
A Long-Term Evaluation of a Short Training Program for the Unemployed: Exploring Administrative Data

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To cite this article:

Miguel Baião, Isabel Guedes, Pedro Martins. (2024). A Long-Term Evaluation of a Short Training Program for the Unemployed: Exploring Administrative Data. *Journal of Human Resource Management*, 12(1), 1-16. <https://doi.org/10.11648/j.jhrm.20241201.11>

Received: November 23, 2023; **Accepted:** December 21, 2023; **Published:** January 11, 2024

Abstract: Training programs can promote lifelong learning and facilitate the mobility of workers towards growing sectors. However, such interventions may require significant time investments from participants and financial investments for governments. Since most active labor market policies (ALMP) studies focus on short-run effects, consistently finding small or negative short-run effects and rarely evaluating if positive long-run effects occur, this study aims to surpass this gap. We evaluate both the short and long-run impact of a Portuguese short training program for the unemployed, launched in 2012, named *Vida Ativa*. We assess its sociological and economic effects on post program, unemployment duration and probability of recurrence. The study draws on four comprehensive administrative databases of the Portuguese Public Employment Services (IEFP), providing individual information over the period of December 2012 to October 2019. The method used is an OLS regression, and each (short and long run) effect is evaluated with different treatment variables and sample restrictions. We found that ALMP participation increases initial unemployment duration but decreases the re-unemployment probability. Furthermore, lock-in effects were found to decrease from the first to the third month and turn insignificant after that period. This result indicates that ALMP may be subject to important time trade-offs and that exclusively short-run analyses may significantly underestimate the effects of ALMP.

Keywords: ALMP, Long Run Effects, Policy Evaluation, Training, Unemployment

1. Introduction

Active labour market policies (ALMP) can make a significant difference to participants' future working conditions and contributions to society. For instance, training can promote lifelong learning and facilitate the mobility of workers towards growing sectors. However, such interventions may require significant time investments from participants. Moreover, ALMP may also equally require long periods until their economic and social benefits are fully perceived and measured. In contrast, most analyses, and evaluations of ALMP tend to cover short periods of time, in many cases shorter than one year. This *status quo* can severely underestimate the private and social contributions of

ALMP if important dimensions of their benefits arise only at the medium and long run. Across the OECD, significant resources have been invested in ALMP - around 2% of GDP per year in the last decade [39].

This study contributes to the ALMP literature by evaluating both their short and long run effects. We hypothesize that there is a trade-off between these two dimensions – the weaker the short run effects, the stronger the long run effects, particularly for training measures. In general, jobseekers may be relatively far from the labour market for extended periods of time during ALMP participation, which may damage their short run perspectives. On the other hand, the intensity of the intervention may pay off later, through longer employment spells and lower

changes of re-employment.

Our empirical evidence is based on a training program in Portugal, ‘Vida Ativa’ (VA henceforth). VA was launched in 2012, during a recession, with a view to reach a large percentage of registered jobseekers. VA sought to increase the skills of participants and to improve their employment chances, not only in the short run but also over longer periods. As the program was based on shorter training modules (comparing to earlier training programs), lock-in effects would be minimized.

We estimate the impact of VA both on the unemployment spell length and on later employment, including the re-employment probability. To assess long run effects, we draw on long administrative data, covering the 2012-2019 period, and drawing on time-invariant individual identifiers. The data cover all registered jobseekers in the third largest job centre in Portugal (covering about 5% of all jobseekers in the country).

The remaining of this paper is as follows. First, we review the international literature over ALMP, especially training programs, and the role of socioeconomic variables, considering both the short and long run. Next, we present our ALMP context including the VA program. Our empirical methodology is described in the following section. In the main section, we present and interpret the results regarding the effects of VA and several robustness checks. Finally, we conclude.

2. Literature Review

The implementation of public policies to tackle unemployment are often focused on economic and sociological frameworks [36]. In fact, ALMP implementation can benefit greatly from its analysis through an articulated approach of both economics and sociological frameworks [17, 42]. This joint approach involves stressing the embeddedness [17] of labour market behavior in networks of social interaction and demographic restrictions. It also involves a focus on research which discloses differences in strategies and underlying assumptions among these two areas of knowledge. In this review, we include and analyses both economics and sociological perspectives.

