Reducing Job Informality and Youth Unemployment in Argentina: A Quasi-Experimental Evaluation of a Sector-Based Skills-Training Program for Young Unemployed People

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To my parents and my husband

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Abstract of Thesis

Reducing Job Informality and Youth Unemployment in Argentina: A Quasi-Experimental Evaluation of a Sector-Based Skills-Training Program for Young Unemployed People

This thesis presented an evaluation of Ce.Fo.Se.'s sector-based skills training program targeted to young unemployed individuals from 2012 to 2016. I used several methodologies to conduct this program evaluation, including a before-and-after analysis, a difference-in-difference econometric model, and semi-structured interviews. From the difference-in-difference analysis, my strongest methodology, I conclude that individuals who graduate from the program are 20.1 percentage points more likely to be formally employed than the control group. I also found that the training had a significantly higher impact for graduates younger to 24 years old: their increased probability of getting a formal job was 6.7 percentage points higher than those between the ages of 24 and 27 and 18.6 percentage points higher than older individuals. These results have strong policy implications since the program can help equip young adults with relevant skills, increasing their employability, and help reduce the formal employment gap among youth and adults. Furthermore, the thesis explores three additional questions: whether the intensity and skills of the training matters; whether unemployment is a lack of skills or a matching problem; and, whether there are any differential effects depending on the financing mechanism –grant vs. fiscal credit. Finally, I carried out a cost-benefit analysis to calculate the total months it could take to recover investing in these types of programs. Using the difference-in-difference estimations and projecting three different scenarios, the repayment period can be between 5 and 30 months from trainees' graduation, indicating a very high return for the government and the individuals trained.

Table of Contents

Dedication iii

Acknowledgments iv

Abstract of Thesis v

Table of Contents vi

List of Figures viii

List of Tables ix

Glossary of Terms x

Chapter 1: Introduction 1

Chapter 2: Literature Review 4

Chapter 3: The Chamber and Ce.Fo.Se.'s Training Program 9

Financing Ce.Fo.Se.'s Training Programs: a Public-Private Partnership 10

Financing Mechanism 1: "MoL-ADIMRA" 11

Financing Mechanism 2: Fiscal Credit for Professional Training 13

Chapter 4: Research Questions and Empirical Strategy 14

Before-and-After Analysis: Sample, Data, and Summary Statistics 18

Difference-in-Difference Analysis: Sample, Data, and Baseline Equivalency 19

The General Econometric Model 23

Survey to Local Metallurgic Firms 25

Chapter 5: Program Evaluation Findings 26

Main Research Question: Training effect on Formal Employment 26

1. Do the intensity of the training and skills matter? 36

2. Do skills matter or is it a problem of matching? 41

3. Do training programs cause different effects depending on the financing method? (Grant vs. Fiscal Credit). Do they need to be publicly financed? 44

Two Final Reflections on Findings: Gender Biases and Overall Employment 47

Discussion on Potential Selection Bias 49

Chapter 6: Cost-Benefit Analysis 53

Chapter 7: Conclusion 58

References 61

Appendices 65

List of Figures

Figure 1. Before-and-After Analysis. Change in Participants' Employment Status. 27

Figure 2. Formal Employment 2012-2016 32

Figure 3. Argentina's Macro-level Indicators 2012-2016 34

Figure 4. Graduates and Specialization 39

Figure 5. Firms Employing Graduates from Ce.Fo.Se. 43

Figure 6. Do you Currently Use Skills you Learnt in Training? 44

Figure 7. Enrollment Motivation and Training Cost 46

Figure 8. Share of Women Employed at Operative-Leve Positions at Surveyed Firms... 48

List of Tables

Table 1. Before-and-After Sample Summary Statitics 19

Table 2. DD Summary Statistics and Baseline Equivalency 22

Table 3. Before-and-After Analysis. Change in Employment Outcomes 28

Table 4. Before-and-After Regressions on Formal Employment 30

Table 5. Before-and-After. Additional Regressions 31

Table 6. Difference-in-Difference Analysis. Employment Variation 2012-2016. 32

Table 7. Difference-in-Difference. Regressions on Formal Employment. 35

Table 8. Intensity of Treatment by Total Courses and Hours Trained 37

Table 9. Type of Skills Trained and Specialization 40

Table 10. Testing Skills vs. Matching Problems 42

Table 11. Testing Differential Effects in Financing Mechanisms 45

Table 12. Accounting for Selection Bias in Difference-in-Difference Analysis 50

Table 13. Cost-Benefit Analysis. Estimation per Trainee in AR Pesos..... 56

Table 14. NPV of Investing in the Skills-Training Program per Trainee. 57

Glossary of Terms

ADIMRA	Asociación de Industriales Metalúrgicos de la República Argentina
BaA	Before-and-After
Ce.Fo.Se.	Centro de Formación y Servicios
DD	Difference-in-Difference
ILO	International Labour Organization
IMF	The International Monetary Fund
INDEC	Instituto Nacional de Estadística y Censos
LLP	Lifelong Learning Plan
MoL	Ministy of Labor
MTEySS	Ministerio de Trabajo, Empleo y Seguridad Social
NPV	Net Present Value
OIT	Organización Internacional del Trabajo
S4YE	Solutions for Youth Employment
U.O.M	Unión de Obreros Metalúrgicos
WB	The World Bank

Chapter 1: Introduction

Sector-based skills-training programs can be a promising tool to reduce income inequality and youth unemployment rates in Latin America, particularly in Argentina. During the 1990s, globalization, new technologies, and international trade liberalization facilitated skill biased technical change in the region, increasing the private sector's demand for skilled labor and spurring income inequality (Gasparini, et al. 2011). Secondary educational systems, which equip the largest group of new workers in the region, have not been able to adapt to these changes, creating a disconnection between the skills high-school graduates have and those that the market demands (Bassi, et al. 2012). Young people are the most affected from these imbalances since, besides lacking relevant skills, they lack experience when entering the labor market. The Solutions for Youth Employment (S4YE) baseline report (2015) shows that youth in Latin America are twice as likely to be unemployed as adults. Argentina's case is even more extreme since the youth unemployment rate in 2014 was 3.6 times greater than that of the overall population.[1]

During the last decade, Argentina's government focused on building a productive workforce to reduce high unemployment rates left from the country's economic crisis in 2001. By 2002, the crisis along with globalization's social impact increased the unemployment and poverty rate to 21.5% and 57.5%, respectively (OIT 2004). As a result, the government implemented "pro-poor economic policies and placed employment at the center of the country's macroeconomic policy" (ILO 2015). A key concern during this decade was to build the necessary skilled labor force in different productive sectors

[1] Based on own calculations using ILO's database (2016).

that had challenges filling job vacancies (Valente 2011), including the metallurgic industry. Thus, the government launched the Lifelong Learning Project (LLP) in 2007, which aim at enhancing people's employability and expanding relevant labor-market skills through training youth and adults in specific occupations needed in different sectors of the economy.

This paper aims at contributing to the existing literature on the effectiveness of sector-based skills-training programs by evaluating the LLP at a local level. Specifically, the *Center for Learning and Services* (Ce.Fo.Se. in Spanish) at the *Chamber of Metallurgic Industries in the Center of the Province of Santa Fe* has been implementing the LLP since 2007, and more intensively since 2012. The center provides skills-training programs specifically related to the metallurgic industry to low-skilled unemployed people, who are mostly between 18 and 33 years old. The type of competency-based courses offered is a result of a continuous consultation between the Ministry of Labor (MoL) and the private sector demands, which are collected through surveys to local firms and regular meetings with ADIMRA, the national association for metallurgic industries, which also finance part of the trainings.

I evaluate the effectiveness of the program from 2012 to 2016 using not only a before-and-after (BaA) analysis but, more rigorously, a difference-in-difference (DD) one with a five-year panel dataset. For the BaA analysis, I gathered data from administrative records and surveyed graduates from the training program. For the DD analysis, I combined data from administrative records with hand-collected employment-status microdata from Argentina's Social Security website. The DD analysis compares a treatment group –composed of all trainees who graduated from the training during these

years–, and a control group –composed of people who pre-enrolled in the training but were not trained. I discuss potential biases to my estimations resulting from the composition of these two groups. Finally, I also surveyed local firms in the metallurgic industry to understand the supply side needs and perspectives on the program.

Overall the program evaluation results from the DD analysis, the most rigorous methodology I used, are significantly positive. In the first place, training increases graduates' probability of having a formal job by 20.1 percentage points above a control group, controlling for demographic variables and fixed effects. The results are similar to Carrillo's et al. (2014) sector-based evaluation in Argentina. Secondly, graduates under 24 years old benefit the most from the training program: their increased probability of getting a formal job is 6.7 percentage points higher than those between the ages of 24 and 27 and 18.6 percentage points higher than older individuals. Thirdly, I find that there are diminishing returns to more training and that the types of skills graduates receive training on matter. In particular, those who graduated and specialized on operator, machining, and welding skills had remarkably better payoffs (a 19.2 to 35.7 percentage points' effect) than other specializations. These findings are consistent not only with firms' responses in a survey I conducted but also when testing whether unemployment is a problem of lack of skills or labor market miss-matches. Finally, although I had expected to find differential effects depending on the financial mechanism –grants from LLP vs. fiscal credit from companies–, I did not find significant differences. These results are consistent with the BaA analysis and qualitative evidence from the surveys I conducted to graduates and firms.

Due to the significant effects of the training program and the need for it to be

financed publicly, I conducted a cost-benefit analysis. Analyzing firms' and trainees' responses on my surveys, I found unlikely that they would be willing or able to finance these type of training programs, leaving the responsibility to the government. Thus, I estimated the costs and benefits of these type of training program using administrative data and the results from the DD analysis. Under three different scenarios –worst, expected, and best case– the investment can be recovered within 5 to 30 months of trainees' graduation.

The rest of the paper proceeds in the following order. Chapter 2 covers a literature review of comparable skills-training program evaluations in Latin America, including those using experimental, quasi-experimental, and non-experimental methodologies. Chapter 3 describes Ce.Fo.Se.'s training program in detail. Chapter 4 presents the research questions and explains the empirical strategy I used for conducting the evaluation. Chapter 5 presents all the findings and Chapter 6 describes the cost-benefit analysis results. Finally, I conclude in Chapter 7.

Chapter 2: Literature Review

There is some evidence on the impact of skills-training programs in Latin America, but almost none of the existent evaluations focus on *sector-based* programs.[2] To the best of my knowledge, there are only six countries in the region that currently have rigorous evaluations on skills-training program: Argentina, Chile, Colombia, Dominican Republic, Peru, and Uruguay. There are only four evaluations that use a Randomized Control Trial, the gold-standard, to evaluate the programs in three of these

[2] Sector-based programs are defined as skills-training programs focus on a specific sector of the economy.

countries. All other use Propensity Score Matching or other econometric techniques to estimate the causal treatment effect. Some evaluations include a cost-benefit analysis of the program.

The four evaluations that used randomized control trials to measure the impact of job-training programs in Latin America are *Jueventud y Empleo* (JE) in Dominican Republic*, Jóvenes en Acción* (JA) in Colombia*,* and *ProJoven* (PJ) in Peru. The three programs were implemented nationwide almost in the same period and were very similar in their design.[3] All three targeted young people and provided three months of in-class training followed up with an internship experience.[4] The experimental evaluations to all three programs found, to some extent, positive impacts. JE program's evaluation found improvements on hourly wages –10 to 17 percentage points higher– and an increment on health-insurance coverage –5 percentage points, conditional on employment–, but did not found significant differences on employment rates nor on the likelihood of having a job [(Card, et al. 2007) and (Ibarrarán, Rosas and Soares 2006)]. JA's program evaluation found mixed effects depending on the graduates' gender: women showed significant wage increases of 19.6 percentage points and a higher probability of having a formal job of 5.3 percentage points while men had modest but positive differences in job formality (Attanasio, Kugler and Meghir 2011). PJ's evaluation found impact on job formality and income increases with some differences depending on age and gender (Díaz and Rosas 2016). Finally, two of these experimental evaluations had a cost-benefit analysis and concluded that the programs were cost-effective.

Although all these four experimental evaluations have significant results, they

[3] JE was implemented from 2001 to 2006, JA from 2001 to 2005, PJ from 1996 to 2010.
[4] JE's on-the-job training duration was two month and JA's and PJ's were three months.

also present measurement validity threats. The most important one is that the skills the programs' courses provided were very diverse. These ranged from general-skills –i.e. work habits, presentation, or résumé building– to specific technical-skills –i.e. welding, bakery, computer, marketing, clerical, or flower cultivation classes.[5] Thus, training programs might not be comparable among themselves or across countries. This is an important measurement validity threat since none of the evaluations used variables distinguishing different courses characteristics, which could have caused different effects on employment outcomes.[6] For example, if there was a shortage of a specific technical skill in the labor market –e.g. welding– or the local economy focused on a specific industry or sector –e.g. metallurgic–, graduates from related technical-courses would have a greater probability of employment than graduates from other courses. Thus, if results are not disaggregated, it could be concluded that all skills-training programs do not increase employment rates or the probability of having a job –as some of the evaluations concluded –, while they may actually do.

Another specific validity threat on the existing experimental evaluations is the lack of dosage differentiation. As all evaluators recognize, courses' duration variability were very high among trainings, but the sample grouped all courses. For example, courses on the JE program could last between 150 and 350 hours. Nonetheless, the evaluation included in the sample any course that lasted at least two weeks (Card, et al. 2007). Thus, three problems arise with this kind of decision. First, it is not clear how many hours of treatment represent those two weeks –e.g. 1h or 40hs a week. Second, the

[5] For details see Ibarrarán, Rosas and Soares (2006), Attanasio, Kugler and Meghir (2011), and Diaz and Rosas (2016).

[6] Although JA program was randomized at the course level, "the treatment effects are weighted average of the effects across many different courses" (Attanasio, Kugler and Meghir 2011, 200)

impact of 2 hours of training can be very different from the impact of 350 hours of training. It can be argued that the probability of behavioral change and learning increases with the total hours of exposure to treatment; thus, trainees' employability may increase with the duration of training. Third, evaluators defined "dropout" as those that did not stayed in treatment for more than two weeks. However, it may be the case that the two first weeks of training were intensive and enough to provide some employability skills to trainees and the dropouts got a job thanks to the JE program. In any of these three cases, the evaluation may fail to accurately measure the real impact of the program.

