***	-0.0249***	-0.0249***
			(0.0051)	(0.0051)	(0.0051)
readwrite			-0.1109	-0.1159	-0.1161
			(0.1266)	(0.1284)	(0.1285)
familyincome			0.1057***	0.1059***	0.1059***
			(0.0094)	(0.0094)	(0.0094)
educ			0.0274***	0.0273***	0.0272***
			(0.0038)	(0.0038)	(0.0038)
interviews				-0.0084	-0.0076
				(0.0080)	(0.0086)
jobs					-0.0046
					(0.0119)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	3,569	3,547	3,547	3,547	3,547
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0384	0.1041	0.1592	0.1595	0.1596

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 20. Impact of the PSE on labor income using maximum continuous variables (Secondary Sample)

Dependent Variable	(1) Log(LABIN-max$_{it}$)	(2) Log(LABIN-max$_{it}$)	(3) Log(LABIN-max$_{it}$)	(4) Log(LABIN-max$_{it}$)	(5) Log(LABIN-max$_{it}$)
time	0.2888***	0.2906***	0.2904***	0.2904***	0.2903***
	(0.0255)	(0.0248)	(0.0239)	(0.0240)	(0.0240)
beneficiaries	0.0122	0.0114	0.0156	0.0203	0.0224
	(0.0392)	(0.0377)	(0.0374)	(0.0376)	(0.0377)
timetreated	0.1098**	0.1100**	0.1105**	0.1105**	0.1105**
	(0.0494)	(0.0477)	(0.0467)	(0.0467)	(0.0467)
categorical	0.2445***	0.2489***	0.2249***	0.2260***	0.2264***
	(0.0301)	(0.0292)	(0.0285)	(0.0286)	(0.0285)
age		0.0073***	0.0071***	0.0071***	0.0071***
		(0.0018)	(0.0017)	(0.0017)	(0.0017)
women		-0.3059***	-0.2834***	-0.2834***	-0.2835***
		(0.0211)	(0.0206)	(0.0206)	(0.0206)
disability		-0.1476***	-0.1077**	-0.1074**	-0.1076**
		(0.0543)	(0.0523)	(0.0523)	(0.0524)
children		-0.0267**	-0.0113	0.0115	0.0114
		(0.0109)	(0.0108)	(0.0107)	(0.0107)
indigenous		-0.0297	0.0439	0.0424	0.0425
		(0.0401)	(0.0382)	(0.0383)	(0.0383)
household			-0.0242***	-0.0243***	-0.0243***
			(0.0049)	(0.0049)	(0.0049)
readwrite			-0.1001	-0.1044	-0.1046
			(0.1172)	(0.1188)	(0.1189)
familyincome			0.0987***	0.0989***	0.0989***
			(0.0092)	(0.0092)	(0.0092)
educ			0.0248***	0.0247***	0.0247***
			(0.0036)	(0.0036)	(0.0036)
interviews				-0.0073	-0.0067
				(0.0076)	(0.0081)
jobs					-0.0036
					(0.0106)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	3,569	3,547	3,547	3,547	3,547
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0971	0.1579	0.2067	0.2069	0.2069

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 21. Impact of the PSE on labor income using average continuous variables without upper outliers (Secondary Sample)

Dependent Variable	(1) Log(LA-BINaver2$_{it}$)	(2) Log(LA-BINaver2$_{it}$)	(3) Log(LA-BINaver2$_{it}$)	(4) Log(LA-BINaver2$_{it}$)	(5) Log(LA-BINaver2$_{it}$)
time	0.1266*** (0.0260)	0.1287*** (0.0252)	0.1284*** (0.0243)	0.1285*** (0.0243)	0.1285*** (0.0243)
beneficiaries	0.0059 (0.0368)	0.0035 (0.0353)	0.0087 (0.0348)	0.0144 (0.0351)	0.0165 (0.0355)
timetreated	0.1349*** (0.0498)	0.1353*** (0.0479)	0.1358*** (0.0467)	0.1357*** (0.0467)	0.1357*** (0.0467)
categorical	0.1249*** (0.0296)	0.1286*** (0.0286)	0.1051*** (0.0279)	0.1065*** (0.0280)	0.1069*** (0.0279)
age		0.0062*** (0.0017)	0.0064*** (0.0016)	0.0064*** (0.0016)	0.0064*** (0.0016)
women		-0.3303*** (0.0214)	-0.3068*** (0.0208)	-0.3067*** (0.0208)	-0.3068*** (0.0208)
disability		-0.1315** (0.0549)	-0.0879* (0.0527)	-0.0089 (0.0079)	-0.0877* (0.0527)
children		-0.0224** (0.0109)	0.0176 (0.0109)	0.0179 (0.0109)	0.0178 (0.0109)
indigenous		-0.0359 (0.0405)	-0.0414 (0.0393)	0.0397 (0.0394)	0.0398 (0.0394)
household			-0.0249*** (0.0049)	-0.0249*** (0.0049)	-0.0250*** (0.0049)
readwrite			-0.1209 (0.1265)	-0.1261 (0.1284)	-0.1263 (0.1285)
familyincome			0.1033*** (0.0091)	0.1035*** (0.0091)	0.1035*** (0.0091)
educ			0.0277*** (0.0036)	0.0276*** (0.0036)	0.0275*** (0.0036)
interviews				-0.0089 (0.0079)	-0.0082 (0.0084)
jobs					-0.0037 (0.0118)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	3,545	3,523	3,523	3,523	3,523
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.0443	0.1132	0.1700	0.1704	0.1704

