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JOB TRAINING THROUGH TURMOIL

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ABSTRACT

We follow the labor market outcomes of applicants who were randomized into job training a year and a half before the pandemic through the subsequent economic turmoil that resulted from COVID-19. Despite persistently improved labor market outcomes of training participants prior to March 2020, we show that job losses resulting from the pandemic washed away all the benefits of the program. A year and a half after the initial scars of the pandemic, there are no visible signs of recovery of trainees' labor market outcomes.

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A primary goal of job training programs is to move people from precarious and informal work to more stable jobs. Several job training programs succeed in improving employment outcomes in the short term.[1] Still, a common fear is that the benefits of such training programs may disappear during economic crises. For example, Hanushek et al. (2017) explain that if training programs are too job-specific, the skills they provide may be insufficient to help adapt to shocks to the labor market.

Assessing such hypotheses empirically, however, is challenging since researchers need to tackle two problems of selection. First, people select into education and training programs. Second, exit from jobs, too, typically results from selection. Overcoming these issues requires a set of two instruments – for both training and for job loss – as well as a longitudinal data-set spanning both the training program and the economic shock.

In this paper we study whether a pre-pandemic job training program targeting young low-income adults is able to sustain its employment benefits through the COVID-19 pandemic. We link applicants randomly allocated into a job training program focused primarily on service sectors in Cali, Colombia that ended in December 2018 to monthly administrative records on employment that include both the initial COVID-19 shock as well as subsequent periods.

In earlier work, Barrera-Osorio et al. (2021) show that the job training program we study succeeded in shifting people to formal employment, paying for itself in just eight months. In this new paper we show that, despite persistent pre-pandemic benefits to earnings (15.81 USD or 18 percent) and employment (8 p.p. or 27 percent), nearly all the benefits of the program disappear just months into the pandemic: those randomly assigned to job training no longer experience any benefits in the labor market. In fact, given the higher pre-pandemic outcomes of applicants assigned to treatment, treated individuals experience negative effects which are almost twice as large as their comparison group counterparts. By August 2021, a year and a half into the pandemic, the situation is no better, with our results indicating no employment recovery.

Our results bring some of the first empirical evidence to bear on the resilience of education and training programs to the effects of economic shocks. In the paper most similar to ours, Beuermann et al. (2021) find a contrasting set of results. They tackle selection into education using regression discontinuities in secondary school admissions that increase female educational attainment by three years. Following their sample through the COVID-19 pandemic with a survey, they find that women who experienced an increase in education

[1] In Colombia, see for example, Attanasio et al. (2011) and Barrera-Osorio et al. (2021). For recent evaluations of job training programs outside Colombia, see for example, Alfonsi et al. (2020) or Chakravarty et al. (2019).

experience significantly fewer employment losses as a result of the pandemic. Our results are also in line with Field et al., (2019), who find cohorts that graduate from vocational programs during economic hardship perform worse. Though they do not focus explicitly on economic shocks, other papers in both Colombia and elsewhere find vocational programs to provide sustained benefits through the 2008 economic crisis (Kugler et al., 2017; Silliman and Virtanen, 2019).

There are several stories that may explain why the benefits of the job training in Cali are washed away by the pandemic. The first of these is the enormity of the COVID-19 induced economic shock – nearly half of families surveyed in Latin America reported a family member losing a job (Bottan et al., 2020). Another reason that the benefits were washed away may be the short duration of the program itself compared to longer-term educational investments such as those studied by Beuermann et al. (2021). Third, the job losses experienced by participants in the Cali job training program may be due to the fact that the service sector – the most common sector for training – was hardest hit by the COVID-19 pandemic (Moehring et al., 2021). Fourth, since employees had no more than a year and half of tenure in their firms, these losses may result from labor market institutions by which the last employees into a firm are most likely to be the first employees out of the firm (Buhai et al., 2014).[2] Unfortunately, the data in our study do not allow us to determine which of these stories underlies our results.