Finally, there are other quasi-experimental and non-experimental evaluations performed to similar job-training programs in Latin America, most of which took place a long time ago. Through Propensity Score Matching (PSM) techniques Castillo V. et al (2014) evaluated the impact of the Lifelong Learning Project in Argentina between 2010 and 2012. They found that overall sector-based courses increased graduates' probability of having a formal job by 14.67 percentage points above a control group, and that this percentage varied depending on the sector –31.23 percentage points for the metallurgic industry. Aedo and Pizarro (2004) evaluated two different phases of *Chile Joven* implemented from 1991 to 2002, also using PSM techniques. They found that participants increased their earnings by 26.5 percentage points above a control group, as well as the probability of being formally employed by 19 percentage points. Burga, C. (2003), Chacaltana and Sulmont (2003), and Ñopo, H. et al (2002) evaluated *ProJoven* in Peru implemented from 1996 to 2007, they all also used PSM techniques.[7] The first one and second one found an increment on graduates' earnings –127 soles and 27 percentage points, respectively– while the second one found an increment in the probability of

[7] This is the same program Diaz & Rosas (2016) evaluated using a randomized controlled trial.

formal employment of 6 percentage points as well as a 5.5 percentage point increment in weekly hours of work. Bucheli and González Rozada evaluated *Opción Joven* implemented in Uruguay from 1994 to 1997, finding a reduction of 8.5 weeks of job search and an increment in earnings between 18 to 20 percentage points (Naranjo Silva 2002). Finally, Elias, V. et al (2004) performed a cost-benefit analysis to Argentina's *Proyecto Joven* from 1993 to 1999 using non-matching and matching techniques. They estimated a 10 percent rate of return of the program.

To sum up, the existing literature on skills-training programs' evaluations in Latin America present promising impacts on labor outcomes, but there are areas for improvement which I aim at studying in this research paper. I address the lack of skills-course and dosage differentiation that almost all evaluations have by studying only courses related to one sector of the economy: the metallurgic industry. Moreover, I study additional aspects of skills-training programs that have not been evaluated in the past, such as whether certain age groups benefit differently from the training, whether there are certain specializations that have better payoffs, whether unemployment is a matter of skills or mismatches, and whether the programs' source of financing –i.e. grants, fiscal credits– makes a difference. In addition, I use qualitative methods to study whether graduates apply in the workplace the skills they learnt and how often. Finally, it is important to note that most evaluations are on programs that took place in upper-middle income economies. My research project can contribute to filling this present evidence gap in high-income countries in Latin America since I focus on an Argentinean program.

Chapter 3: The Chamber and Ce.Fo.Se.'s Training Program

The *Chamber of Metallurgic Industries of the Center of the Province of Santa Fe* (the Chamber) was founded in Gálvez in 2002. The institution is a regional chamber of ADIMRA –the national association for metallurgic industries– and its aim is to improve the competitiveness and development of local metallurgic firms in the center of the Province of Santa Fe. The chamber has 12 board members who are in charge of representing the interest of all metallurgic firms in the region –about 384 firms–, but particularly the interest of 45 member firms.[8]

In 2007, the chamber created within the institution the Center for Training and Services (Ce.Fo.Se. in Spanish) specifically focused on the metallurgic sector, which became a nationally recognized center and the main pillar of the Chamber. Ce.Fo.Se.'s goal is to increase the industry's labor productivity through providing learning and professional training opportunities. Although the center offers training to all productive levels of a firm, it has distinguished itself for training people in operative related occupations. The training institution is certified in ISO norm 29,990, which guarantees the quality in management systems of training-providers. Two national institutions endorse Ce.Fo.Se. as a formal training center: the Ministry of Labor (MoL) and ADIMRA. In 2008, the MoL declared Ce.Fo.Se. a Professional Training Institution and, in 2011, made it a member of Argentina's Lifelong Learning Network. And, ADIMRA made Ce.Fo.Se. a member of its Professional Training Network.

Throughout the years, Ce.Fo.Se. has offered a great variety of courses to satisfy the present and future labor demand of local metallurgic firms (see Appendix A for a list

[8] Based on own calculations from the last census to firms in Santa Fe (INDEC 2003).

of current training programs offered). Most of the courses the center offers are technical ones and are based on certified competency-based norms and curricula, offering graduates a national certification. The great majority of courses last 48 hours each and can train up to 25 individuals at a time. The courses offered vary in a yearly basis according to firms' demands. However, throughout the years, there has been a persistent demand for three main occupations within the field: machinist, welder, and assembler. All operative level courses are tuition free to students while those for mid-level and supervisory positions may have a fee. Students can take as many courses as they wish, but not simultaneously. According to the center's administrative records, currently, the center offers about 40 courses in a yearly basis, training on average 460 people a year. Since 2012, the training institution has conferred 1,852 certifications on competency-based training and, on average, graduates have completed 2.21 courses. It is important to note for my analysis that students are usually unemployed (77%), young (70%), and male (93%). [9]

Financing Ce.Fo.Se.'s Training Programs: a Public-Private Partnership

In order to provide relevant training for the local metallurgic industry, Ce.Fo.Se. involves in the process three key stakeholders: member firms, the MoL, and ADIMRA. Members firms are critical to the process since they are the ones that first express their interest and jumpstart the demand for skills-training programs. Particularly, Ce.Fo.Se. gathers information from firms on skills-shortage or future skills' demand using two mechanisms: the chamber's monthly meeting, where just the 12 chamber's board members meet and communicate the industry's problems and interests; and, an end-of-

[9] In this paper I consider young people those who are between 18 to 33 years old.

the-year annual survey sent to all member firms with the specific goal of inquiring foreseen needed skills.

After Ce.Fo.Se. collects information on training demands from metallurgic firms, the training institution designs the courses and looks for ways to fund them. For the operative-level courses, which are tuition free, Ce.Fo.Se. use two funding mechanisms. The first one pools funds from, what I call, "MoL-ADIMRA" funds which combines funds from the MoL's Lifelong Learning Program and ADIMRA. The second mechanism is through the MoL's "Fiscal Credit for Professional Training" normative. The following sections describe the main differences between these two financing mechanisms.

Financing Mechanism 1: "MoL-ADIMRA"

When there is a general consensus in the local metallurgic industry for a specific skill, the funding for the courses comes from the "MoL-ADIMRA" mechanism. The MoL's Lifelong Learning Plan (LLP) finances the greatest part of the competency-based training programs offered at Ce.Fo.Se. and ADIMRA finances the remaining portion.

LLP is a nationwide project launched in 2007 with the technical and financial cooperation of the World Bank. The project aims to enhance employability and expand relevant labor-market skills through training youth and adults in specific occupations needed in different sectors of the economy. One of LLP objectives is to have in place a "labor competency-based certification system," which comprises sector-based training-curriculums, competency-based norms, certified training institutions, and training for trainers. The creation of the competency-based norms and their respective curriculums was a multilateral process where the MoL, firms' representatives, trade unions, chambers of industry and commerce, and other associations participated (WBG 2007, 7). In the

particular case of the metallurgic industry, there are 45 competency-based norms up to date. Each norm describes the particular occupation and tasks to which it applies, the competencies someone with a certain occupation must have in order to obtain a certification, and how to evaluate the person's performance and knowledge on a certain occupation (MTEySS 2016). Since 2011, Ce.Fo.Se. has been part of LLP's Network and has offered sector-based courses that meet the requirements of LLP's norms and curriculums. Thus, the MoL has been willing to finance great part of the courses the training institution offers. However, due to LLP's spending limits, Ce.Fo.Se. also receives support from other sources to fully fund its courses.

ADIMRA provides the additional funding needed for financing Ce.Fo.Se.'s competency-based courses. ADIMRA was founded in 1904 to represent and protect the interests of metallurgic companies in Argentina, by congregating 59 sectoral and regional chambers. Through the collective bargaining agreement No. 58/01, metallurgic firms are obliged to finance ADIMRA by contributing 1 percent of their total gross accrued employees' remunerations (MTEySS 2001). With this budget, the association focuses in three main goals: designing industrials policies that would develop the industry; being a liaison between firms, the public government, and national and international organizations; and promoting learning and professional training at all levels (ADIMRA 2016). To achieve this last goal, ADIMRA's Training Committee finances competency-based courses provided at its network training centers, with Ce.Fo.Se. being one of them. ADIMRA also signed a public-private partnership with the MoL in 2012 to co-finance specific competency-based courses for the metallurgic industry. Thus, when the cost of Ce.Fo.Se.'s training programs exceeds LLP's spending limits, ADIMRA finance the

residual (see Appendix B for 2016 LLP's spending limits and ADIMRA's contribution to Ce.Fo.Se.'s signature courses).

Financing Mechanism 2: Fiscal Credit for Professional Training

The second mechanism to finance Ce.Fo.Se.'s courses is the Fiscal Credit for Professional Training normative. In 1980, Law 22,317 established the legal framework for allowing companies to obtain a fiscal credit by investing in technical education, either for their own employees or for unemployed people. The law allows a maximum deduction depending on the size of the company: for SMEs it is up to 8% of the previous 12 month salaries while for big companies the deduction is up to 0.8% (MTEySS 2016).[10] This law allows companies to offer training opportunities at Professional Training Institutions (as Ce.Fo.Se. is) at zero cost since if firms did not use the fiscal credit they would have to pay the same amount for taxes. Thus, the center uses this type of financing method to provide firms a specific training for their employees or for training unemployed people in occupations with a shortage, or foreseen, labor supply for a specific firm. In most cases, big firms are the ones that use this financing mechanism. For example, firms have trained their employees in "Driving a Forklift Truck" and have also trained unemployed people for welding occupations.

To summarize, the way Ce.Fo.Se. sets up the whole process for providing a course ensures an active participation of both the public and the private sector. In one hand, the MoL, under both financial mechanisms, has to verify that the training curriculums meet established labor competency-based norms, so that the training institution can award graduates the matching national certification. Doing so helps the

[10] However, in neither case the total deduction can exceed $500,000 for year 2016. Moreover, the law defines SMEs from 6 to 80 employees and Big as more than 80 employees (MTEySS 2016).

MoL accomplish its objective of enhancing people's employability and expanding relevant labor-market skills. In the other hand, the private sector participates through three main ways: first, jumpstarting the demand for training programs; second, financing the courses through fiscal credits or, indirectly, through paying ADIMRA 1 percent of their total gross accrued employees' remunerations (used for financing the courses); finally, through ADIMRA's representation in ministerial meetings with the MoL.

Chapter 4: Research Questions and Empirical Strategy

The main research question I attempt to answer is whether Ce.Fo.Se.'s sector-based skills-training programs increased the probability of formal employment on young people who were trained between 2012 and 2016. Considering Argentina's context and employment goals, it is relevant to focus my question on "formal employment" and "young people". Argentina's top priority goals agreed with the International Labour Organization through its third, and most recent, Decent Work Country Program (2012-2015) were to "reduce job insecurity and un-registered and informal employment" and to "improve employability and accessibility conditions through creating a better articulation between the private sector and the education and labor-training system," prioritizing certain groups (e.i. young people) (OIT 2013). Thus, measuring the effectiveness of these types of training programs can help understand whether they help achieve these set goals. Moreover, between 35 to 60 percent of Argentineans who are considered employed have informal, precarious, and uncertain jobs: 35 percent of those working for a firm and 60 percent of those who are self-employed (Bertranou y Casanova 2014). Finally, the focus on young people is pivotal since although the unemployment rate between 2012 and 2016 has decreased in Argentina, the youth to adult unemployment ratio has consistently

increased and is currently above 2.5.[11] Thus, I will not only measure the overall effectiveness of the program on young people, but also study whether there are differential effects depending on trainee's age groups.

If Ce.Fo.Se.'s training program is effective, due to a resource constraint and allocation problem, three additional sub-questions arise. First, it is important to try to determine whether the intensity of the training matters and whether there are specific training skills or occupations that are more effective in increasing formal employment. Secondly, it is relevant to understand the cause of unemployment: whether it is a lack of skills or a matching problem. This can be explored through testing whether graduates get the formal job because of the earned skills or because of the training institution's networks. Finally, in order to provide some evidence on the best way to finance these types of training, my third sub-question will explore whether there are any differential effects depending on the financing mechanism –grant vs. fiscal credit– and whether these programs should be publicly funded.

All these research questions try to determine if there is a causal relationship between participating in the program and the probability of being formally employed. Applying Angrist and Pischke (2008) methodology, we could determine this causal relationship by comparing the change in the employment status of an individual after being trained and what that status would had been had the individual not being trained (so that the only explanation to the employment status difference is the training). To describe the problem more precisely, we can think of D_i as a binary variable determining whether someone was trained or not, taking the value 1 or 0 respectively. The outcome of interest,

[11] According to own calculations using the World Development Indicators from the World Bank Group database.

formal employment status, is another binary variable denoted by Y_i. Thus, for every individual there are two potential variables:

$$\text{potential outcome} = \begin{cases} Y_{1i} \; if \; D_i = 1 \\ Y_{0i} \; if \; D_i = 0 \end{cases}$$

where Y_{1i} is the individual's employment status if he had been trained and Y_{0i} is the employment status of the same individual had he not been trained. The observed outcome can be written as

$$Y_i = \; Y_{0i} + (Y_{1i} - Y_{0i})D_i$$

where the causal effect, what we intend to measure if it was possible, is the difference between the two potential outcomes ($Y_{1i} - \; Y_{0i}$). Since it is impossible to compare the same individual in these two situations we need a counterfactual, which allows to measure through a control group what would have happened if the individual had not being training (Y_{0i} when D_i=0). With the counterfactual, it is possible to compare the averages on the employment status of individuals who were and were not trained, which is equal to

$$E\,[\,Y_i \mid D_i = 1\,] - E\,[\,Y_i \mid D_i = 0\,]$$

However, in order to determine that the training causes the observed difference in average employment, we need to make sure the control and treatment groups are comparable. Thus, there should not be selection bias since, as Angrist and Pischke (2008) show, the observed difference in outcomes is equal to

$$E\,[\,Y_{1i} \mid D_i = 1\,] - E\,[\,Y_{0i} \mid D_i = 1\,] \quad + \quad E\,[\,Y_{0i} \mid D_i = 1\,] - E\,[\,Y_{0i} \mid D_i = 0\,]$$

average causal effect of training on those who were trained — *selection bias*

Therefore, the gold-standard for the estimation of the counterfactual is through assigning participants to treatment randomly since it creates two groups, treatment and control, with statistically equivalent averages for all their characteristics, making D_i independent of the potential outcome (Angrist and Pischke 2008). Thus, the difference in average Y_{0i} is the same between those who received and did not the training, making the selection bias zero. Evaluations that randomly assign participants to treatment are called Randomized Control Trial (RCT) evaluation.