The long-run effects of ALMP have been studied since the 1950s. Mincer’s [35] seminal article underlined that the period(s) spent in training courses establish a delay of earnings to later periods. Later, Schultz [41] and Becker [2, 3] concluded in the same direction, by arguing that most investments in human capital raise earnings, from work or employment on the long run, at older ages, because gains are added to earnings then, and reduce them at younger ages. Also, Fitzenberger, Osikominu and Völter [15] concluded that there is a negative lock-in effect immediately after the beginning of a program and positive treatment impacts on employment rates in the medium and long run. On a different perspective, the social investment theory [14, 19], while a socioeconomic framework, focuses on how people invest in their human capital (e.g., education and/or training),

throughout their lifetime cycle (on the short and long run). This theory suggests that these investments can lead to greater economic growth and productivity, as well as higher levels of employment, work, or even social mobility. The theory also emphasizes the importance of labour market policies that strengthen and promote social investment, such as access to education and training programs [19].

According to Brown [6], governments have tried to tackle unemployment through several ALMP such as subsidized employment, training programs, and general employment services (e.g., support to jobseekers to find suitable vacancies). Furthermore, as countries’ budget constraints tighten, the need to find the most cost-effective ALMP increases. Several studies have been conducted on this topic, some studying specific countries and policies [5, 8], others through meta-analyses [9, 46] or over age or ethnic groups [7, 12, 45].

As ALMP were created to tackle unemployment [36], their effectiveness should be related to the reduction of unemployment for participant groups. [9], in a meta-analysis study, found that on-the-job training programmes have lower effectiveness in the short run than in the medium run, after two years. The lower short-run impacts might be explained by the lock-in effect [47]. As described by Lechner et al. [30], lock-in effects happen when, during the training program, jobseekers reduce their job searching effort, which decreases the probability of employment in those periods. In this same article, lock-in effects of training are found in the short run, while positive employability and earnings effects were found in the following ten-year period. Similar conclusions were stated by Vooren et al [46] by arguing that some training schemes show negative effects in the short run, which can be related to the fact that, during the training, the participants are not active on the labour market.

Crépon et al. [13] argue that training could act as a signal ([16, 44] towards potential employers, hence decreasing the length of the unemployment spell. However, training might also increase reservation wages [18], resulting in longer unemployment. The results of Crépon et al. [13] show no significant effects of training courses in reducing unemployment spells. They also found that long training programs (more than one year) increase the unemployment spell duration when compared to shorter options. This article further investigates the effects of training programs on the duration of the subsequent employment spell: in this case, long courses have positive effects (increasing the duration of the following employment spell).

Betcherman [4] concluded that the design of a program is critical for ensuring positive outcomes. They found that some training programs have positive results in employment odds. Martin et al. [31], concluded that training programs should tighten the target participant groups; keep the programs small in scale; deliver qualifications or certificates recognized in the market; and have a strong on-the-job component.

The diverse effects of these policies on different demographic groups (gender, age, economic status) are important to analyze. In a study focused on women, Jenkins

[27] concluded that lifelong learning which leads to qualifications is strongly associated with a higher probability of unemployed women returning to work. Other studies found that women benefit more from training programmes or bring more consistent results than men [4, 10, 31]. Arellano [1] observed that training programmes are effective in reducing unemployment duration. However, gender segregation in the labour market persists, since women are at disadvantage in unemployment levels. Other articles found no significant gender differences in the effect of training, as Card et al. [9] meta-analyses, and Crépon et al. [13].

Across age groups, lower training effects for the young were found by Card et al. [9] compared to untargeted programmes. Similar results were stated by Kluge [28], Card et al. [10] and Betcherman [4], which noticed that youth problems are addressed more efficiently through education interventions. Mixed results were found by Caliendo and Schmidl [8]: for less than half of the programmes/sub-groups, positive effects were found; and for the majority, insignificant or even negative effects of ALMP, particularly in training programmes. [10] identified three studies that suggest that ALMP are more effective in periods of high unemployment. [30] explain that, when unemployment is high, the lock-in effect of training has a lower opportunity cost. There might also exist positive outcomes for the most disadvantaged workers, breaking down the negative consequences of the “outsider” phenomena [33].

3. Background

The 2008 financial crisis had a large negative effect across the OECD countries, including in Portugal [36] According to [37], total employment fell by 15% between the middle of 2008 and early 2013 in the country. While the EU average unemployment rate rose to around 10% during this period, unemployment in Portugal surpassed 15%, reaching 16.8% in 2013. After the recession years, fell to 6.9% in 2017 [38].