Our findings also extend existing research on heterogeneity in the costs of economic shocks. For example, Farber et al. (2011, 2015) study the 2008 recession and document that economic shocks tend to be most disruptive for people with the lowest levels of education. Likewise, Kauhanen and Riukula (2019) find that people working in jobs with routine tasks have higher costs of job loss than people working in socially intensive roles. We find that, relative to pre-pandemic employment, the costs of job-loss (employment and earnings) were higher for applicants who entered the formal sector as a result of job training than for other applicants. One reason for this is that compared to their peers in the comparison group, individuals randomized to job training had better pre-pandemic outcomes: they had farther to fall. Another potential reason for this is because the job training mainly targeted service sectors, the occupations most harmed by COVID-19. This suggests that the qualitative nature of or the reasons for economic shocks may come with disparate effects.

These results highlight the enormous economic costs of the COVID-19 pandemic, suggesting that even active labor market and social programs that functioned well before the

[2]Additionally, they may reflect the narrow nature of the skills received by participants of the program in Cali (Deming and Noray 2021; Hanushek et al., 2017; Acemoglu and Autor, 2011; Krueger and Kumar, 2004).

pandemic may require rethinking in the post-pandemic world.

1 Context

Our study is situated in Cali, the third largest city in Colombia with a population of 2.2 million people. We focus on applicants to an oversubscribed job-training program that took place between June and December 2018. In total, this program provided 18 classes, each lasting 160 hours, in 8 different areas of the service sector: sales and client services, general services, surveillance and security services, cashiers, quality control assistant, cooking assistant, delivery assistant and storage assistant.[3]

Applicants registered voluntarily into classes in response to a call for registrations by the Carvajal Foundation.[4] The Foundation established this program to help the poorest in the community access jobs. Thus, the foundation reaches broadly to enroll participants through radio, social media, loud-speakers in cars that go through poor neighborhoods, flyers, and through the public employment office and offices that provide other public services to the poor. As reported in the next section, most individuals who registered for these courses were in the lowest socio-economic strata according to the Census of the Poor in Colombia.

Individuals who were interested in registering for the classes attended an informational meeting and registered for the specific classes they wanted to take. Each class had between 23 and 31 spots and registration in each class ranged from 28 to 47 registrations per class. Given over-subscription in the classes, the foundation randomly selected individuals to either receive a spot or not receive a spot in the course. The lotteries for each course were recorded by video to ensure everyone knew people were allocated into the courses by luck. Those who did not win a spot in the training courses through the lottery were in the control group and were not provided other services by the Carvajal Foundation for an entire year following registration. As shown in the next section, the randomization divided people into groups that were very similar on average in terms of their characteristics, thus giving credibility that the lottery worked well in terms of randomly assigning individuals into and out of the classes. There were initially 663 people who registered in the courses and of these, 451 were randomly assigned to the training and 212 were assigned to the control group.[5]

[3]The program offered two of each of these types of courses, except for 4 courses in General Services. These courses varied in duration from between 4 and 10 weeks depending on the daily number of hours (between 5 and 8) of training. While one course ended in July and one in August of 2018, the vast majority ended in the Fall of 2018 (4 in September, 2 in October, 8 in November and 2 in December).

[4]The Carvajal Foundation is a non-profit foundation devoted to help with social programs in Cali including programs to support entrepreneurship, education initiatives, training, and employment programs. We partnered with the Carvajal Foundation who ran and implemented the program.

[5]Although they are not the focus of this paper, the full underlying experimental design included further

Given that some people in the control group were taken off wait-lists, and not everyone who was assigned to treatment enrolled in the program, randomization to the treatment group increased enrollment in the training program by 60 percentage points.

2 Descriptive data and context

The primary data for this project come from Colombian Social Security Records, and contain information on monthly days of formal employment and earned income. In addition to using a measure of days of employment, we create a measure of whether or not individuals were employed at all each month. The administrative data span the time period from June 2016 to August 2021.

Descriptive graphs detailing each of these three outcomes for the period between June 2017 and August 2021 are shown in Figure 1. These graphs suggest that the outcomes of applicants to job training receiving spots in the training programs and those who did not are parallel prior to random assignment. In the period after the end of job training (second red dotted line), applicants admitted to job training experience markedly improved outcomes compared to other applicants. Further, in March 2020, all applicants appear to lose ground in the labor market. Soon after the beginning of the pandemic-induced shock, workers admitted to job training no longer maintain their advantage compared to their peers wait-listed for job training. Finally, there are no signs that applicants admitted to the job training program regain their advantages in the recovery period following the pandemic.