Instead of conducting an RCT I used two econometric models to answer the research questions: a before-and-after (BaA) analysis and a difference-in-difference (DD) one with a five-year panel dataset. An RCT in Ce.Fo.Se.'s case is not possible to conduct not only because of the limitations of one person conducting such ambitious project but also due to timing and the training institution's procedures in enrolling participants into the program. Thus, I first conducted a BaA analysis on a sample of people who received training between 2012 and 2016. As explained above, this analysis does not determine the causal effects the program produced since it only tracks changes in outcomes for the participants over time. In other words, it assumes that the outcome for a participant would have been exactly the same if the training had not existed, using the pre-training outcome as the counterfactual (Gertler, et al. 2011, 22). Although this assumption almost never holds, a BaA analysis provides a first insight on outcomes and whether more analysis is worthwhile conducting. Then, to estimate the causal effect of training on the probability of being employed, I conducted a DD analysis with panel data on all people who graduated from the trainings between 2012 and 2016 and a control group. This is the most rigorous method I used since it estimates the variation on the outcome of interest

over time between the people who graduated from the program and those who did not (the counterfactual) (Gertler, et al. 2011, 95). However, since people were not randomly assigned to the training, there results of the evaluations might be biased. Thus, a final discussion on how to mitigate the potential bias will follow after the findings section.

Before-and-After Analysis: Sample, Data, and Summary Statistics

The sample for the BaA analysis consist of 158 individuals, who were selected at random using Ce.Fo.Se.'s Administrative database. The training institution provided me a list with contact information on all the individuals who had been trained with a certified competency-based curriculum between 2012 and 2016. Since the research question is concerned with young people, I created a sample on individuals who were between 18 and 33 years old –about 70% of graduates– at June 2016. From 412 individuals with this characteristic, half were randomly assigned for being surveyed, but only 158 were surveyed due to time constraints. Individuals were initially contacted through telephone or WhatsApp to agree the interview date and time.

The data available for this sample came from two sources: administrative data and a survey. Ce.Fo.Se.'s administrative data includes demographic and employment data before training. The in-person or telephone survey, depending on individual availability, was designed as a structured interview and included demographic data, employment data before-training, employment data after-training, and some qualitative questions (see Appendix C for the complete set of questions in the survey). The training institution hired an intern, who I trained and who helped me carry out all the surveys. Once we finished surveying people, I cross-referenced the surveys with the administrative data.

Table 1 shows the summary statistics for the sample of the Before-and-After

analysis. Almost all graduates are young, male (97%), and have internet access (89%). About half of trainees have not achieved a high-school degree. Although most of them live in Galvez, a significant number (19%) travels from nearby cities to get trained. On average, surveyed trainees have 0.52 dependent, which is high considering their average age.

Table 1. Before-and-After Sample Summary Statistics

Variable	Mean	Std. Dev.	Percentile			Total Obs.
			25th	50th	75th	
Age (before training)	22.73	4.55	20	22	24	158
Age (after training)	24.77	4.75	21	24	27	158
Male	0.97	0.18	1	1	1	158
Education*	3.51	1.05	3	4	4	158
High School Graduate	0.39	0.49	0	0	1	158
More than High School	0.12	0.33	0	0	0	158
Lives in Galvez	0.81	0.39	1	1	1	158
Health Insurance	0.35	0.48	0	0	1	158
Total Dependents	0.52	0.83	0	0	1	158
Has Internet Access	0.89	0.32	1	1	1	158

* Education varies from 1 to 8, being 1 if individual got some primary education, 2 if graduated from primary education, 3 if got some high-school education, 4 if graduated from high-school, 5 if got some tertiary education, 6 if got a tertiary degree, 7 if got some university education, and 8 if graduated from university.

Difference-in-Difference Analysis: Sample, Data, and Baseline Equivalency

The sample for the Difference-in-Difference analysis includes 474 individuals with annual data over the period of 2012 to 2016. I created the sample from the administrative database the training institution provided me. The sample includes all individuals who were younger than 33 years old (at June 2016). 386 of them graduated from at least one course while the remaining 88 were pre-enrolled to take a course but never attended it, either because of space availability or decided not to take it (I discuss in a further section the potential selection bias problem this could cause to the evaluation).

Since people graduated at different points in time between 2012 and 2016, the control group is not only composed of the 88 individuals who never graduated but also of people who haven't taken the course by the studied year. Thus, the composition of the treatment and control groups for the panel is as follow:

Year	*2012*	*2013*	*2014*	*2015*	*2016*
Control	297	266	202	109	88
Treatment	65	137	242	362	386
Totals*	**362**	**403**	**444**	**471**	**474**

*Totals are not the same for all years since I excluded individuals who at each year were younger than 18 years old for two main reasons: first, the training program is designed for people 18 years or older; second, the federal law obliges people younger than 18 years old to be in the formal educational system.

The panel data set for the Difference-in-Difference analysis came from two sources. First, the same administrative database used for the before-and-after analysis. Secondly, hand collected employment microdata from Argentina's Social Security website for each of the 474 individuals on the first of July of each of the five studied years. The employment data from this source includes whether the individual is formally employed or not, is registered as a self-employer, participates in an employment plan, has health insurance, and receives unemployment insurance, among other data.

Table 2 shows baseline equivalency on almost all the observable characteristics of the sample on each year of the panel. The last column of the table shows the average difference and whether it is statistically different from zero when performing a t-test. The average age is statistically the same for both groups throughout all years. The average of education seems to be slightly higher on the treatment group, but different from zero just in year 2014. The proportion of male is slightly higher in the treatment group for 2013, which is consistent with the efforts of the training institution of including more women

into the program. The proportion of individuals younger than 25 years and with a health insurance is statistically the same across the two groups. Lastly, since there is no administrative data on total years of formal experience, the "accumulated experience since 2012" variable measures the total years of formal experience the individual accumulated over the years since 2012, which was calculated with data available through the Social Security website microdata. For this variable, there are some differences between the two groups in years 2011 and 2013, being the treatment higher. Besides these small differences, there seems to be baseline equivalency between the control and treatment group in the five years of the panel, making the groups comparable for regressions (I discuss the potential selection bias problems that could arise from these differences in a further section).

Table 2. DD Summary Statistics and Baseline Equivalency

Variable	Control Group			Treatment Group			t-test
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Treatment - Control
Age							
2012	297	22.90	4.39	65	23.55	3.71	0.66
2013	266	23.30	4.63	137	23.61	4.06	0.31
2014	202	23.76	4.91	242	23.85	4.37	0.09
2015	109	25.07	5.27	362	24.22	4.58	-0.85
2016	88	26.09	5.21	386	25.20	4.77	-0.89
Education							
2012	294	3.45	0.92	65	3.63	0.65	0.18
2013	263	3.44	0.92	137	3.51	0.75	0.07
2014	198	3.36	0.94	242	3.51	0.81	0.15 *
2015	105	3.32	0.88	362	3.46	0.86	0.14
2016	84	3.33	0.92	386	3.45	0.85	0.12
Male							
2012	297	0.93	0.26	65	0.97	0.29	0.04
2013	266	0.91	0.29	137	0.96	0.19	0.05 **
2014	202	0.94	0.25	242	0.93	0.26	-0.01
2015	109	0.94	0.23	362	0.93	0.25	-0.01
2016	88	0.95	0.21	386	0.93	0.26	-0.02
Health Insurance							
2012	297	0.37	0.48	65	0.48	0.50	0.10
2013	266	0.33	0.47	137	0.38	0.49	0.04
2014	202	0.30	0.46	242	0.36	0.48	0.06
2015	109	0.25	0.43	362	0.32	0.47	0.07
2016	88	0.26	0.44	386	0.29	0.45	0.03
Accumulated Experience since 2012							
2012	297	0.33	0.47	65	0.45	0.50	0.11 *
2013	266	0.63	0.84	137	0.73	0.84	0.10
2014	202	0.86	1.17	242	1.10	1.16	0.23 **
2015	109	1.39	1.57	362	1.37	1.48	-0.03
2016	88	1.95	1.98	386	1.87	1.69	-0.09

** indicates that the difference is statistically significant at the 5% level, and * indicates that the difference is statistically significant at the 10% level.

The General Econometric Model

In accordance with other program evaluations on the literature review, the following is the general regression specification of the econometric model for both analyses, which measure the training effect on formal employment:

$$Y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 CVs_{it} + u_{it} \text{ where,}$$

for the before-and-after analysis,

- *i* indicates the individual;
- *t* indicates whether the observation corresponds to before (0) or after the training (1);
- the dependent variable is y_{it}, which is binary indicating whether the individual *i* was formally employed (1) or not (0) at time *t*;
- the D_{it} or *Treatment* variable is also binary, indicating whether the training occurred (1) or not (0) for individual *i* at time *t*;
- β_2 is a vector of slopes of each of the control variables in CVs_{it} that vary depending on the model specification, including age, highest education achievement, formal experience in the labor market, family status[12], gender, city, quantity of dependents, internet access, and year of treatment; and,
- u_{it} is the error term.

And for the Difference-In-Difference analysis with five-year panel data,

- *i* indicates the individual;

[12] I used Health Insurance before age 25 as a proxy for family status. The reasoning behind it is that an unemployed person younger than 25 years old has health insurance coverage either if she/he can afford it or, according to Article 9 of Law 23.660, if her/his parents are formally employed since employers are obliged by federal law to provide health insurance to employees and their children younger to 25 years old (Senado de la República Argentina 1989).

- t indicates the year of the observation: 2012, 2013, 2014, 2015, or 2016;
- the dependent variable is y_{it}, which is binary indicating whether the individual i was formally employed (1) or not (0) at time t;
- the D_{it} or *Treatment* variable is also binary, indicating whether the individual received training by time t (1) or not (0);
- β_2 is a vector of slopes of each of the control variables in CVs_{it} that vary depending on the model specification, including age, highest education achievement, formal experience accumulated since 2012, family status[13], gender, city, quantity of dependents, internet access, time effects (which captures aggregate common factors through time, such as the state of the economy), and individual effects (which captures the average individual characteristics that are constant over time, such as intelligence); and,
- u_{it} is the error term.

The statistical significance of β1, the D_{it} or Treatment coefficient, is the value of interest. In the case of the before-and-after analysis, it measures the expected variation in the probability of being formally employed associated with taking the training, controlling for all other variables in the model (CVs_{it} vector). For the difference-in-difference analysis, it measures the expected variation in the probability of being formally employed attributable to having being trained when compared to its counterfactual (the control group that has not been trained), conditional on other variables

[13] I used Health Insurance before age 25 as a proxy for family status. The reasoning behind it is that an unemployed person younger than 25 years old has health insurance coverage either if she/he can afford it or, according to Article 9 of Law 23.660, if her/his parents are formally employed since employers are obliged by federal law to provide health insurance to employees and their children younger to 25 years old (Senado de la República Argentina 1989).

in the model (CVs_{it} vector). It is important to note that the before-and-after analysis does not determine causality while the difference-in-difference aims to do so.

I will use similar regressions for the three additional research questions I have, modifying the definition of the key independent variable (D_{it}). For the first additional question, I will explore the importance of the intensity of treatment by using variables measuring the total courses and hours an individual got trained. And, for exploring the differential effects depending on the type of courses, I will use a variable measuring the total courses in a certain skill in which a trainee graduated and also a dummy variable indicating the specialization the trainee achieved. For the second additional question, in order to determine if unemployment is a skills or matching problem, I will include the D_{it} variable and one that counts the total courses a trainee graduated from. Both should be statistically significant if skills matter. Lastly, for the third question on the differential effect depending on the financing method, I will interact the D_{it} variable with a binary variable capturing whether an individual graduated from a training financed through a fiscal credit or not.

Survey to Local Metallurgic Firms

Besides conducting a survey to graduates, I also carried out semi-structured interviews to owners and managers of metallurgic firms to complement the econometric findings. The motivation behind these structured-interviews was to validate whether the findings in the econometric models corresponded to actions and opinions of leaders and labor-demand representatives in the industry. I interviewed almost all firms that are currently members of the Chamber, 37 in total. Since these firms are the most likely to hire graduates from the program, the goal behind the interviews was to understand the type of firms that are

hiring Ce.Fo.Se.'s graduates and gather their perspectives on the usefulness of the training program, their labor force demands and their approach to satisfy it, their training needs and activities, and whether they would train new hires if Ce.Fo.Se. did not exist (Appendix D show the complete survey for firms).

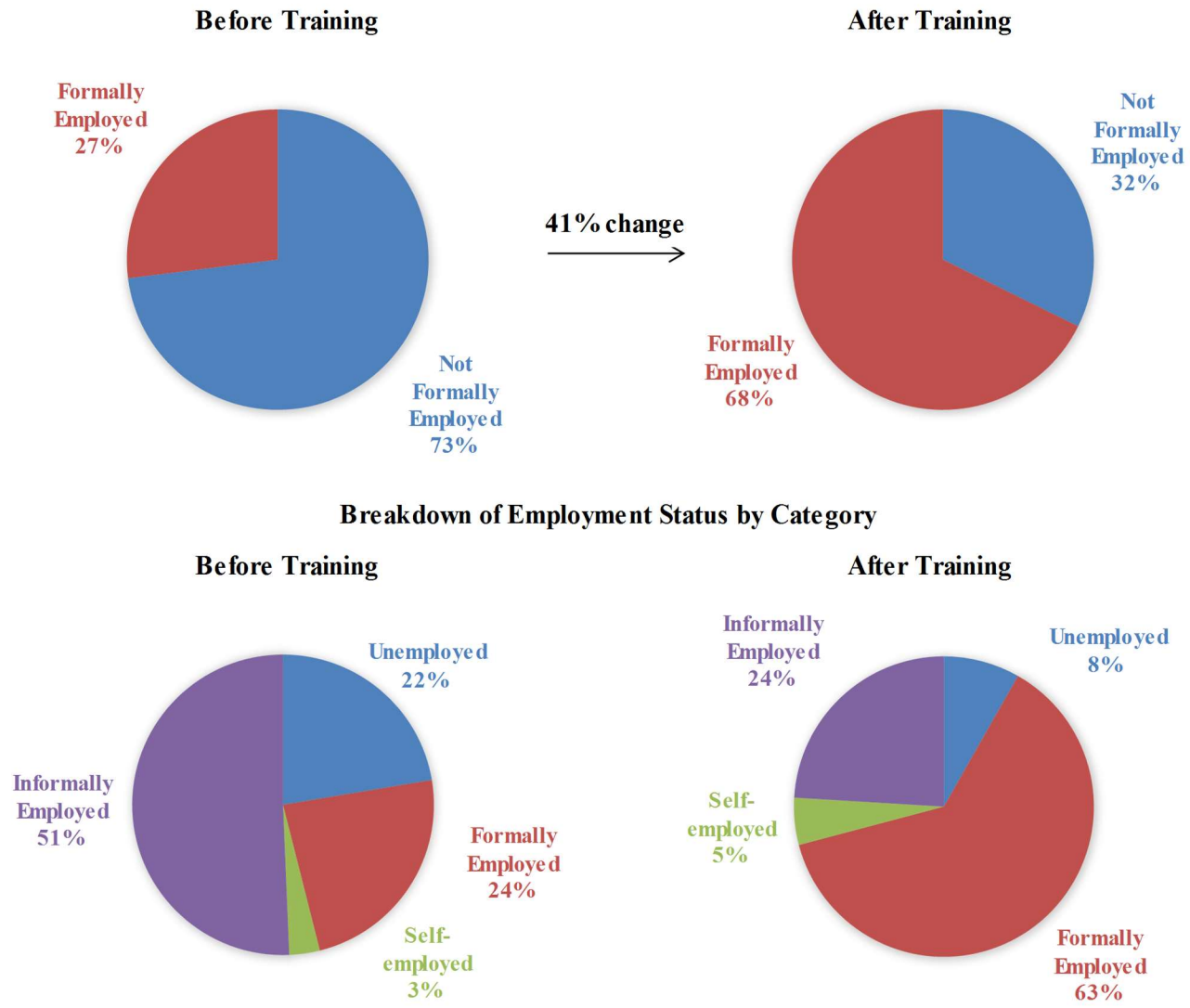
Chapter 5: Program Evaluation Findings

In this section I present and discuss the findings on all the research questions: the main one and the three additional sub-questions. For each research question I will first present the before-and-after (BaA) regression outputs. Then, I will present the difference-in-difference (DD) ones. Finally, I will conclude with a discussion on the results and complement these with qualitative data gathered from the surveys to trainees and firms.