In this crisis period, the labour market was characterized by high segmentation: a large share of temporary workers [40] and low skilled labour supply (ILO, 2018). In this context, the governments over the period adopted several reforms, including new ALMP. Employment protection, collective bargaining, and unemployment benefits converged to OECD practices [37]. ALMP were introduced to activate jobseekers collecting unemployment benefits more effectively and in a more differentiated way (ILO, 2018).

With the goal of increasing skills and promoting employability, the short-term training programme VA was implemented by the Portuguese Government in 2012. It aimed to strengthen the matching between vocational training and labour market and jobseekers' needs, through the increase of their professional, social, and entrepreneurial skills combined with official validation of prior skills [34] and qualifications, in the context of a PES modernization drive. VA also acted upon the findings of an evaluation report [20], that indicated that there were many training courses of a long-term duration, with few participants at their

end (because of dropouts, retirements, and exits to employment), leading to high costs per participant.

The VA programme structure included three key dimensions: a) Short term modular training courses; b) On-the-job training, to complement earlier modular training or skills; c) Official validation and certification of skills acquired in previous formal or informal experiences. Only available for registered jobseekers, VA prioritized those jobless for more than six months; low-educated jobseekers (without the lower secondary education); and single parents or families where one of the parents is unemployed. In December 2013 a new version of the programme, “VA Jovem” (VA Youth), was introduced, focused on entrepreneurship and digital skills for youngsters.

All registered jobseekers in Portugal have their own Personal Employment Plan, which consists in a bundle of steps needed for job market (re) integration. Training programmes are part of this plan; hence, VA was one of the possible paths to follow. By own initiative or suggested by an employment counsellor, the candidate should pre-enroll in a course, mentioning their interests and aspirations. After the application period, the (private or public) training provider creates the training groups (classes of 20 up to 30 people) with a specific subject, that meets the job market needs. [21], considering the interests, the prior skills, and profiles of the applicants.

The different courses available encompass distinct qualifications levels, hence the training sessions are designed by matching the previous skills and qualifications. The available programmes are: Specific Technological Training (skills for a particular job); Basic or Sociocultural Training (equivalent to lower or upper secondary level); Behavioral Training (quality, safety, hygiene, and citizenship); Entrepreneurship Skills Training (foster independence on (re) integration into the job market); and Basic Skills Training (training for inclusion of the lower qualified).

The courses last from 25 to 300 hours, adding an extra component of “on-the-job training” for courses longer than 100 hours, especially for the lower qualified people. The programme is delivered during the worktime and implemented in a part-time or full-time basis (up to two to four days per week). During the teaching period, participants must keep searching for a job. [23]. This requirement may be important to minimize the lock-in effects [47] typically present in training ALMP.

According to the VA regulation [21], the PES should evaluate the programme regarding the integration process; target population; skills increase; reinforcement of the active job search, aiming to increase the effectiveness of VA. However, until today no PES report was publicly presented for that purpose. Only the OECD, in 2017, published a preliminary assessment of the Portuguese ALMP [37], including an evaluation of this programme. To contribute to this evaluation gap, the present study, also will analyze the VA programme in the period from 2012 to 2019, starting by describing our data in the next section.

4. Data

The study draws on four comprehensive administrative databases, providing individual information over the period December 2012 to October 2019: jobseeker registrations in each month, job placement registrations, unemployment cancellations (driven by a different reason than matching job centre work), and VA records (course participants, start/end dates, area, and reason for leaving course).

Similarly to Costa Dias *et al.* [11], this PES data contains all the historical information of each jobseeker during the full 2012-2019 period. It includes individual and socio-demographic variables, such as birth date, sex, nationality, schooling, as well as previous job and intended job area.

For the sake of simplicity, the data set was transformed to list only one observation per jobseeker. For each person, socio-demographic characteristics were collected from the person's first record. Additional socioeconomic variables were added to summarize their unemployment history (unemployment spells start and ending dates, participation or not in VA training programme and its features).¹

The analysis is centered on the VA courses in which jobseekers participated during the "first spell" (the first

unemployment spell recorded in the database), so that its effects could be studied in each person's current and subsequent unemployment spells. Individuals whose first spell lasts longer than 82 months (length of the time range available) were deleted (Figure A2.). People who participated in more than one VA training programme in the first spell were also removed. Finally, people whose first spell ended for any reason that makes it impossible for the job centre to have subsequent data (transfer of job centre; emigration; retirement; prolonged or permanent incapacity; death) were also removed. The final sample contains 59,009 observations (distinct individuals), described next.