To assess balance between admitted and other workers prior to random assignment, we complement the administrative data with baseline survey data collected prior to random assignment to job training (see Table 1). Column 1 of this table shows the descriptive statistics detailing the population in the comparison group. The table suggests that the majority of participants in our sample are from quite disadvantaged backgrounds, and two thirds of the participants are female. For more information on all the baseline and endline survey measures collected prior to the pandemic, see Barrera-Osorio et al. (2021).

3 Empirical approach

We ask three related questions: i) How does admission to job-training affect pre-pandemic employment and earnings?; ii) How does the Covid-19 induced economic shock affect workers?; iii) How does exposure to job-training affect employment in the recovery period following the initial economic shock?

treatment branches that varied the emphasis on social or technical skills (see Barrera-Osorio et al., 2021).

Before estimating any effects of the program, we use survey data collected at baseline to check for balance between treated and comparison individuals. Since we are unable to include course fixed effects in our analysis with the administrative data, we check for balance across all variables also without the inclusion of course fixed effects (Table 1, Column 3).

To estimate the effect of job-training on pre- and post- pandemic employment and earnings, we take advantage of random assignment to oversubscribed job-training programs (see Section 1). This approach is operationalized through the following equation, using data from December 2018 to February 2020 (pre-period) and from April 2020 to September 2021 (post-period):

$$Y_{it} = \alpha_0 + \alpha_1 D_{it} + \pi_t + \eta_{it} \tag{1}$$

This equation estimates the relationship between outcomes (Y_{it}) for individual i in month t and their random assignment into job-training (D_{it}). The variable D takes the value of 0 prior to randomization for all applicants and the value of 1 for applicants randomized to receive job training after randomization. The equation includes month fixed effects. The coefficient α_1 measures the effects of job-training on labor market outcomes. Standard errors are clustered by person in all the analysis. The estimates from this equation are shown in Panels A and B of Table 2.

Randomization to treatment increased enrollment in the job training program by 60 percentage points (Barrera-Osorio et al., 2021). For simplicity, all analysis in this paper focuses on a reduced form analysis of the effects of the program. To estimate treatment effects on treated individuals, we can divide all effects by 0.6 to scale the effects by enrollment.

Next, we estimate the magnitude of the Covid-induced economic shock for both treatment and control groups by examining the labor market outcomes of applicants to job training in the initial four months following March 2018 compared to the prior twelve months (See Table 2, Panel C). According to the Colombian statistical agency, Departamento Administrativo Nacional de Estadistica - DANE (2021), the national economy contracted 16 percent in the second quarter of 2020.[6]

$$Y_{it} = \beta_0 + \beta_1 COVID_t + \beta_2 (D_i * COVID_t) + \beta_3 Months_t + \beta_4 (Months_t * D_i) + \lambda_i + v_{it} \tag{2}$$

In this equation the term $COVID_t$ is a binary variable given the value of zero for the

[6] While the causes of an economic shock may occur before the economic shock itself, in the case of COVID-19, the economy experienced a shock almost as soon as the world was beginning to learn about its health effects.

period before March 2020 and 1 for the period afterwards. By interacting randomization into job training with the economic shock, we allow for the economic consequences of Covid-19 to be different for treated and untreated workers. Given that there looks like there is a linear trend in outcomes over this period, we include a linear time variable. We interact this with treatment status so that treated and untreated individuals are allowed to have different labor market trajectories. We also include individual fixed effects so that all the variation comes from within individuals over time. The term β_1 measures the effect of the pandemic for untreated workers and β_2 measures the differential effect of the pandemic on workers randomized to receive job training.