Main Research Question: Training effect on Formal Employment

The before-and-after analysis presents promising results on the change of participants' employment status after the training. When measuring the change on employment status, Figure 1 shows a remarkable 41 percentage point increase of formal employment after training occurred. Breaking down the employment status into sub-categories can help explain this important variation: informal employment and unemployment decreased by 27 and 14 percentage points, respectively, while registered self-employment and formal employment increased by 2 and 39 percentage points, respectively.

Figure 1. Before-and-After Analysis. Change in Participant's Employment Status.



Moreover, besides formal employment, other employment outcomes had a statistically significant increment when comparing graduates' before-and-after status. Table 3 shows that an additional 14 percent of graduates were employed after the training, either formally or informally. The table also shows that there was an important transition from being informally employed to formally employed (39% increment) and that there are an additional 35 percent of graduates who are now working in the metallurgic industry, directly applying the skills they learned. Lastly, formal work experience increased on average by 1.22 years and the total weekly hours of work by 14.93 hours.

Table 3. Before-and-After Analysis. Change in Employment Outcomes

	After Treatment			Before Treatment			T-Test
Employment Variables	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**After-Before**
Fromally Employed	**0.68**	0.47	158	**0.27**	0.44	152	0.41 ***
Employment Status*	**2.21**	1.07	158	**1.28**	1.06	152	0.93 ***
Employed	**0.92**	0.28	158	**0.78**	0.42	152	0.14 ***
Formally Employed given Employed	**0.74**	0.44	145	**0.35**	0.48	118	0.39 ***
Employed Metalurgic Industry	**0.70**	0.46	100	**0.35**	0.48	120	0.35 ***
Formal Work Experience (years)	**2.95**	4.01	158	**1.73**	3.52	158	1.22 ***
Weekly Hours of Work	**36.98**	13.97	152	**22.05**	22.33	80	14.93 ***

* 0 = Not Employed, 1= Informally Working, 2= Self-employed, 3= Formally employed. *** , **, * denote statistically significant at the 1%, 5% , and 10% level, respectively.

Regarding before-and-after (BaA) regressions, Table 4 reports the training coefficient estimates where formal employment is the dependent variable. Column (1), (2), and (3) shows that, after controlling for several demographic variables, the associated variation in the probability of being formally employed for taking the training is between 29.9 and 31 percentage points. The vector of control variables included age, education, formal experience, health insurance, and gender in all regressions. Regression (1)

included additional control variables which I removed in the later regressions due to their statistical insignificance; these included: city, number of dependents, whether graduate uses internet, and knowledge of companies. Regression (2) and (3) are identical, except that (3) controls for the year in which the individual graduated.

I also studied whether training had differential effects on formal employment depending on trainees' age groups. This is possible to do since there is a big age variation in the sample, from 18 to 33 years. Regression (4) shows that being trained is associated with a much greater variation on the probability of being formally employed for individuals who are younger to 24 years old compered to older trainees (45.2% compared to 17.1% for those between 24 and 27 years, and 8.4% for those older than 27 years). These differential effects imply promising results for training programs, since younger people are usually more difficult to employ. Thus, it is important to corroborate whether the effect remains statistical significant when performing the DD analysis.

Table 4. Before-and-After Regressions on Formal Employment

	(1)	(2)	(3)	(4)
Treatment	0.299 ***	0.304 ***	0.310 ***	0.452 ***
	[0.05]	[0.05]	[0.05]	[0.06]
Treatment*Age 24 to <27				-0.281 **
				[0.12]
Treatment*Age 27 and Above				-0.368 ***
				[0.11]
Year of Treatment			Yes	Yes
R^2	0.41	0.39	0.39	0.38
n	310	310	310	310

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5%, and 10% level, respectively. All regressions include the constant and age, education, formal experience, health insurance, and gender as control variables. Regression (1) includes additional control variables (city, dependents, internet usage, and knowledge of companies), which were excluded on the other ones since they were not significant. Regression (2), (3), and (4) have same demographic control variables. I also regressed all specifications using probit model, all coefficients remained to be equally statistically significant.

The available data from the BaA surveys also provides some insights to whether training increased the probability of having a formal job, particularly, in the metallurgic industry and on the total weekly working hours on graduates. I used the same general specification model, but different dependent variables to answer these questions. Table 5 shows the regression outputs. The first column shows that being trained is related to an increased probability of being formally employed in the metallurgic industry of 20.8 percentage points, when controlling for demographic variables and graduation's year effect. Similarly, Column (2) shows that being trained is related to an increment of 12.65 weekly working hours, after controlling for descriptive characteristics. Unfortunately, I will not be able to corroborate these findings with the DD analysis since my panel dataset does not have data on industry the individual is employed at and hours of work.

Table 5. Before-and-After. Additional Regressions

Dependent Variables	(1) Formal Job in Metallurgic Ind.	(2) Weekly Working Hours
Treatment	0.208 ***	12.654 ***
	[0.05]	[2.66]
R^2	0.40	0.39
n	310	310

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed in the metallurgic industry (1) and weekly working hours (2). Robust standard errors are in brackets. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5%, and 10% level, respectively. All regressions include the constant and age, education, formal experience, health insurance, gender, city, dependents, internet usage, and knowledge of companies as control variables. I also regressed all specifications using probit model, all coefficients remained to be equally statistically significant.

Finally, although it is not evidence of causal effect, most surveyed graduates who are currently working attribute their employment status to the training. 39 percent believes that they got their current job thanks to the referral of the training institution and an additional 17 percent believes that without the training they would not have gotten the job they currently have. Moreover, the timing when graduates got their current job does not toss out a possible causal effect: only 20 percent of graduates who are now formally employed were employed before the training while 34 percent got the job while being trained and 46 percent after graduating.

Since the BaA analysis present promising outcomes on my main research question, I now turn the attention to the DD analysis with the five-year panel dataset. Table 6 shows that the treatment and control group had statistically the same proportion of individuals who were formally employed in 2012. This is consistent with baseline equivalency since most individuals were not trained. However, after 2012, the treatment

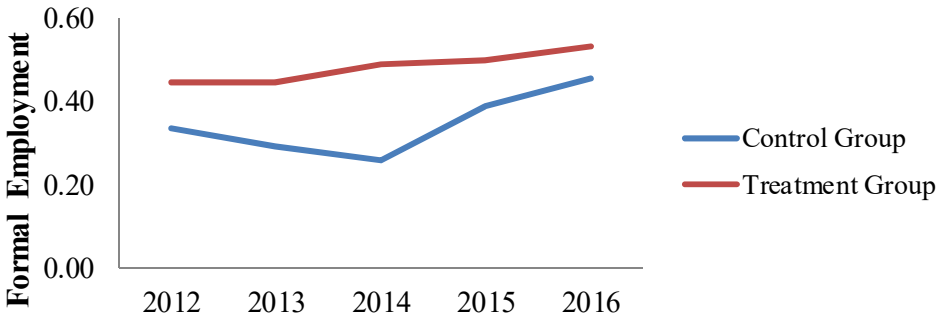
group has a statistically higher proportion of formal employed individuals; I analyze later whether it is a consequence of the training.

Table 6. Difference-in-Difference Analysis. Employment Variation 2012-2016

Variable	Formal Employment						
	Treatment Group			Control Group			T-Test
	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Diff. Treat - Cont
2012	65	0.45	0.50	297	0.33	0.47	0.11
2013	137	0.45	0.50	266	0.29	0.46	0.15 ***
2014	242	0.49	0.50	202	0.26	0.44	0.23 ***
2015	362	0.50	0.50	109	0.39	0.49	0.11 *
2016	386	0.53	0.50	88	0.45	0.50	0.08 *

***, **, * denote the difference is statistically different from zero at 1%, 5%, and 10% level, respectively.

Figure 2. Formal Employment 2012-2016



The drop in the control's formal employment outcome might look suspicious until contextualized with Argentina's macro-level statistics. From Figure 2, it is notable that while the treatment group's formal employment outcome increased steadily between 2012 and 2016 that of the control group worsened between 2012 and 2014 and then recovered during the following two years. The difference in trends might be suspicious regarding whether the control group is appropriate for the estimation of the treatment counterfactual or whether there is a measurement error. However, two macro-level indicators, GDP and unemployment, can help explain the employment fall in the control

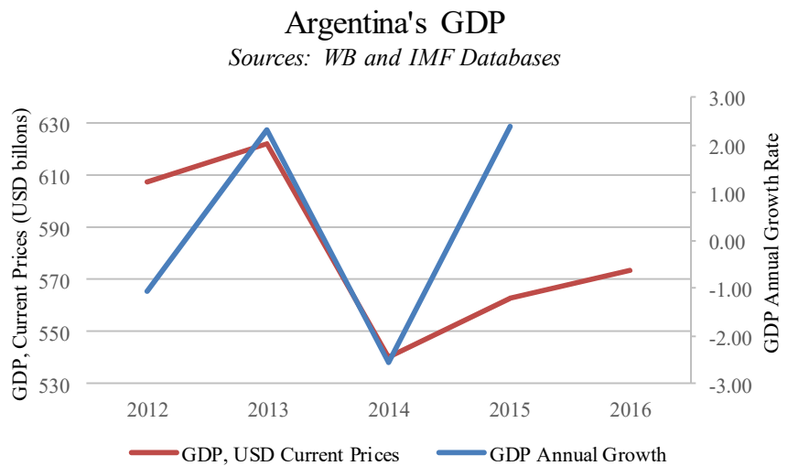
group. As the graphs in Figure 3 shows, Argentina's GDP significantly decreased by 2014 and mildly recovered in 2015.[14] Regarding the country's unemployment rate, it increased in year 2014 and the increment was particularly higher for young people –up to 24 years old. The graphs on the second-row show the employment and unemployment rates in the main nearby urban areas of my sample.[15] The employment rate notably declines during the last quarter of 2013 and first three quarters of 2014 while the unemployment rate significantly increases during the same timeframe. All these trends perfectly mimic the drop in the percentage of formally employed people in my control group sample in 2014, particularly if we remember that the data points were collected at June of each year.

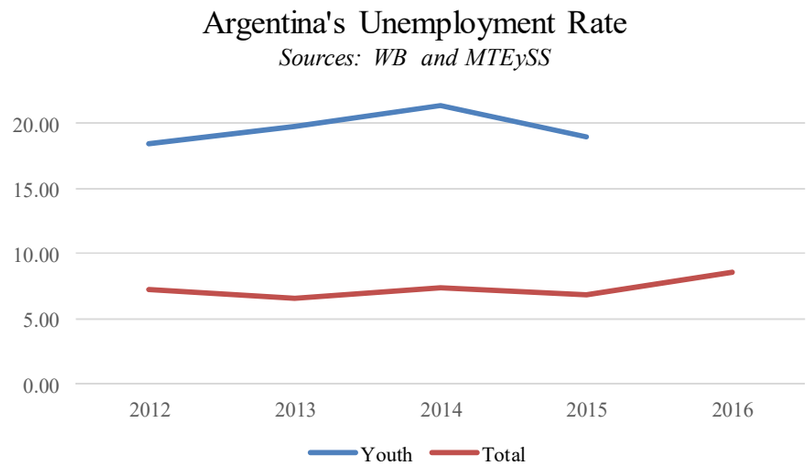
It is important to note that if the control group mimics an appropriate counterfactual, training might make graduates' employability more resilient to economic downturns. The treatment group's formal employment outcome remained steady and continued to rise while the control group suffered some declines. Thus, when unemployment rises, firms might be more willing to keep individuals who have more skills – those who were trained– and fire those with less skills – those who were not trained.

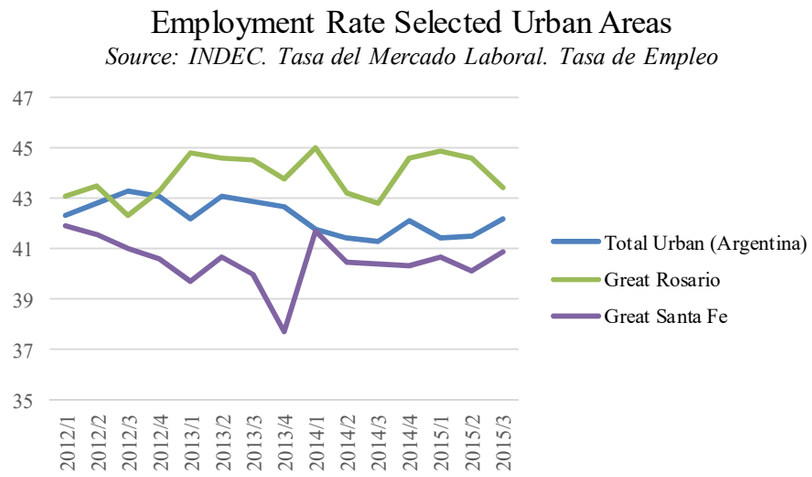
[14] GDP growth rates are from World Development Indicators (WB database), when consulted no data was available for 2016. GDP in current prices are from the World Economic Outlook (IMF database); the amounts for year 2015 and 2016 are IMF's projections.