Table 1 presents the descriptive statistics of the selected sample. The statistics are divided into individuals who participated in the VA programme in their first unemployment spell (13.17%) and those who did not (86.83%), plus an additional column representing the entire sample. In the full sample, there are almost as many men as women jobseekers (49.1% and 50.9% respectively). This proportion is slightly higher among programme participants (52.7%), which suggests that women are slightly more prone to participate than men.

Table 1. Descriptive Statistics.

	Participated in VA Programme in first spell		Total
	No	Yes	
Total	51239.00	7770.00	59009.00
	86.83	13.17	100.00
Gender			
Male	25273	3672	28945
	49.3%	47.3%	49.1%
Female	25966	4098	30064
	50.7%	52.7%	50.9%
Age Group			
< 29	20610	2136	22746
	40.2%	27.5%	38.5%
30-39	13155	1912	15067
	25.7%	24.6%	25.5%
40-49	9818	1896	11714
	19.2%	24.4%	19.9%
50 +	7656	1826	9482
	14.9%	23.5%	16.1%
Nationality			
Portuguese	39118	6409	45527
	76.3%	82.5%	77.2%
Foreign	12121	1361	13482
	23.7%	17.5%	22.8%
Age	35.06	38.99	35.57
School	9.52	9.43	9.51
Number of Spells	1.65	1.52	1.63
Length of 1st spell (months)	11.46	21.25	12.75

Age cohorts were created following the unemployment benefits framework [42], as these vary with number of years of previous work and age (less than 29, 30 to 39, 40 to 49 and, more than 50). The largest portion of individuals is younger than 29 (48.5%); 16.1% are older than 50. Amongst the participants, the average age is higher (38.99 compared to 35.57). 22.8% of the full sample are non-Portuguese, the largest portions from Cape-Verde (7.88%), Guinea-Bissau (4.05%) and Brazil (3.68%). The proportion of foreigners

among programme participants is slightly lower (17.5%). On average, individuals in the sample have 9 complete years of education (9.51). VA participants' mean education is slightly lower (9.43). Lower-educated people might be more motivated to participate in VA to increase their skills.

During the available time period, each individual has on average 1.63 unemployment spells. This average is similar but smaller for the VA participants (1.52). Fewer spells for training participants might reveal positive consequences of

the courses, or may be related to other characteristics, common to programme participation. Interestingly, the duration of the first spell in months, which is our focus, is much higher for VA participants (21.25) than for non-participants (11.46) and the overall group (12.75). As seen in the literature, lock-in effects will result in short-run lower employability when attending training programmes ([9], potentially increasing unemployment duration due to the lower job searching during the training period. The relationship between VA participation and spell duration will also be explored, evaluating if the higher length of first spell among programme participants is a pre-condition to or a consequence of programme participation.

After 12 months following the end of the programme the participants' employability rate was 81.22%. We interpret this to indicate that, that after finishing the programme, 81.22% of participants have left unemployment (Table A2.).

5. Method

To assess the effects of participation in VA programme in two different labour outcomes, the analysis was based on the OLS estimation of the following equation:

$$Y_i = c + \alpha T_i + \beta X_i + \varepsilon_i \quad (1)$$

Here, Y_i is the outcome variable of interest; and T_i is the dummy variable representing the treatment status (VA_I): its value is 1 when the individual is treated (participated in VA Programme in the first spell), and 0 if non-treated (non-participant in VA courses although might have participated in other ALMP). α is the parameter of interest, representing the effect that being treated exerts on the dependent variable. Its interpretation should be cautious since less skilled, more disadvantaged, or socially excluded jobseekers, might be more frequently advised to participate in VA, or, at the same time, more proactive individuals might be more prone to voluntarily apply. These characteristics will likely be related to how long it takes these individuals to find a job, which induces variations in the outcome variable and could be picked up by the α parameter. In order to minimize the above, we also control for X_i , a vector of observable covariates (exogenous demographic information), and β a vector of their respective impact on Y_i . Finally, ε_i is the error term, which will capture other forces that might be determining the dependent variable but are not included in the analysis, as for example unobserved personal attributes (as socioeconomic status, marital and parental status, initiative, persistence, etc).