Third, we estimate the effects of job training on recovery following the initial pandemic-induced shock. In this approach we focus on the months from March 2020 to August 2021 (through this entire period, D_i takes the value of one for the treated group). We define the initial period of the shock as the first four months after March 2020 (the period of the deepest economic shock), and the following months as the recovery period. By 2021, the economy began to experience large growth, growing by 27 percent in the second quarter of 2021 (DANE, 2021).

$$Y_{it} = \gamma_0 + \gamma_1 MonthsPost_t + \gamma_2(D_i * MonthsPost_t) + \delta_i + \omega_t + \tau_{it} \tag{3}$$

In this equation the coefficient of interest is γ_2, which measures the monthly improvement in labor market outcomes for individuals receiving job training compared to their peers in the comparison group (Table 2, Panel D).

We complement these estimates of the effects visually with monthly event-study style estimates of the differences in outcomes for individuals randomized into job training and their peers in the comparison group. These are estimated using the following equation:

$$Y_{it} = \sum_{t=1}^{T} \delta_t D_i + \psi_t + \xi_{it} \tag{4}$$

This equation is estimated using all months of data in the full sample. The variable ψ_t is a vector of month dummy variables, and takes out all temporal variation in the control group. Here the variable D_i takes the value of 1 for individuals assigned to the treatment group already prior to randomization into job training. This is useful for measuring the differences in outcomes by treatment status each month both prior to the job training program as well as through the pandemic.

4 Results

Table 2 and Figure 2 present the three above estimates for the three outcomes: days of formal employment, months of formal employment, and monthly SS contributions (a proxy of labor income). The results follow closely the descriptive trends displayed in Figure 1. Prior to randomization individuals applying to job training were on parallel trajectories regardless of treatment status. Post training, individuals enrolled in job training outperform their peers once they enter the labor market (Panel A). Their gains show no signs of dissipating through the period prior to the COVID-19 pandemic. After March 2020, both treated and untreated applicants experience negative shocks to their labor market trajectories (Panel C). After these shocks, there appears to be no differential recovery between treated and untreated individuals.

Assignment to job training improved all outcomes observed in the administrative data prior to the pandemic by about 20 percent compared to the comparison group in the same period (Table 2, Panel A). Formal employment increased by 1.8 days a month, with people being 8 percentage points more likely to work each month. Monthly earnings increased by 15.81 USD.

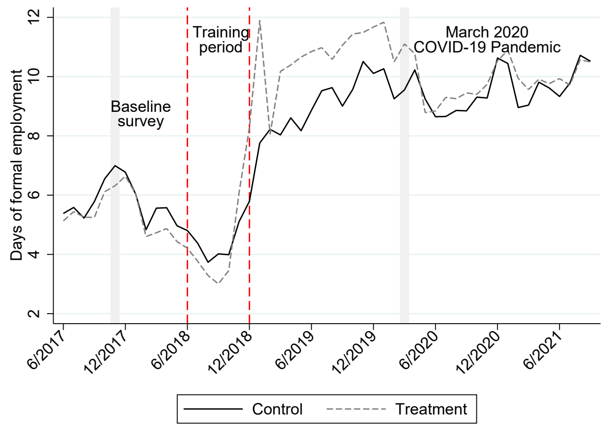
After the COVID-19 induced economic shock after March of 2020, the benefits of the job training program disappear altogether (Panel B). In fact, compared to the twelve months prior to the pandemic, applicants assigned to job training end up experiencing nearly twice the losses as applicants in the comparison group (Panel C). These negative shocks are bigger for applicants who gained entry to job training, potentially because they had farther to fall.

Finally, compared to applicants in the comparison group, applicants assigned to job training experience no relative improvements after the initial negative COVID-19 induced shock (Panel D).

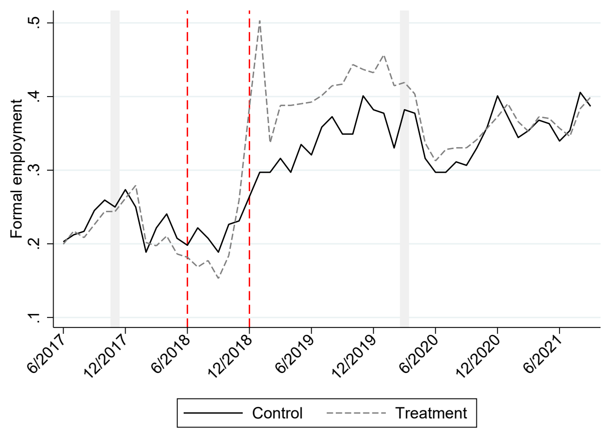
5 Discussion

In this paper, we study the effects of a job training program through the period before and after the COVID-19 induced economic crisis. The program, in Cali, Colombia, improves pre-pandemic formal sector earnings and employment by about twenty percent. Despite these marked improvements in the outcomes of applicants assigned to the job training program prior to March 2020, all benefits of the program disappear with the onset of the pandemic-induced crisis. Moreover, participants in job training appear to experience no relative improvements in the subsequent recovery period after the initial economic shock. The results suggest that substantial investments are required for workers to overcome deep recessions.