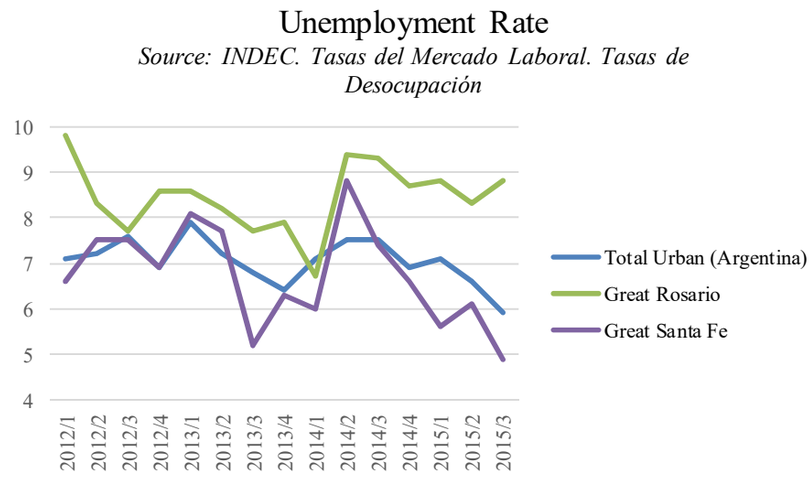
[15] The quarterly employment and unemployment rates are from the national statistics bureau (INDEC in Spanish). At the time, there is no public and definitive data on employment and unemployment rate for the last quarter of 2015 and those in 2016.

Figure 3. Argentina's Macro-level Indicators 2012-2016









Regarding the regression outputs for the DD econometric model, Table 7 shows that the training has a positive 20.1 percentage point effect on the probability of formal employment and younger people are better off. Regression (1) and (2) have identical control variables and results, but are estimated with different models: (1) uses GLS random-effects while (2) uses fixed effects.

Table 7. Difference-in-Difference. Regressions on Formal Employment

	(1)	(2)	(3)
Treatment	0.201 ***	0.201 ***	0.259 ***
	[0.03]	[0.03]	[0.04]
Treatment*Age 24 to<27			-0.067
			[0.06]
Treatment*Age 27 and above			-0.186 ***
			[0.06]
Time Effects	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes
R^2	0.65	0.56	0.57
n	2136	2136	2136
# of groups	470	470	470

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5% , and 10% level, respectively. All regressions include the constant and age, education, accumulated formal experience since 2012, health insurance as control variables. Regression (1) uses GLS random-effects (RE) model while (2) and (3) use Fixed Effect model. The education variable was dropped of model (2) and (3) because of linear collinearity.

No matter the model, we can see that, all else equal, training increases graduates' probability of being formally employed by 20.1% above the control group. The effect is logically lower than the estimated one with the BaA analysis (29.9% to 31%) since it is the net effect between the two groups. Moreover, column (3) shows that the impact is higher for younger age groups: controlling for demographic variables, time and individual effects, graduates younger to 24 years old were the most benefitted from the

training program since it increased their probability of formal employment by 25.9 percentage points above the control group. The training effect was lower for those between the ages of 24 to 27 (19.2 percentage points) and older (7.3 percentage points).

To summarize, I have showed that training causes an important variation on graduates' probability of being formally employed and that younger people are even better off. My results are consistent with evidence from other skills-training programs' evaluations in Latin America covered in the literature review. Particularly, the results are quite similar to Carrillo et al (2014) sector-based evaluation in Argentina. Moreover, the training differential effects by age groups have important policy implications. The S4YE baseline report (2015) shows that youth in Latin America are more than twice as likely to be unemployed as adults and that about 65 percent of employed youth have an informal job.[16] The report identifies as the main constraint to youth employment the lack of networks and the lack of cognitive, non-cognitive and technical skills. Thus, if training has differential effects and younger people are the most benefited, these types of programs can help increase youth employability. I now turn the discussion to the three additional research sub-questions, which are important for optimizing limited public resources.

1. ***Do the intensity of the training and skills matter?***

For answering this two-folded question, I changed the general specification model. For the first part of the question, whether the intensity of treatment matters, instead of using D_{it} as a binary variable, indicating whether the individual was trained or not, I used independent variables capturing the intensity with which the individual was trained. Moreover, I made the model more flexible to allow for a non-linear relationship.

[16] S4YE (2015) defines Youth as individuals age 15 to 29.

Table 8. Intensity of Treatment by Total Courses and Hours Trained

	Total Courses		Log of Trained Hours	
	BaA (1)	DD (2)	BaA (3)	DD (4)
Total Courses	0.109 ***	0.098 ***		
	[0.02]	[0.01]		
Total Courses Squared	-0.007 ***	-0.005 **		
	[0.00]	[0.01]		
ln(total hours trained)			0.063 ***	0.051 ***
			[0.01]	[0.01]
R^2	0.39	0.54	0.39	0.55
n	310	2136	310	2136
# of Groups		470		470

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5% , and 10% level, respectively. All regressions include the constant and age, education, experience, health insurance, gender and time effects as control variables. Regression (1) and (3) uses the before-and-after analysis' model and data while (2) and (4) uses the DD ones. (2) and (4) use Fixed Effect model. I also regressed (1) and (3) using probit model, all coefficients remained to be equally statistically significant.

Table 8 presents the regressions' output of this model, showing that the intensity of treatment matters and that there are diminishing returns to more training. Regressions (1) and (2) use as independent variables total courses that the individual took –0 if control group– and total courses squared. From the BaA model (column 1) we see that, when controlling for demographic variables, an additional course is related to an increment on the probability of being formal employed of 10.9 percentage points while diminishing at a marginal rate of 0.07 percentage points. Similarly, but even more important because of its causal implication, the DD analysis (column 2) shows that an additional course increases the probability of being formally employed by 9.8 percentage points with a diminishing rate of 0.05 percentage points. On average, individuals in the treatment group graduated from 2.21 courses, with 75% of the sample graduating from up to 3

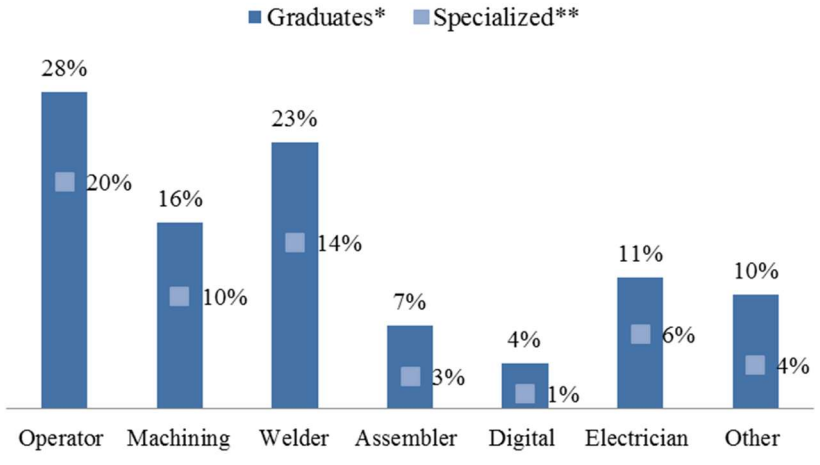
courses. Regression outputs in columns (3) and (4) show similar results but using log hours, making the interpretation easier. For regression (3), a one percent increase in the hours trained is related to an average increase on the probability of being formal employed of 0.06 percentage points. Similarly, for regression (4), a one percent increase in the hours trained increases the probability of formal employment by 0.05 percentage points above the control group, controlling for demographic characteristics and fixed effects.

In order to answer the second part of the question, whether training has differential effects depending on the type of skills learnt, I also changed the general specification model. For this question, instead of using D_{it} as a binary variable, I use independent variables capturing the total courses trained in the occupation the center offers. Since people could have taken different skills but usually specialized in one occupation, I also tested the question by creating dummy variables indicating in which occupation graduates specialized, if any.

The regressions' outputs in Table 9 show that training causes different effects to the probability of being formally employed depending on the skills the individuals got trained in. From the BaA regressions (column 1) we observe that, when controlling for demographic characteristics, taking an additional course in the operator, welding, electrician, or "other" occupation is related to an increment in the probability of formal employment while it is not the case for the remaining occupations. The results are somewhat different when considering graduates' specialization: in column (3) we see that specializing in all but digital and other skills is related to an increment in formal employment. However, these results might not be reliable because, besides the lack of

counterfactual, the sample size might be too small, causing big standard errors. Instead, the DD analysis is more helpful for answering the question. Column (2) shows that, taking an additional course in the operator, machining, or welding occupation has a significant effect in the probability of being formal employed (12.2%, 9% and 8.9%, respectively) above the control group, controlling for demographic characteristics and fixed effects. An additional course in any of the other occupation has no statistically significant effect on formal employment. Similarly, when looking into graduates' specialization, column (4), we see that these results are consistent. Specializing in Operator's skills increases the probability of formal employment by 19.2 percentage points, in machining by 35.7, and in welding by 27.3 above the control group, controlling for demographic characteristics and fixed effects. In this case, specializing in digital skills is statistically significant. From Figure 4 we see that 67 percent of trainees graduated in these three occupational skills, but 44 percent specialized in them.

Figure 4. Graduates and Specialization



**Graduates: percent of total graduates in each skills-training*
***Specialized: percent of total graduates specialized in each skill*

Table 9. Type of Skills Trained and Specialization

	By Quantity of Courses		By Specialization	
	BaA (1)	DD (2)	BaA(3)	DD (4)
Operator	0.116 *	0.122 ***	0.204 *	0.192 ***
	[0.06]	[0.04]	[0.12]	[0.04]
Machining	0.031	0.090 ***	0.279 ***	0.357 ***
	[0.02]	[0.02]	[0.08]	[0.06]
Welder	0.066 **	0.089 ***	0.339 ***	0.273 ***
	[0.03]	[0.03]	[0.07]	[0.05]
Assembler	-0.043	-0.035	0.360 ***	-0.060
	[0.07]	[0.03]	[0.14]	[0.08]
Digital	-0.047	0.034	0.130	0.264 **
	[0.07]	[0.04]	[0.19]	[0.12]
Electrician	0.116 **	-0.021	0.377 ***	0.025
	[0.05]	[0.04]	[0.08]	[0.07]
Other	0.127 *	-0.049	0.192	0.114
	[0.07]	[0.04]	[0.16]	[0.08]
R^2	0.40	0.65	0.39	0.60
n	310	2136	310	2136
# of Groups	-	470	-	470

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. All regressions include the constant and age, education, experience, health insurance, and gender as control variables. Regression (1) and (2) uses the before-and-after analysis' model and data with year controls. Regressions (3) and (4) uses the DD model, using Fixed Effecs, with time and individual effects. Independent variables in regression (1) and (3) represent quantity of courses taken while in (2) and (4) are dummy variables. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5% , and 10% level, respectively. I also regressed (1) and (2) using probit model, all coefficients remained to be equally statistically significant.

These results are consistent when analyzing surveys to employers. From 37 firms I interviewed in the metallurgic industry, 69 percent have technical requirements when hiring new employees. Although the specific required skill varies according to the main product, all of them require candidates either to have a high-school degree at a technical school, or to know a specific skill –the most common they require are welding,

machining, and assembling–, or to have skills usually needed in the metallurgic industry –i.e. operator. A smaller percent of firms (35%), of which most of them are small, find that it is difficult to find motivated and responsible employees.

2. Do skills matter or is it a problem of matching?

A common question on the labor economic literature is whether people are unemployed because they do not have the relevant skills firms need or because supply and demand do not find each other. Understanding the causes of unemployment is key to identifying the most efficient policy that can help reduce it: whether something more like a skills-training program is needed or more like a job placement agency. Thus, the second complementary sub-question aims at shedding light on this problematic, by not only including the D_{it} binary variable, but also the total courses from which trainees graduated. The statistical significance of these two variables will provide us the answer we are looking for. If only the treatment variable (D_{it}) is significant, then, it could be thought that what it matters is to connect individuals to the training institution irrespective of the total courses they take –my measure of skills acquired. Whereas if both variables are significant, skills also would matter for getting a job, explaining part of the variation in the employment variable. In other words, lack of skills would be part of the unemployment problem.

Table 10 shows the regression outputs for the BaA and DD models. When looking to the BaA regression (column 1), we could conclude that the unemployment problem is a matter of mismatches since the treatment coefficient is statistically significant while the one on total courses is not. However, it is important to remember, that the BaA sample size is smaller, increasing the variation of the standard error. On the other hand, in the DD analysis (column 2), with a greater sample, both coefficients are statistically

significant. Thus, we could conclude that skills matter as well.

Table 10. Testing Skills vs. Matching Problems

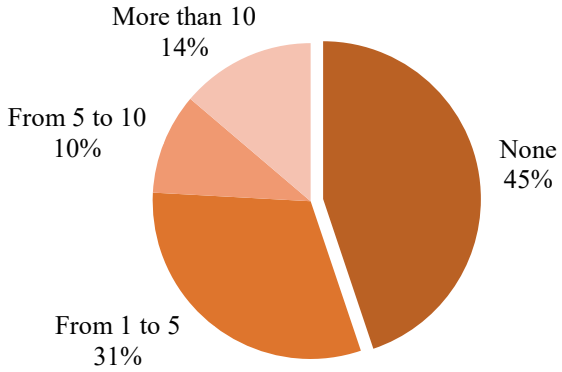
	(1) Before-and-After	(2) DD
Treatment	0.270 ***	0.140 ***
	[0.07]	[0.04]
Total Courses	0.010	0.038 ***
	[0.02]	[0.01]
R^2	0.39	0.65
n	310	2136
# of groups		470

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. All regressions include the constant and age, education, experience, health insurance, and gender as control variables. Regression (1) uses the before-and-after analysis' model and data with year controls. Regressions (2) uses the DD model, using Fixed Effecs, with time and individual effects. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5% , and 10% level, respectively. I also regressed (1) using probit model, all coefficients remained to be equally statistically significant.

The results from these DD regressions are consistent when analyzing the surveys to firms. According to employers there is a mixture of both problems, but lack of skills is more relevant. 84 percent of firms recognize they have great difficulties to find skilled workers and consider that the main reason is because there is not enough skilled-labor supply. In particular, smaller firms complain that big companies are those who absorb the little available skilled-labor supply, creating a vicious circle: since there is no skilled labor, small companies hire unskilled labor that end up learning by doing; once they earned enough skills they look for better paid jobs at bigger firms, leaving the smaller firms without trained resources and needing to re-train new unskilled labor. Furthermore, employers also use Ce.Fo.Se. as an employment referral agency, recognizing that the training institution plays an important role in matching workers to vacancies. Although

medium and big firms have an established application process, they first contact Ce.Fo.Se. for getting referrals of possible candidates. This is reflected on the fact that 59 percent of firms have a strong preference to hire individuals who have been trained at the training institution because they make sure graduates have the skills. Moreover, 55 percent of firms declared to be currently employing one or more graduates (see Figure 5 for detail). The percentage of graduates employed at member firms might be even bigger since firms not always are aware of the courses employees took. Actually, 82 percent of formally employed graduates, who I interviewed, work at a member firm.