Our analysis will be divided between the short-run and long-run impact of VA. The short-run will be evaluated through the impact of the programme in the duration of the first unemployment spell² (in which individuals participate or not in the programme), and the long-run outcome will be measured by the probability of recurrence of unemployment, after finishing the first spell³.

The controls (X_i) used were the demographic information available for each individual: gender, age, nationality (Portuguese or foreign) and years of schooling. For the analysis of age, individuals were divided in the same age

cohorts for which the unemployment benefits change (the base dummy is the youngest cohort - under 29 years old). Finally, controls for previous job group (CPP) will be added (J_i), as well as controls for year fixed effects based on the spell starting year (vector D_{ji}). This leads to the following extended equations:

$$Y_i = c + \alpha VA_1_i + \beta X_i + \gamma_1 J_i + \gamma_2 D_{ji} + \varepsilon_i \quad (2)$$

$$X_i = \beta_1 fem_i + \beta_2 foreign_i + \beta_3 age_30_39_i + \beta_4 age_40_49_i + \beta_5 age_50_i + \beta_6 school_i \quad (3)$$

Furthermore, interactions of the treatment variable (VA_I) with the controls are added to evaluate the heterogeneity of the effects across different groups (vector I_{ji}).

$$Y_i = c + \alpha_1 VA_1_i + \beta X_i + \delta_1 VA_fem_i + \delta_2 VA_foreign_i + \delta_3 VA_30_39_i + \delta_4 VA_40_49_i + \delta_5 VA_50_i + \delta_6 VA_school_i + \varepsilon_i \quad (4)$$

5.1. Spell Duration (Short Run) Analysis

In the short run analysis, we evaluate how VA influenced the time until finding a job. Hence, only the number of months after taking the VA course, until end of unemployment should be considered. To include this factor in the regression, dummy variables for each month in which the courses were taken are added to the model.

In these regressions, the results should be interpreted depending on the timing of the VA within the spell. Hence the counterfactual should be restricted for each month analyzed. Individuals who participate in the programme in the n^{th} month of unemployment should be compared to non-participants who have been unemployed for at least n number of months, so that the outcome compared will be the duration of unemployment after those n months [29] The control group must be individuals who have neither exited unemployment nor entered the treatment at the moment that treated individuals starts the programme. If the effects differ from different timings, it provides evidence on the optimal timing of VA participation in terms of duration of the first unemployment spell – should VA be assigned mostly in the first months or later the spell? This specification uses the following model:

$$\log_dur_spell1_i = c + \alpha VA_month_*_i + \delta_{ji} I_{ji} + \beta X_i + \varepsilon_i \quad (5)$$

Note: The * in the dummy variable represents each month analyzed

For the short-run analysis, the sample is restricted to individuals whose first spell started until December 2016 (50,754 observations). Since we are analyzing the results until October 2019, this restriction will provide enough time (almost three years) for jobseekers to participate or not in VA, end their first spell, and experience VA effects.

5.2. Recurrence (Long Run) Analysis

Unemployment recurrence is evaluated using a dummy variable, $spell2$, as the dependent variable. This is 1 if the

individual has more than one spell of unemployment, and 0 if not. The parameter of interest (α) will, in this case, indicate how the programme changes the probability of returning to unemployment.

$$spell2_i = c + \alpha VA_{-1}_i + \delta_{ji}I_{ji} + \beta X_i + \varepsilon_i \quad (6)$$

In this analysis, the sample was restricted to individuals who finished unemployment until December 2018 (54,507 observations), so that they have 10 months to return to unemployment, if that is the case.

6. Results

6.1. Analytical Results and Analysis

In this section, findings from previous models are presented and interpreted. Table 2 presents the estimates from the different models described in the previous section.

The first three columns present three regressions of the short run analysis, and the last two are the analysis of the probability of recurrence.

Before the analysis of the treatment variable, we observe the effects of the exogenous demographic characteristics. Being a woman is associated with a longer unemployment spell, by around 2.8% on average, and an increase in the probability of recurrence of 2.6%. Foreigners are associated with shorter spells (around 16.6% lower). This effect might be explained by their lower reservation wage, allowing them to find a job faster. Another possible explanation for the shorter spells is that foreigners might have worked for shorter periods or did not have a declared job before, hence receiving unemployment benefit for shorter period (which decreases their reservation wage). However, their probability of unemployment recurrence is higher than for the Portuguese.