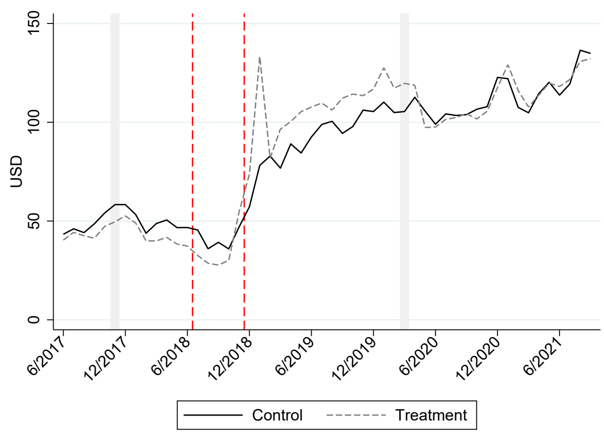
Figure 1: Descriptive graphs from administrative registers



(a) Days of employment



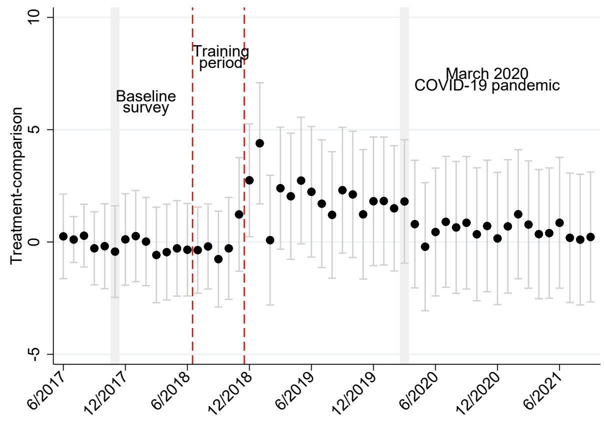
(b) Employment



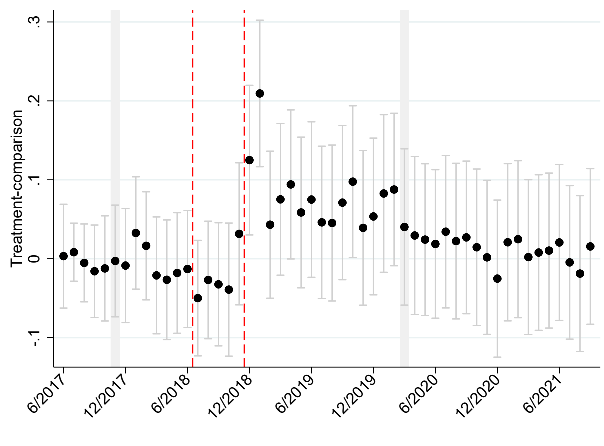
(c) Contributions

Notes: Figure 1 displays mean outcomes by treatment status. As shown in Figure 1(a), the gray vertical regions mark the baseline data collection and March 2020 – the first shock of the Covid-19 pandemic, and the red vertical lines indicate the beginning and end of the treatment periods.