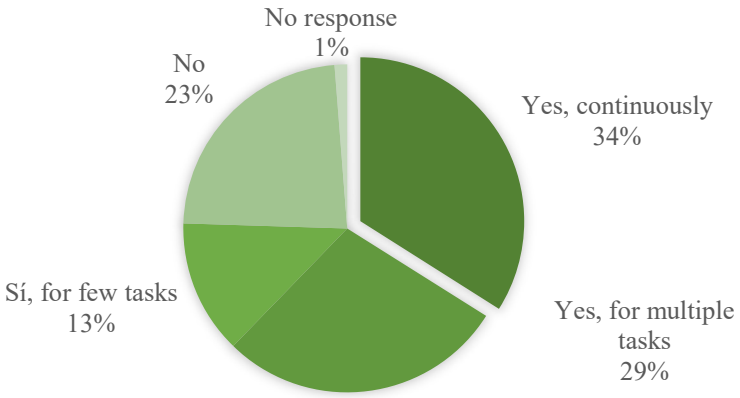
Figure 5. Firms Employing Graduates from Ce.Fo.Se.



Surveys to graduates also revealed the importance of the skills learnt at Ce.Fo.Se.'s training programs. One of the questions of the survey was target to understanding how often graduates who are working (either formally or informally) use the skills learnt in the training programs. Figure 6 shows that 76 percent of graduates use the learnt skills while 34 percent use it in a continuous basis. From those who do not currently use the skills (23%), only a third did not find it useful at all; all others either used the skills when they first got a job or recognize that the training was a signaling

mechanism to prove knowledge on the industry and get their current job. Thus, skills do matter since if it was just a matter of mismatch a higher percentage of graduates would not be using the skills they learnt.

Figure 6. Do you Currently use Skills you Learnt in Training?



Finally, surveys to graduates also reveal the importance of the training institution as a matching mechanism. 39 percent of graduates who are employed attribute finding a job thanks to the training institution's network and an additional 17 percent thanks to having earned a training certificate from Ce.Fo.Se.

3. ***Do training programs cause different effects depending on the financing method? (Grant vs. Fiscal Credit). Do they need to be publicly financed?***

The final additional sub-question attempts to determine the most efficient way to finance these skill courses. As described above, there are two main mechanisms for financing Ce.Fo.Se.'s training programs: grants from the MoL-ADIMRA partnership and direct Fiscal Credits from companies. My hypotheses is that financing trainings with fiscal credit money should be more effective in helping people get a formal job because companies are more involved in the process. For answering this question I included the

D_{it} binary variable, but also a binary variable describing whether the training was financed with a fiscal credit. If this second variable is positive and statistical significant we could conclude that training financed with a fiscal credit is more effective than those financed through the other mechanisms.

Table 11 shows that there is no statistical difference among the two financial mechanisms. In both analyses the coefficient on the fiscal credit dummy variable is not different from zero. However, the DD analysis (column 2), the most rigorous method with biggest sample size, shows that the coefficient is positive.

Table 11. Testing Differential Effects in Financing Mechanisms

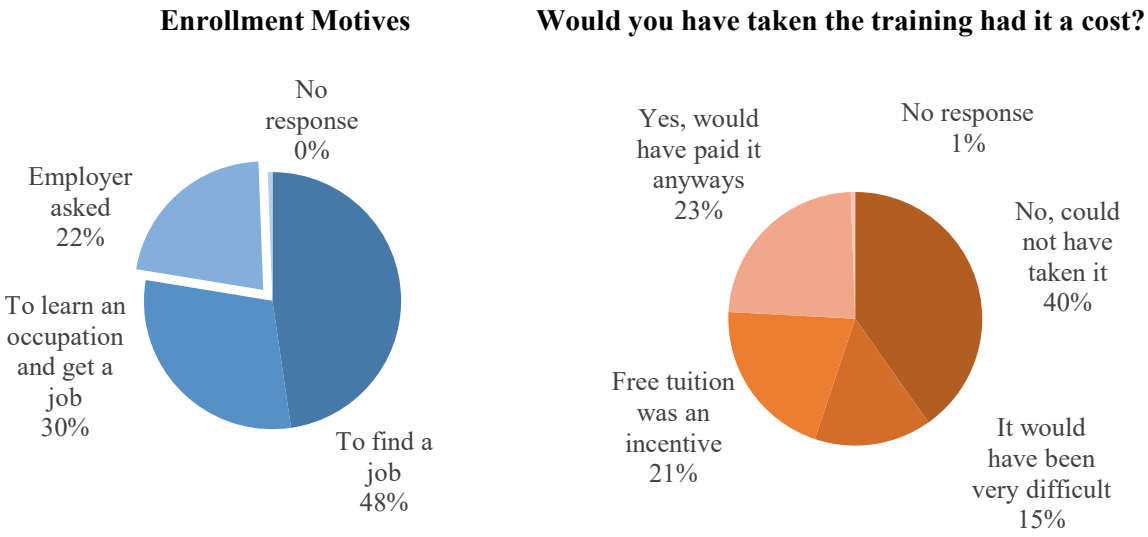
	(1) Before-and-After	(2) DD
Treatment	0.336 ***	0.174 ***
	[0.06]	[0.04]
Financed w/ Fiscal Credit	-0.076	0.048
	[0.07]	[0.05]
R^2	0.39	0.64
n	310	2136
# of groups		470

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. All regressions include the constant and age, education, experience, health insurance, and gender as control variables. Regression (1) uses the before-and-after analysis' model and data with year controls. Regressions (2) uses the DD model, using Fixed Effects, with time and individual effects. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , **, * denote statistically significant at the 1%, 5% , and 10% level, respectively. I also regressed (1) using probit model, all coefficients remained to be equally statistically significant.

Although there are no significant differences between the two methods, a relevant concern is whether they should be financed with public funds or should firms or students pay for them. The surveys to firms and graduates shed light on this sub-question. Firms' current behavior towards training does not show willingness to pay for these programs.

Only 25 percent of firms train employees in a regular basis, when needed; however, these are all medium size and big companies that can use the fiscal credit mechanism or that are obliged to provide training due to quality norms or standards. 37.5 percent of surveyed firms do not provided training at all. And the remaining 37.5 only teaches

Figure 7. Enrollment Motivation and Training Cost



informally, but only when it is strictly needed. When asking firms why they do not train their employees, the most frequent answers are the following ones: cannot stop the production, it is too costly, it takes too much time, there are too many things that need to be coordinated. Thus, if firms are not paying to train their own employees, it is highly unlikely that they would pay for training unemployed people.

Students are also unlikely to fund their own education for three main reasons. First, only 27 percent had a formal job, thus, probably limited resources. Second, as shown in Figure 7 "Enrollment Motives" the primary reason students enroll into training is because they need to find a job (48%), or to learn an occupation which will lead to a job (30%), or their employer required them (22%). Moreover, the survey asked whether

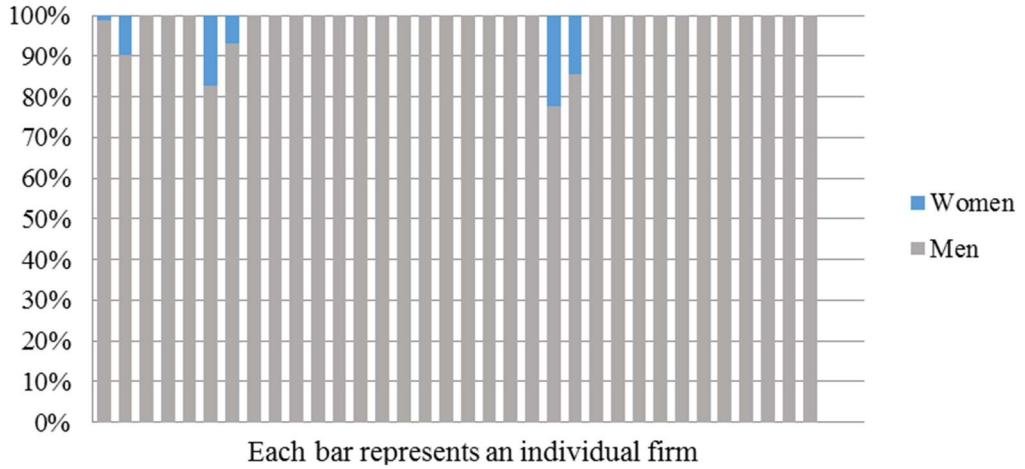
the student would have taken the training if it had a cost. 40 percent responded that they definitely would not have taken the course and an additional 15 percent responded that it would have been difficult to do so. Only 23 percent responded positively. However, when decomposing this number half were sent by employers and a quarter was formally employed. Thus, it is reasonable to conclude that neither students nor employers would be willing to pay for these skills training programs. A final note that is relevant to financing the courses is that in Argentina there is public and free education at all levels: from primary school to university. Thus, seems also appropriate to fund training programs that prove to be cost-effective, which I will discuss in a further section.

Two Final Reflections on Findings: Gender Biases and Overall Employment

Firms in the metallurgic industry claim to have difficulties finding qualified employees (84% surveyed firms), but are systematically discarding women as potential candidates for cultural reasons. Women face great barriers to entering the metallurgic industry. As mentioned, almost all graduates of Ce.Fo.Se. skills-training programs between 2012 and 2016 were male. During these years, the training institutions made some efforts to incorporate more women to the trainings, but the proportion of women graduating from trainings changed only from 3% to 7% (see Table 2). These statistics reflects the fact that jobs in the metallurgic industry have been traditionally dominated by male occupation, being about 9 percent the proportion of women employed in this sector between 1996 to 2006 (Castillo, et al. 2008). From all firms I surveyed only 6 have at least one woman at operative-level positions, and the women-to-men ratio is almost null (see Figure 8 shows). Furthermore, those women who are employed only work at jobs which require fine motor skills –specifically, winder occupations. When asked, 94% of

surveyed firms have a strong preference towards hiring men for operative-level occupations. The reasons always fell within the following statements: "the job requires workers to get dirty, it is a male environment, and facilities are not prepared for women" (40%), "job tasks involve lifting and handling up to 10kg[17]" (31%), "job entails using a machine, such as a forklift" (25%), "never received an application from a woman" (4%). On the other side, when surveyed graduates were asked whether they think women can perform well the occupation's task most responded they definitely can do it (75.5%) while few believes it depends on the task (9.4%), and only 15% believes they cannot do it. These results beg the question on how to close these gender disparities by providing more opportunities to women in this industry. Incorporating them would not only create a more inclusive society but also can help firms find more easily qualified employees.

Figure 8. Share of Women Employed at Operative-Level Positions at Surveyed Firms



Finally, a common concern for policy makers and these type of employment programs is whether people trained are replacing employed people, which would mean a

[17] Argentina law specifies maximum kilograms' amounts workers can lift depending frequency needed and irrespective of genders, all maximums exceed 10 kg (MTEySS 2003).

zero effect on overall employment. However, this is improbably the case given two main reasons. First, according to the surveys to firms, the main reason why employees stop working at their companies is either that they left for better job, or that they were fired because of a justified cause, or that the contract expired. Secondly, it would be an irrational financial decision: there are no financial incentives to hire trained people and firing an employee has a compensation cost of one month per year of tenure (Ley de Contrato de Trabajo 1976).Thus, the cost would be too high considering that on average employees working at the surveyed firms have 10.3 years of tenure. Finally, although the graduate have acquired skills, it is unlikely that he will have the same on-the-job training and skills as an employee with that average of tenure.

Discussion on Potential Selection Bias

As discussed in the methodological section, the established causality through the DD analysis might suffer from selection bias. Since the evaluation I performed is not an RCT, the control group might not mimic an appropriate counterfactual for the treated group. For example, those who enrolled and graduated from the training are probably those who first pre-enrolled into the training. Since the training institution call participants in a first-pre-enrolled first-served basis, then, those who signed up earlier, and got trained, might have been more motivated to find a job than those in the control group. If this is the case, the training effect might be overestimated. However, the control group might also be composed of two other types of individuals, which may cause a different bias sign. First, there might be people that were equally motivated to find a job as the treated group, but just didn't take the training because of space availability (no

bias).[18] Second, there might be people that when they received the call to get enrolled they had already gotten a job. If this is the case, the estimated causal effect of the training might be smaller than what it really is.

Table 12. Accounting for Selection Bias in Difference-in-Difference Analysis

Reg. #	Sub-Group Descriptions	Coeff.	Std. Err.	R^2	N	# Groups
(1)	**Everyone (original)**	0.201 ***	[0.03]	0.56	2136	470
(1.1)	with Health Insurance when Unemployed	0.169 ***	[0.05]	0.49	706	191
(1.1.1)	and Educational Level (More Primary to H-S)	0.169 ***	[0.06]	0.47	604	164
(1.2)	without Health Insurance when Unemployed	0.205 ***	[0.04]	0.58	1430	340
(1.2.1)	and Educational Level (More Primary to H-S)	0.185 ***	[0.04]	0.60	1192	284
(2)	**Just Treated**	0.206 ***	[0.04]	0.57	1564	346
(2.1)	with Health Insurance when Unemployed	0.138 ***	[0.06]	0.53	534	144
(2.1.1)	and Educational Level (More Primary to H-S)	0.116 **	[0.06]	0.52	453	124
(2.2)	without Health Insurance when Unemployed	0.230 ***	[0.04]	0.58	1030	249
(2.2.1)	and Educational Level (More Primary to H-S)	0.191 ***	[0.04]	0.60	861	209

Notes: This table reports estimates where the dependent variable is the percentage of people formally employed. Robust standard errors are in brackets. All regressions include the constant and age, education, experience, health insurance, and gender as control variables. All regressions use the DD Fixed Effecs model, with time and individual effects. I rounded standard errors to the nearest decimal point and, in the case of coefficients' estimates, to the nearest centesimal. *** , ** denote statistically significant at the 1% and 5% level, respectively.

In order to reduce the possible selection bias present on the DD analysis, I run regressions refining the treatment and control groups in ten sub-groups. It is important to clarify that due to the limited demographic characteristics on the dataset, it is impossible to solve the possible threat of selection bias. However, refining the control and treatment group can help reduce the possible selection bias. Table 12 shows the regressions output for each of ten sub-groups I defined. Regression (1) is the original regression with a

[18] It is possible to think that people in the control group had these characteristics since in order to enroll people have to go in-person to the training institution and fill-out a form. The institution is in the periphery of the city, thus, those pre-enrolled had certain motivation to take the course.

20.1% effect on formal employment. Regression (1.1) is this same group, but excluding people who did not have health insurance when unemployed. The logic behind this sub-group is that unemployed people without health insurance might belong to a different socioeconomic status than unemployed people with health insurance, thus, they might not be comparable. In this case, the effect of the training drops only by 3.2 percentage points. When further excluding from the analysis individuals whose highest educational achievement is elementary school (too low education) and those who attended higher education (too high), the training effect does not change –regression (1.1.1). Moreover, regression (1.2) does the opposite, it excludes from the analysis those who when they were unemployed had health insurance. In this case, the treatment effect is slightly higher (20.5%) than the original regression (20.1%). And when excluding from this sub-group those individuals whose highest educational achievement is elementary school and those who attended higher education, the training effect decreases by 1.6 percentage points from the original estimate –regression (1.2.1).