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 22. Impact of the PSE on labor income using maximum continuous variables without upper outliers (Secondary Sample)

Dependent Variable	(1) Log(LABIN-max2$_{it}$)	(2) Log(LABIN-max2$_{it}$)	(3) Log(LABIN-max2$_{it}$)	(4) Log(LABIN-max2$_{it}$)	(5) Log(LABIN-max2$_{it}$)
time	0.3041*** (0.0247)	0.3060*** (0.0239)	0.3057*** (0.0231)	0.3057*** (0.0231)	0.3058*** (0.0231)
beneficiaries	0.0048 (0.0371)	0.0034 (0.0356)	0.0081 (0.0350)	0.0131 (0.0353)	0.0147 (0.0356)
timetreated	0.1218** (0.0477)	0.1220*** (0.0459)	0.1225*** (0.0449)	0.1225*** (0.0448)	0.1225*** (0.0448)
categorical	0.2416*** (0.0295)	0.2452*** (0.0285)	0.2234*** (0.0279)	0.2246*** (0.0279)	0.2249*** (0.0279)
age		0.0061*** (0.0016)	0.0062*** (0.0015)	0.0062*** (0.0015)	0.0062*** (0.0015)
women		-0.3090*** (0.0204)	-0.2873*** (0.0199)	-0.2872*** (0.0199)	-0.2873*** (0.0199)
disability		-0.1379*** (0.0537)	-0.0981* (0.0517)	-0.0977* (0.0517)	-0.0979* (0.0518)
children		-0.0213** (0.0105)	0.0156 (0.0106)	0.0158 (0.0106)	0.0158 (0.0106)
indigenous		-0.0281 (0.0385)	0.0428 (0.0371)	0.0412 (0.0372)	0.0413 (0.0372)
household			-0.0243*** (0.0047)	-0.0243*** (0.0047)	-0.0243*** (0.0047)
readwrite			-0.1107 (0.1170)	-0.1153 (0.1187)	-0.1155 (0.1187)
familyincome			0.0956*** (0.0087)	0.0957*** (0.0087)	0.0957*** (0.0087)
educ			0.0251*** (0.0034)	0.0251*** (0.0034)	0.0250*** (0.0034)
interviews				-0.0078 (0.0075)	-0.0073 (0.0080)
jobs					-0.0027 (0.0104)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	3,545	3,523	3,523	3,523	3,523
Mean	1,255.18	1,255.18	1,255.18	1,255.18	1,255.18
Adjusted R^2	0.1098	0.1731	0.2229	0.2232	0.2232

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 23. Impact of the PSE on Employment Quality (Secondary Sample)

	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
Dependent Variable	(1) $BENEFIT_{it}$	(2) $BENEFIT_{it}$	(3) $BENEFIT_{it}$	(4) $BENEFIT_{it}$	(5) $BENEFIT_{it}$
time	0.1037*** (0.0127)	0.1030*** (0.0127)	0.1025*** (0.0127)	0.1028*** (0.0127)	0.1030*** (0.0127)
beneficiaries	-0.0581*** (0.0205)	-0.0522** (0.0206)	-0.0536*** (0.0206)	-0.0545*** (0.0208)	-0.0564*** (0.0210)
timetreated	0.1752*** (0.0262)	0.1686*** (0.0262)	0.1686*** (0.0262)	0.1684*** (0.0262)	0.1682*** (0.0263)
age		0.0026*** (0.0009)	0.0026*** (0.0009)	0.0026*** (0.0009)	0.0026*** (0.0009)
women		-0.0025 (0.0112)	-0.0012 (0.0113)	-0.0011 (0.0113)	-0.0009 (0.0113)
disability		0.0227 (0.0267)	0.0256 (0.0267)	0.0256 (0.0267)	0.0257 (0.0267)
children		-0.0001 (0.0060)	0.0003 (0.0061)	0.0002 (0.0061)	0.0003 (0.0061)
indigenous		-0.0273 (0.0221)	-0.0260 (0.0221)	-0.0259 (0.0221)	-0.0262 (0.0221)
household			0.0001 (0.0026)	0.0001 (0.0026)	0.0003 (0.0026)
readwrite			-0.0692 (0.0811)	-0.0688 (0.0811)	-0.0691 (0.0811)
familyincome			0.0106** (0.0046)	0.0106** (0.0046)	0.0106** (0.0046)
educ			0.0096*** (0.0020)	0.0096*** (0.0020)	0.0096*** (0.0020)
interviews				0.0015 (0.0040)	0.0008 (0.0042)
jobs					0.0035 (0.0057)
Year FE	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES
Observations	7,578	7,530	7,530	7,530	7,530
Mean	0.3493	0.3493	0.3493	0.3493	0.3493
Pseudo R^2	0.0331	0.0367	0.0373	0.0374	0.0374
Correctly Classified	60.72%	61.16%	61.35%	61.26%	61.24%

Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 24. Impact of the PSE on Individual Employment Benefits (Secondary Sample)

Dependent Variable	(a) $bonus_{it}$	(b) $secbonus_{it}$	(c) $healthcare_{it}$	(d) $maternity_{it}$	(e) $compensation_{it}$	(f) $fiveyearterm_{it}$	(g) $pension_{it}$
	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects	Average Marginal Effects
time	0.0980*** (0.0127)	-0.0249*** (0.0066)	0.1294*** (0.0116)	0.0284*** (0.0065)	0.0407*** (0.0087)	0.0240*** (0.0068)	0.1159*** (0.0094)
beneficiaries	-0.0598*** (0.0209)	-0.0347*** (0.0111)	-0.0527*** (0.0205)	-0.0224* (0.0126)	-0.0583*** (0.0159)	-0.0533*** (0.0136)	-0.0234 (0.0173)
timetreated	0.1770*** (0.0261)	0.0446*** (0.0136)	0.1483*** (0.0246)	0.0422*** (0.0143)	0.0594*** (0.0189)	0.0450*** (0.0156)	0.0482** (0.0202)
age	0.0026*** (0.0009)	0.0006 (0.0007)	0.0026*** (0.0008)	0.0001 (0.0004)	0.0020*** (0.0006)	0.0007 (0.0005)	0.0016*** (0.0006)
women	-0.0011 (0.0112)	0.0001 (0.0058)	-0.0473*** (0.0103)	-0.0023 (0.0056)	-0.0125 (0.0077)	-0.0155** (0.0061)	-0.0179** (0.0080)
disability	0.0290 (0.0265)	-0.0136 (0.0153)	0.0334 (0.0248)	0.0135 (0.0137)	-0.0026 (0.0191)	0.0306** (0.0145)	0.0237 (0.0197)
children	0.0015 (0.0060)	0.0059* (0.0032)	0.0078 (0.0057)	0.0117*** (0.0031)	0.0052 (0.0042)	0.0085** (0.0033)	0.0103** (0.0044)
indigenous	-0.0185 (0.0219)	-0.0055 (0.0120)	-0.0384* (0.0210)	-0.0081 (0.0122)	-0.0194 (0.0160)	-0.0186 (0.0133)	-0.0488*** (0.0175)
household	-0.0007 (0.0026)	-0.0065*** (0.0022)	-0.0038 (0.0025)	-0.0045** (0.0021)	-0.0096*** (0.0025)	-0.0049** (0.0021)	-0.0082*** (0.0025)
readwrite	-0.0808 (0.0804)	0.0425 (0.0548)	-0.0311 (0.0808)	-0.0132 (0.0405)	0.0338 (0.0606)	0.0029 (0.0477)	-0.0350 (0.0615)
familyincome	0.0089** (0.0046)	0.0247*** (0.0022)	0.0223*** (0.0041)	0.0176*** (0.0021)	0.0192*** (0.0029)	0.0200*** (0.0022)	0.0243*** (0.0031)
educ	0.0086*** (0.0019)	0.0010 (0.0010)	0.0180*** (0.0019)	0.0058*** (0.0011)	0.0048*** (0.0014)	0.0040*** (0.0011)	0.0080*** (0.0015)
interviews	-0.0004 (0.0041)	0.0046** (0.0018)	-0.0010 (0.0038)	-0.0017 (0.0022)	0.0043* (0.0024)	0.0043** (0.0018)	0.0029 (0.0029)
jobs	0.0047 (0.0055)	0.0084** (0.0039)	0.0047 (0.0050)	-0.0078 (0.0048)	0.0135*** (0.0038)	0.0076** (0.0035)	-0.0043 (0.0058)
Year FE	YES	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES	YES
Observations	7,530	7,521	7,530	7,521	7,530	7,521	7,521
Mean	0.3312	0.0775	0.2118	0.0419	0.1004	0.0583	0.0812
Pseudo R^2	0.0384	0.0603	0.0684	0.0675	0.0414	0.0616	0.0689
Correctly Classified	62.31%	92.87%	69.99%	93.51%	87.01%	92.24%	84.94%

Robust standard errors are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.