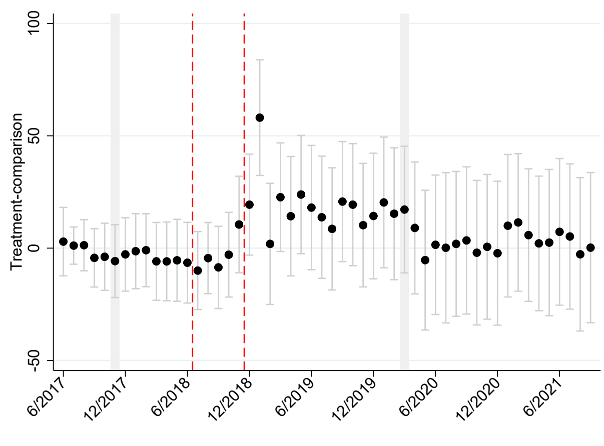
Figure 2: Treatment-comparison differences in monthly outcomes



(a) Days of employment



(b) Employment



(c) Contributions

Notes: Figure 2 displays mean monthly differences between the treatment and comparison group. As shown in Figure 2(a), the gray vertical regions mark the baseline data collection and March 2020 – the first shock of the Covid-19 pandemic, and the red vertical lines indicate the beginning and end of the treatment periods.

Table 1: Covariate balance check

		Treatment-comparison difference	Difference without course FE
Male	0.34	0.00	0.03
	(0.03)	(0.03)	(0.04)
Age	26.21	-0.61	-0.25
	(0.44)	(0.57)	(0.51)
Years of education	11.31	-0.06	-0.01
	(0.11)	(0.15)	(0.14)
Black	0.55	0.00	0.01
	(0.03)	(0.05)	(0.04)
Mestizo	0.17	-0.01	-0.01
	(0.03)	(0.03)	(0.03)
Indigenous	0.03	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Disability	0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Primary education	0.99	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Secondary education	0.94	-0.02	-0.02
	(0.02)	(0.03)	(0.02)
Technical higher education	0.29	0.02	0.02
	(0.03)	(0.04)	(0.04)
Professional higher education	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)
Enrolled in school	0.07	-0.03	-0.01
	(0.02)	(0.02)	(0.02)
Using Public Employment Service	0.37	-0.04	-0.04
	(0.03)	(0.04)	(0.04)
Household size	4.45	0.13	0.10
	(0.13)	(0.16)	(0.15)
HH income per day (USD)	19.23	4.78	2.84
	(4.25)	(5.78)	(5.65)
HH with electricity	1.00	-0.01	-0.01
	(0.00)	(0.01)	(0.01)
HH with water	0.99	0.00	0.00
	(0.01)	(0.01)	(0.01)
HH with sanitation	0.98	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Joint significance		F-test = 0.75	F-test = 0.59
		p-val = 0.75	p-val = 0.91
Course/Stratification FE	No	Yes	No
Observations	212	663	663

Notes: The table reports the control mean and differences between treatment and control groups, along with standard errors. All comparisons between treatment and control groups are within stratification group. Significance levels (* = 0.10, **= 0.05, *** = 0.01).

Table 2: Results

	Days of formal employment	Months of formal employment	Monthly SS contributions
	Panel A: Effects of job training before March 2020		
Treated	1.77 **	0.08 ***	15.81 *
	(0.85)	(0.03)	(9.12)
	Panel B: Effects of job training after March 2020		
Treated	0.28	0.01	-0.21
	(0.96)	(0.03)	(12.13)
	Panel C: COVID-19 induced economic shock		
Untreated	-1.06	-0.07 **	-7.52
	(0.87)	(0.03)	(10.04)
Treated	-2.04 ***	-0.10 ***	-21.40 ***
	(0.53)	(0.02)	(5.56)
Difference	-0.98	-0.03	-13.87
	(1.01)	(0.03)	(11.47)
	Panel D: Recovery from COVID-19 shock		
Untreated	0.07	0.00	1.67 *
	(0.07)	(0.00)	(0.89)
Treated	0.04	0.00	1.60 ***
	(0.04)	(0.00)	(0.56)
Difference	-0.03	-0.00	-0.07
	(0.08)	(0.00)	(1.05)
Observations	663	663	663

Notes: The same individuals are followed through all three periods we study: job training, the COVID-19 induced economic shock, and the recovery period after COVID-19. The estimates in Panel A are based on data from the months between June 2017 and March 2020; those in Panel B are based on data from the 12 months prior to March 2020 as well as the four first months of COVID-19 induced job loss; the estimates in Panel C are based on data after March 2020. Significance levels (* = 0.10, **= 0.05, *** = 0.01).

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