The remaining five sub-groups in Table 12 exclude from the analysis those who were never trained, in case they were too different from the treatment group. Thus, this analysis will exclude observations from 2016 since there will not be a control group in this year (everyone would have graduated by then). It is important to note that the effect for this analysis might logically be lower since reducing a year of comparison might not giving enough time for those who graduated to get a job. Regression (2) shows almost the same results as the original one, with an increment of 0.5 percentage points. Such similar results highlight the original's treatment and control group comparability. Regression (2.1) excludes those who were unemployed without a health insurance. In this case the

drop is higher than in (1.1), decreasing the estimate of the treatment effect to 13.8 percentage points. And when further excluding those with too low and too high educational level (regression 2.1.1), the treatment effect falls even more to 11.6 percentage points. Lastly, regression (2.2) does the opposite, it excludes those who were unemployed but had a health insurance. In this case, similarly to (1.2), the treatment is slightly higher than the original regression, by 2.9%. And when excluding from the analysis those with too low or two high educational level, it is a 1 percent difference points from the original estimates.

To conclude, although there is evidence of some selection bias, the treatment effect continues to be significant even when creating sub-groups and excluding individuals from the analysis. When controlling for demographic characteristics and fixed affects, the training increases the probability of being formally employed between a 11.6 to a 23 percentage points compared to a control group. Finally, the most vulnerable group of people were the most benefited from the training program since the estimate is higher when just including those who when they were unemployed they did not have a health insurance coverage (regressions 1.2 and 2.2).

Chapter 6: Cost-Benefit Analysis

In this last section, I perform a cost-benefit analysis of the evaluated skills-training program. Table 13 shows the analysis, where all amounts are in Argentinean Pesos and calculated per trainee. The analysis includes three possible scenarios: worst, expected, and best case. Still, in all cases the assumptions are quite conservative. The analysis considers three main stakeholders involved: trainees, the government, and firms.[19]

The cost section includes three main expenses and is the same for all scenarios. First, the direct cost of the training at the local level (at the training institution). I used the average total cost of courses per trainee according to the institution's administrative records. The amounts include the direct cost of providing the training to a single student and a 20% overhead cost, which is reasonable according to the training institution (see Appendix B for details). Second, the analysis includes indirect costs that exist at the national level in order to administer and monitor the program, adding an estimated 20%. Finally, I included trainee's opportunity cost of $715, which is an estimate of how much the trainee loses for taking the training instead of being working. All cases assume that the trainee was earning the minimum wage (about $35.74 an hour) and that trainees stop working 20 out of the 48 hours trained.[20] This is reasonable when considering that only 33 percent is formally employed and the training is provided outside usual labor hours, usually starting at 6:30pm. Thus, the total one-time cost for training an individual is $4,184 for all scenarios. However, since the average total courses graduates took was

[19] Of course, the society also might benefit when more people are included in the economic system, but I did not include it in the economic analysis due to lack of data availability.

[20] I could have made different scenarios for the foregoing worked hours, but I purposely avoid doing so since it may make too extreme the analysis: the worst case will be too bad and the best case too good.

2.21, the total one-time cost adds up to $9,247.

On the other hand, the benefits the training provides can be divided into four: additional graduate's earnings, firms' added productivity, additional sales tax collected, and reduced childcare allowance provided. The calculated earning differential is the difference between the pre and post salary. I assume that the individual was earning the minimum federal wage ($6,180) for formally employed people before the training, which is a quite conservative assumption considering that only 33% were formally employed. Regarding the wage after the training, I did different assumptions for the three scenario. For the worst case, I assumed that the trainee gets the agreed minimum wage in the metallurgic industry ($10,363). For the expected case, I assumed he gets the average wage of the industry, which adds up to $11,904 ($62.50 per hour x 44 hours a week x 4.33 weeks in a month). And for the best case, I assumed he earns the highest hourly wage in the industry ($77.4) adding to $14,748.[21] Therefore, the earning differential is $3,553, $5,094 and $7,938, respectively. The second benefit is related to firm's productivity. In the surveys to firms, employers declared that trainees in the long run were not necessarily more productive than other employees, but that they learnt quicker to do their job when hired. Thus, the best way to assign firm's earned productivity is by calculating the opportunity costs of training new employees. For the worst case I assumed that there was no productivity gains while for the other cases I assumed that employers would not need to train new employees using their existent resources, such as a supervisor. Thus, I estimated the productivity gain to be $1,454 a month, which is a reduced hour a day using a supervisor's hourly wage ($67.2 x 1 hour x 5 days a week x 4.33 weeks a month). The third benefit the training provides is the additional sales tax

[21] For sources and wages in the metallurgic industry see Appendix E.

(I.V.A. in Spanish) the government collects thanks to the increment in consumption caused by the additional income graduates have.[22] Finally, the fourth benefit is the reduction of child allowance the government provides to unemployed people for every child younger to 18 years old (2009). For the worst case scenario I assumed no-one stops receiving the allowance, which is quite conservative since the benefit is only for non-formally employed people. For the other cases, I assumed that those who have children stop receiving it. According to the surveys to graduates, on average each graduate have 0.52 children. Thus, the reduced allowance is $574 per trainee ($1,103x0.52). Therefore, we can conclude that the total monthly benefit the training would provide to a graduate who got a job is between $4,152 and $11,305, depending on the scenario.

The monthly benefit attributable to the training depends on the causal effect on the probability of formal employment this generates, since not everyone who takes the training gets a formal job. For the worst case scenario, I assumed that the causal effect is 11.6 percent, which is the lowest estimate from the DD analysis. And for the other two cases, I assumed the causal effect is the original 20.6 percent. Thus, the estimated amount of the benefit attributable to the training is $482 a month for the worst case scenario and $1,604 and $2,272 for the expected and best case, respectively.

[22] For calculations see Appendix F.

Table 13. Cost-Benefit Analysis. Estimation per Trainee in AR Pesos.

	Worst	Expected	Best	Stakeholder	Assumptions and Notes
Costs					
Direct and Indirect Cost (at local level)	$ 2,891	$ 2,891	$ 2,891	Government	Average cost of courses according to Appendix B
Indirect Cost (at national level)	$ 578	$ 578	$ 578	Government	20% of "Direct and Indirect Cost (at local level)"
Trainee Opportunity Cost	$ 715	$ 715	$ 715	Trainee	Hourly wage before treatment x 20 hours of training. All cases assume the trainee was earning the minimum wage.
Total Cost per Course per Trainee	**$ 4,184**	**$ 4,184**	**$ 4,184**		
Average Courses Trainee Graduates From	2.21	2.21	2.21		According to Adminsitrative Records
Total One-time Cost	**$ 9,247**	**$ 9,247**	**$ 9,247**		
Increased Monthly Benefits					
Wage before training	$ 6,810	$ 6,810	$ 6,810	Trainee	All cases assume that the trainee was earning the minimum wage, which is the federal minimum salary paid to formally employed people.
Wage after training	$ 10,363	$ 11,904	$ 14,748	Trainee	Worst case assumes the minimum salary in the industry (see Appendix E), Expected case assumes the average and Best case the
Earning Differential	$ 3,553	$ 5,094	$ 7,938	Trainee	Difference on wages before and after
Earned Productivity	$ -	$ 1,454	$ 1,454	Firms	Firms do not have to train new employee using existing resources. Calculated as one hour of a supervisor (official wage on Appendix A) a day.
Additional Tax Collected (I.V.A.)	$ 599	$ 859	$ 1,339	Government	For calculations see Appendix F, based on tax percentages and Argentina's Household Consumption Survey.
Reduced Child Allowance (A.U.H.)	$ -	$ 574	$ 574	Government	Worst case assumes no reduction while Expected and Best all individuals with children stop receiving it.
Total Monthly Benefits	**$ 4,152**	**$ 7,981**	**$ 11,305**		Total monthly benefits if everyone got a formal job.
Increased Probability of Finding a Formal Job	**11.6%**	**20.1%**	**20.1%**		Probabilities from DD regressions. For worst case I used the lowest estimate from Table 13.
Expected Monthly Benefits	**$ 482**	**$ 1,604**	**$ 2,272**		Total monthly benefits x Increased Probability of Finding a Formal
Monthly Interest Rate	2%	2%	2%		Based on an annual nominal interest rate of 29.8% (IMF 2016).
Total Months to Repay Investment after Completion	**30**	**7**	**5**		Rounded up. Benefits starting six months after investment (2 courses). No annual wage adjustment.

Note: since the investment is repaid within a year, no adjustment to wages nor additional for tenure were calculated. Income tax was excluded since the minimum taxable wage exceeds in all cases the wage after training. One month is equivalent to 4.44 weeks.

Considering the estimated one-time costs and monthly benefits, I calculated for each scenario the investment's break-even point and its net present value (NPV). Using IMF's (2016) projected yearly interest rate of 29.8%, the investment would be repaid in 30 months in the worst case scenario and in 5 months in the best case (see last row of Table 13). However, wages are always adjusted annually through collecting bargaining, according to the annual's inflation rate. Thus, Table 14 shows the estimated present value depending on how long the effect of the training lasts, adjusting wages in a yearly basis and using different annual interest rates the IMF (2016) projected for Argentina in its Country Report No. 16/346 for the years 2016 to 2021. The NPV is only negative for the first two years in the worst case scenario. All other cases have a positive NPV ranging from $2,719 per trainee –in the first year of the expected case– to $114,275 in the best case after five years.

Table 14. NPV of Investing in the Skills-Training Program per Trainee

With Annual Wage Adjustments and Effect Lasts (years):	Worst	Expected	Best
1	$ (5,648)	$ 2,719	$ 7,703
2	$ (859)	$ 18,641	$ 30,255
3	$ 4,145	$ 35,277	$ 53,819
5	$ 14,918	$ 77,958	$ 114,275

Notes: All calculations assumes benefits start after three month of training. Wages are adjusted every year according to IMF's projected annual inflation. The discount interest rate varies every year according to IMF's projected LEBAC nominal interest rate. Source: IMF Country Report No. 16/346.

Chapter 7: Conclusion

This thesis presented an evaluation of Ce.Fo.Se.'s sector-based skills training program from 2012 to 2016. Ce.Fo.Se. provided competency-based courses related to the metallurgic industry, mostly to young individuals –between 18 and 33 years old. Since the training institution is located within the Chamber of Metallurgic Industries in the Center of the Province of Santa Fe, it decides which training skills will offer through continuous consultation with local firms and a strong private public partnership between the Ministry of Labor and ADIMRA –the two main financing entities of the courses. My main research question focused in "formal employment" and "young people," which I answered using two methodological approaches: before-and-after analysis and, more rigorously, difference-in-difference using a five-year panel dataset.

In the first place, I found that sector-based skills-training programs cause a significant effect on helping graduates get a formal job. Job informality is an existing problem in all Latin American countries. In Argentina's case, the informality reaches to 35 to 60 percent of employed workers (Bertranou y Casanova 2014). Thus, it is relevant to understand how these types of programs contribute to solving this problematic. Using the difference-in-difference methodology, individuals who graduate from the program are 20.1 percentage points more likely to be formally employed than the control group. Furthermore, two main results from my estimations show that the types of skills graduates are trained on matters. First, skills related to operator, machining, and welder occupations had greater payoffs than other skills offered at the training institution. Secondly, after controlling for having taken or not a course, the DD analysis show that

more skills matter. Thus, skills explain better the variation in the outcome variable – formal employment– than just connecting individuals to jobs. These results are consistent with the response of 84 percent of surveyed firms, claiming they have difficulties finding skilled labor, and 59 percent of firms, which have strong preference to hire Ce.Fo.Se.'s graduates. Lastly, the results are also consistent with findings from the survey to graduates since only 7.7 percent consider the skills they learnt were irrelevant.

In the second place, which is also important for policy implications, the training had differential effects depending on graduates' age group. The impact of the training on formal employment was significantly higher for graduates younger to 24 years old: their increased probability of getting a formal job was 6.7 percentage points higher than those between the ages of 24 and 27 and 18.6 percentage points higher than older individuals. These are significant results considering that younger people usually have more difficulties in finding formal employment (Goldin, et al. 2015) and that they suffer from higher unemployment rates than older workers; in Argentina's case, youth unemployment rate is 3.6 times greater than that of the overall population. Thus, these types of programs can help equip young adults with relevant skills, increasing their employability, and help reduce the formal employment gap among youth and adults.

Finally, although I did not find different effects depending on the program's financing mechanisms the government is the only likely stakeholder that can fund these types of programs. The program's effect on formal employment is statistically the same when using public grants or fiscal credits from companies. However, when analyzing the two surveys conducted, I concluded that neither firms nor trainees are likely to pay

for the program, even when both benefit from it. Only big companies formally train their employees and only 11.5 percent of graduates would have taken the training if it had a cost. Thus, I carried out a cost-benefit analysis to calculate the total months it would take to recover the investment in these types of programs. Using the DD estimations and projecting three different scenarios, the repayment period can be between 5 and 30 months from trainees' graduation date, with just 7 months being the expected scenario, indicating a very high return for the government's and the individuals' investment in this type of targeted training.

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Appendices

Appendix A.

Appendix A. Training Programs Offered at Ce.Fo.Se.: Courses and Levels

	Occupations	Curse #	Inicial		Curse #	Advanced
Competency-Based Training Curriculums	**Operator**	11	Operator of Metallurgical Processes			
	Machiner	21	Parallel Lathe Machining	→	22	Parallel Lathe Preparation and Operation
		31	Universal Milling Machine Machining	→	32	Universal Milling Machine Preparation and Operation
		41	CNC Milling Machine and Lathe Programing	→	42	CNC Milling Machine and Lathe Operator
	Welder	51	Operations with Oxy/acetylene and Electrode Coating Machines	→	52	Operations with MIG MAG Machines
		53	Welding Material	→	54	Welding Electrode Coatings and MIG MAG Process
	Assembler	61	Mechanical Assembly Preparation	→	62	Mechanical Assembly
		63	Electrical/Mechanical Assembly Preparation	→	64	Electrical/Mechanical Assembly
	Electrician	81	Electricity Level I	→	82	Industrial Electricity
Other	**IT**	71	3D Modeling Level I	→	72	3D Modeling Level II
		73	AutoCAD	→	74	SolidWorks
	Mid-Level & Mgment.	91	Management and Supervision			
	Stand-Alone or In-Company	101	Health and Safeness in the Workplace			
		102	Firefight			
		111	Firm Specific - Fiscal Credit			
		121	Other		122	Gas and Water Installation

Appendix B.