Table 2. OLS Estimations.

VARIABLES	(1) log_dur_spell1	(2) log_dur_spell1	(3) log_dur_spell1	(4) spell2	(5) spell2
VA_1	0.934*** (0.010)		1.130*** (0.034)	-0.043*** (0.006)	-0.042* (0.023)
VA in month 1		0.258*** (0.080)			
VA_fem			0.066*** (0.019)		-0.007 (0.012)
VA_foreign			0.035 (0.024)		0.036** (0.017)
VA_30_39			-0.017 (0.025)		-0.014 (0.017)
VA_40_49			-0.072*** (0.026)		-0.011 (0.017)
VA_50			-0.113*** (0.029)		-0.036* (0.018)
VA_school			-0.020*** (0.003)		0.001 (0.002)
fem	0.028*** (0.008)	0.039*** (0.008)	0.020** (0.009)	0.026*** (0.004)	0.027*** (0.004)
foreign	-0.166*** (0.009)	-0.190*** (0.010)	-0.169*** (0.010)	0.065*** (0.005)	0.061*** (0.005)
age_30_39	0.146*** (0.010)	0.181*** (0.011)	0.149*** (0.011)	-0.022*** (0.005)	-0.021*** (0.006)
age_40_49	0.270*** (0.011)	0.343*** (0.012)	0.281*** (0.013)	-0.042*** (0.006)	-0.041*** (0.006)
age_50_	0.452*** (0.013)	0.557*** (0.014)	0.472*** (0.015)	-0.117*** (0.007)	-0.111*** (0.007)
school	0.010*** (0.001)	0.012*** (0.001)	0.013*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)
Constant	3.469*** (0.041)	3.445*** (0.039)	3.439*** (0.041)	0.309*** (0.014)	0.310*** (0.014)
Previous Job Area	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	50,574	50,574	50,574	54,507	54,507
R-squared	0.460	0.389	0.461	0.035	0.035

Notes: Robust standard errors are in parentheses and stars represent significance of the coefficient (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

“Previous Job Area” and “Year fixed effects” mean that the area of the previous job and the year when unemployment spell started, respectively, are being controlled for. The number of observations from 1st to 3rd regression represent people who have started first registered unemployment spell until December 2016; for 4th and 5th regressions, observations are restricted for people who ended unemployment spell before January 2019.

As seen before, unemployment benefits increase with years working and age. Indeed, compared to the base cohort (under 29 years old), each older cohort is associated with longer unemployment spells (coefficients are significant and increasing with age groups). Moreover, the probability of returning to unemployment decreases with age.

Schooling is probably associated with higher reservation wage, which might explain the slightly longer unemployment spells (an extra year of schooling increases spell length by approximately 1%). Moreover, more schooling may lead to a more stable job, which will decrease the probability of re-employment (one extra year of school decreases probability of having a second spell of unemployment by 1%).

Focusing on the effects of the VA courses in duration of first unemployment spell, the results reveal that the programme is associated with longer spells, after controlling for demographics. According to results, participating in these short-term training courses increases the length of unemployment spells by 154%, on average, *ceteris paribus*, comparing to non-participants ($\exp(0.934) - 1 \times 100 = 154\%$)⁴. Such increase in spell length could represent lock-in effects. However, in this case, the increase goes largely beyond the duration of the programme⁵. This suggests that the treatment variable is capturing other characteristics associated with programme participation that have large effects on unemployment duration, leading to omitted variable bias. Although VA sought to decrease lock-in effects of long training courses, this analysis does not allow us to be conclusive on this respect.

Next, we control for participation timing. Individuals who have started the programme later should not be compared to people who were not unemployed for at least the same number of months. The second column includes the dummy variable representing participation or not in the VA programme in the first month of the unemployment spell. The model reveals that frequently the courses in the first month unemployed are associated with a significantly longer unemployment spell. However, the difference of participants and non-participants is lower than in the previous, general participation analysis ($\exp(25.8) - 1 \times 100 = 29.4$), suggesting a reduced scope of endogeneity issues.