Appendix B. Ce.Fo.Se. Training Programs - 2016 Budget per Student (May 2016)

Course Title	Course Code-Level	Total Training Hours	ADIMRA's Contribution (AR$)	MoL's Contribution (AR$)	Other Sources (AR$)	Overhead Cost (20%) (AR$)	Total Cost* (AR$)	Total per Student (AR$)
Operator of Metallurgical Processes	11	60	$ 5,558	$ 24,632	$ -	$ 6,038	$ 36,228	$1,811.40
Parallel Lathe Machining	21	48	$ 4,446	$ 18,794	$ -	$ 4,648	$ 27,888	$1,859.23
Parallel Lathe Preparation and Operation	22	48	$ 4,446	$ 18,949	$ -	$ 4,679	$ 28,074	$2,807.39
Universal Milling Machine Machining	31	48	$ 4,446	$ 21,374	$ -	$ 5,164	$ 30,984	$2,065.59
Universal Milling Machine Preparation and Operation	32	48	$ 4,446	$ 21,773	$ -	$ 5,244	$ 31,463	$3,146.26
CNC Milling Machine and Lathe Programing	41	48	$ 4,446	$ 17,699	$ -	$ 4,429	$ 26,575	$2,657.46
CNC Milling Machine and Lathe Operator	42	48	$ 4,446	$ 23,120	$ -	$ 5,513	$ 33,080	$3,307.98
Operations with Oxy/acetylene and Electrode Coating Machine	51	48	$ 11,408	$ 24,503	$7,000	$ 8,582	$ 51,493	$5,149.29
Operations with MIG MAG Machines	52	48	$ 8,336	$ 18,683	$7,000	$ 6,804	$ 40,823	$2,721.51
Welding Material	53	48	$ 9,417	$ 21,510	$7,000	$ 7,585	$ 45,512	$4,551.15
Welding Electrode Coatings and MIG MAG Process	54	48	$ 10,512	$ 18,399	$7,000	$ 7,182	$ 43,094	$4,309.37
Mechanical Assembly	61	48	$ 4,446	$ 20,124	$ -	$ 4,914	$ 29,484	$1,965.61
Mechanical Assembly Preparation	62	48	$ 4,446	$ 24,525	$ -	$ 5,794	$ 34,766	$2,317.74
Mechanical Assembly Preparation II	63	48	$ 4,446	$ 24,234	$ -	$ 5,736	$ 34,416	$3,441.58
Mechanical Assembly II	54	48	$ 4,446	$ 20,567	$ -	$ 5,003	$ 30,015	$3,001.53
3D Modeling Level I	71	64	$ 5,928	$ 21,164	$ -	$ 5,418	$ 32,510	$2,031.89
3D Modeling Level II	72	64	$ 5,928	$ 20,804	$ -	$ 5,346	$ 32,078	$2,004.89

*Total Cost includes trainers' fees, teaching supplies, teaching materials and tools, overhead costs.

Source: Ce.Fo.Se. internal documentation - Anexo II

Appendix C.

Appendix C. Survey to Graduates Template (translation from Spanish version)

Survey to Ce.Fo.Se.'s Graduates: The participation on this survey is anonymous, voluntary, and strictly confidential.

Name:

DNI: ____ DOB: ___ Age: ___ Gender: _

City where you live: _____

1 . Which courses did you take at Ce.Fo.Se.?

___ Introduction to the Metallurgic Operations

___ Machinery ___ Assembler ___ IT

___ Welding ___ Electrician ___ Other: _____

2 . Which of the courses you took were more useful to you? Why? _____

3 . What is the highest educational level you have accomplished?

___ Some Primary ___ Some Secondary ___ Some Tertiary ___ Some College

___ Primary ___ Secondary ___ Tertiary ___ College

4 . Which method of communications you usually use?

___ Telephone ___ Cellphone ___ e-mail

___ Facebook ___ WhatsApp ___ Other:

5 . Do you have dependents? How many? _____

6 . Before taking the course at Ce.Fo.Se. were you working?

___ Yes, Formal Employment ___ Yes, Informal Employment

___ Yes, Self-Employed ___ No, not working

6 .a. Was the job in the metallurgic industry? ___ Yes ___ No

6 .b. Was the job stable? ___ Yes ___ No

6 .c. Do you keep this job? If yes, have you improved your working conditions since you graduated? How?

7 . How many years of experience you have in formal jobs? _____

8 . Are you currently working?

___ Yes, Formal Employment ___ Yes, Informal Employment

___ Yes, Self-Employed ___ No, not working. How long have you been without a jo?

8 .a. When did you start working in this job? Before, during, or after the training took place?

8 .b. Is your current job in the metallurgic industry?

8 .c. Which is your occupation in your current job?

8 .d. How did you get youth current job?

___ Through Ce.Fo.Se. ___ Through newspaper/internet posting

___ Through family and friends connections ___ Going to the company

8 .e. Did Ce.Fo.Se. helped you somehow in getting your current job? How?

___ No ___ Professors' Networks ___ Ce.Fo.Se. provided references

___ The firm contacted me through the institution ___ Other

9 . How many hours do you work a week? ___

9 .a. Would you like to work more hours? ___

10 In your current job, are you applying the skills you learnt at Ce.Fo.Se.?

___ Yes, continuously ___ Yes, for some tasks

___ Yes, but infrequently ___ No

11 . Are you currently actively looking for a job? ___ Yes ___ No

11 .a. Could you start working now? ___ Yes ___ No

11 .b. How many months have you been looking? ___

Appendix C. (cont.)

11 .c. In the last week, what have you done to look for a job?

___ I signed up on a list\ ___ I sent my CV ___ I posted signs

___ I introduced myself at a company ___ I looked online ___ I did not look actively

___ I used the Employment Office ___ I looked on my neighborhood

11 .d. How often do you look for a job? ___

11 .e. Why do you think you are not getting a job?

___ Just starting looking ___ I don't have enough skills ___ I do not know

___ I do not have networks ___ Because of my age ___ Other:

___ There are no jobs ___ I don't have experience

12 . Which federal subsidy do you receive?

___ None ___ Social Income for Work ___ PROG.R.ES.AR

___ Unemployment Insurance ___ Plan Más y Mejor Trabajo ___ Training for Work

___ A.U.H. ___ Ellas Hacen ___ Other

13 . Did you receive the someone before taking the course? Which ones and which ones not?

14 . What was your main motivation to take the course?

___ Get a job ___ My firm required me to do so ___ Learn a new occupation

___ Stability ___ Other:

15 . What do you think about the courses being free? _____

15 .a. In that moment, would you have taken the courses if they had a cost?

___ Yes, I would have taken them anyways ___ No, I could not have taken it

___ Yes, but it would have been hard to take them ___ I don't know

16 . Did you learn about companies in the area you were not aware before? _____

17 . Do you think the course provided you job skills?

___ None ___ Few ___ Some ___ Many

18 . Did you learn: ___ What you were expecting ___ More than expected

___ Less than expected

19 . Rate the courses regarding: 0 to 5 being 5 the best qualification

___ Duration ___ Professors ___ Hours ___ Content

___ Theory-Practice Balance

20 . Do you think these courses are appropriate for women? Why? _____

21 . Would you recommend these courses to a friend? Why? _____

22 . What do you like the most about being trained at Ce.Fo.Se.? _____

23 . Do you think that thanks to the courses you will improve your labor status? Why? In what sense? _____

24 . Do you want to take more courses at Ce.Fo.Se.? _____

25 . Is there a course or occupation you would like to take but it is not offered at Ce.Fo.Se.? _____

26 . What could Ce.Fo.Se. improve? _____

27 . Can I contact you back in a few months? _____

Thank you!

Appendix D.

Appendix D. Survey to Member Firms (translation of Spanish version)

Company Name	City
Year of Establishment:	Size
Sector	Principal Product
Name of Surveyed	Position

Company Composition:

1 How many employees does the firm has?
2 How many of them are in the productive level?
2 .a. How many of them are women?
3 What is the average age of your empl Tenure?
4 How many employees do you hire a year for the productive level?
5 What requirements you have for hiring new employees in the productive leave?
5 .a. Do you have difficulties in hiring employees in the productive leave? Why?
6 Through which channels do you get new employees?

____Posts ____Through employees/family/friends _____Employment Office
____Through Ce.Fo.Se. ____Contacting other firms _____Other

7 How many weeks it takes to fill up a vacancy since you realize you need a new hire?
8 When you need to hire someone in the operative level, do you prefer to hire:

____A women ____A men ____Is the same

8 .a. Why you have this preference?
8 .b. Do you notice there are productivity differences among the genders?
8 .c. Do you value differently someone who has being trained at Ce.Fo.Se.?
9 How many of your employees have been trained at Ce.Fo.Se.?
9 .a. Employees trained at Ce.Fo.Se. are:

____More Productive ____Equally Productive ____Less Productive _____I don't know

9 .b. The time it takes a Ce.Fo.Se.'s graduate to learn to do its job is:

____More ____Equal ____Less than someone who did not graduated.

10 What incentives you have to retain your employees?

____Economic incentives ____Non-economic incentives _____Career Paths
____Productivity incentives ____Performance evaluations

11 How many employees in the productive level stop working at the company in a yearly basis?
11 .a. What is the main motive someone stops working?

____Leaves/Retirement ____Fired ____Professional growth
____Better offer someplace else ____Finds the same job in another firm
____Leaves to a better paid industry ____Other

13 How many employees in the productive level do you plan to hire within the next year?

Training:

1 Does the firm train its employees?

____No (unipersonal) ____Yes ____Yes, but not often _____No

1 .a. Are the trainings usually: ____Within working hours ____Outside working hours

.b. To which levels/sectors do you offer training?

____Productive ____Technical ____Management _____Sales
____Quality Control ____Administration ____Human Resources _____Other

.c. How often in a year do you provide training?

Appendix D. (cont.)

.d. Do you register training hours?
.e. To how many employees do you offer training in a year?
.f. Are these training preferably: ____ Within company ____ External _____ Depends
If they are external: How many of them are through Ce.Fo.Se.?
____ None ____ Some ____ The great majority _____ All
In what other places do you train your employees?_____
Why you do not train internally?
____ Because there are external options _____ Not enough time
____ Because it is too costly _____ We don't know how to
____ Because there are too many/few employees to train _____ Coordination issues
.g. Why do you train employees?
____ Improve productivity levels _____ Use un-used hours _____ Quality requirement
____ Employees request it _____ To avoid union problems _____ Other
If you do not provide training, why you don't do it?
____ No interest ____ There are no good courses _____ Too costly
____ There is no time ____ It is not responsibility of the firm _____ Coordination issues
____ Not to stop production ____ To avoid union problems _____ Other
____ Too few employees need it ____ To avoid loosing experienced labor

3 Do you think your employees need more training? In which areas?

Other

1 Do clients participate on the design of the product?
2 Do you meet with other firms to collaborate, create networks, exchange experiences, or solve common problems?
3 Is the firm connected or work with the following entities?
___ Universities ____ Consultants ____ Public Entities _____ Institutes
What for?
4 What importance do you give to the union-firm relationship/activity?
____ None ____ Some ____ I participate _____ I always participate
5 What are the firm's limitations to grow?
____ Financing ____ Initiative ____ Market _____ Other
____ Time ____ Human Resources ____ Economy _____ Public Policies
6 What national or provincial public programs do you know on financing and training?

Regarding the Chamber Services:

1 Do you find any benefit to be associated to the chamber? Which one?
2 What services the chamber provides that you are aware of?
2 .a. How often do you use these services?
2 .b. Why do you use it or not?
2 .c. Do you think you could use them more? Why?
3 What additional services do you need for improving/growing your firm?
4 Do you need new technologies? Which ones?
5 Did you hire a consultant during 2015 or 2016? What for?
6 In your opinion, what should the Chamber do better?

Thank you!

Appendix E.

Appendix E. Argentina's Wages 2012 to 2016

	Apr-12	Jul-13	Jul-14	Jul-15	Jul-16
Federal Minimum Wage (Salario Mínimo Vital y Mobil)	$ 2,670	$ 3,300	$ 4,400	$ 5,588	$ 6,810
In the Metallurgic Industry: the greatest between					
Minimum Wage in the Industry (Ingreso Mínimo Global de Referencia, IMGR)	N/A	N/A	N/A	**$ 8,160**	**$ 10,363**
and					
Calculation of the hourly wage and additional:					
Hourly Wages					
Ingresante	$ 18.6	$ 23.1	$ 30.0	$ 38.3	$ 48.6
Operario calificado	$ 20.1	$ 25.0	$ 32.5	$ 41.5	$ 52.7
Medio oficial	$ 21.7	$ 26.9	$ 35.0	$ 44.7	$ 56.8
Operario especializado	$ 23.2	$ 28.8	$ 37.4	$ 47.8	$ 60.7
Operario especializado multiple	$ 24.5	$ 30.4	$ 39.6	$ 50.5	$ 64.2
oficial	$ 25.7	$ 31.8	$ 41.4	$ 52.9	$ 67.2
oficial multiple	$ 27.7	$ 34.3	$ 44.6	$ 57.0	$ 72.3
Operadores CNC		$ 36.7	$ 47.7	$ 70.0	$ 77.4
Additional					
Tenure	1%xYear	1%xYear	1%xYear	1%xYear	1%xYear
Historic Annual Adjustments		**24%**	**30%**	**28%**	**27%**

Sources: Federal Minimum Wages were extracted from "Resolución C.N.E.P.S.M.V.M N2" for each of the years shown. Wages from the metallurgic industries are from "C.C.T. N260/75 -Salarios - Anexo A" for each of the years shown.

Appendix F.

Appendix F. Calculation of Additional Sales Tax Collection (I.V.A.)

Additional Tax Collected	Average Income Spent per Category	Tax Percentage per Category	Worst Case	Expected Case	Best Case
Wage / Earning Differential			$ 3,553.0	$ 5,094.2	$ 7,938.2
Consumption Categories					
Food and Beverages	39%	16.7%	$ 231	$ 331	$ 516
Clothing and Shoes	9%	21.0%	$ 69	$ 99	$ 154
Properties, gas, water, and electricity	8%	27.0%	$ 80	$ 114	$ 178
Home equipment and manteinance	7%	13.7%	$ 33	$ 48	$ 75
Health	5%	2.2%	$ 4	$ 5	$ 8
Transport and Communications	17%	16.2%	$ 98	$ 140	$ 218
Leisure	7%	17.4%	$ 42	$ 60	$ 94
Learning	3%	1.5%	$ 1	$ 2	$ 3
Various Goods and Services	6%	21.0%	$ 42	$ 60	$ 93
Additional Tax that could be Collected			**$ 599**	**$ 859**	**$ 1,339**

Sources: INDEC's Household Comsumprion Survey, 2013. Tax percentages: AFIP, 2008. IVA