Additional analyses (Table A4. and Table A5.) restrict the sample so that the control group is composed of individuals who have been unemployed for at least the same number of months as the months until programme participation. This allows one to evaluate the impact that participating in programme, in each month of unemployment, has in the post-programme duration of unemployment. The results show that participating in the programme until the third month is associated with a significant, but smaller than in first month, increase in post-programme duration of unemployment, compared to people who have been unemployed for at least the same number of months until participants take the course. After the fourth month, the results present negative but non-significant coefficients. These results suggest that the lock-in

effects are minimized if participation takes place after the third month of unemployment.⁶

Furthermore, interactions of the treatment dummy with demographic variables are added in the third column of Table 2. The results indicate that, in the case of older individuals, participating in VA reduces unemployment duration after the course, compared to the younger jobseekers. Having a higher level of education decreases the magnitude of the negative short-run effect of the programme. Interestingly, lower schooling levels are not associated with larger reward from the programme. Moreover, women benefit less from VA: women VA participants experience longer unemployment than men VA participants.

For the recurrence analysis, the effect of the programme is positive, as the VA coefficient is negative and significant. Hence, programme participation is associated with lower probability of re-employment by 4.3 percentage points. As before, the treatment variable might be capturing unobserved characteristics that will bias our results. The results could be underestimated if VA participants are less proactive and resilient, hence, more prone to unemployment, or overestimated, in the opposite case.⁷

The heterogeneous effects reveal that, similarly to previous studies, as Card et al. [9] and Crépon et al. [13], there are no significant gender differences in programme effects, as well as no significant differences according to age or education. The only exception is the case of foreigners.⁸

6.2. Limitations

The credibility of previous models relies on the randomness of VA assignment. However, individuals participating in VA might be more or less skilled in ways that are not controlled for. Future analyses may also consider survival (or duration) models. The study could also be expanded to evaluate the impact of additional VA participations over the years (not only in first spell). Critically, registered jobseekers may participate in several other ALMP, including other training programmes. However, our data has no information on other programme participations.

Our analysis is focus on VA impact on unemployment duration and recurrence. Several different features of VA (course duration; on the job component; class composition; course matching - labour market and individual interests) should also be explored to better understand its outcomes⁹. Furthermore, as seen in the literature review, the opportunity cost of the lock-in effects of training programmes is smaller in recessions, therefore, it would be interesting to differentiate the socioeconomic effects of the programme during economic expansions. It would also be interesting to explore the effect of VA on earnings and labour contracts.

7. Conclusions

Across the OECD, significant resources have been invested in ALMP - around 2% of GDP per year in the last

decade [39]. About half of this amount was invested in training programmes. Given this context, this study assessed the impact of the VA training programme, in participants' unemployment spell length and unemployment recurrence.

Our results indicated that VA participation is associated with an increase in the unemployment spell length. However, our estimations reveal that VA is also associated with a lower likelihood of recurrence. This means that despite having a longer unemployment spell, participants are less prone to return to an unemployment status.

In the first (short run) analysis, an exploratory approach was taken, to assess if participating in the programme in the initial unemployed months, or later, will have differentiated impact in the length of the remaining time of unemployment. The results reveal that the programme is not effective in reducing that time if participated before the fourth month of unemployment. This conclusion is in line with the human capital theory [2, 3, 35, 41], regarding long run effects. Furthermore, following this approach, no lock-in effects were found if VA participation takes place after the third month of unemployment. From a sociological point of view, our research underlines that short run training programmes can contribute, on the long run, to improved individual socioeconomic outcomes, as well to influence the labour market structure. This conclusion is in line with the work of Esping-Andersen [14] and Hemerijck [19]. On the other hand, it follows closely the idea of embeddedness of the labour markets [17]. Our contributions rely on the originality of the research, focusing on variables and data sets that have not been explored before. It has limitations, on the interpretation of the results because of endogeneity issues, but it may support further research in this area.

Finally, further research would be important. It would be

interesting to explore how the matching of the courses' areas, with the interests and previous experience of participants, as well as with employers' interests. The long database allows one to explore the programme effects regarding other socioeconomic variables and outcomes, as the employment period after the programme, the percentage of time in unemployment, or the distinct reasons and effects of taking the programme more than once.

Funding

This article was supported by Fundação para a Ciência e Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019, UIDB/04521/2020, and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

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Acknowledgments

We are very grateful to Beatriz Corral for the English language review and helpful comments, as well to IEFP for the data set used in this article.

Conflicts of Interest

The authors declare no conflicts of interest.

Appendix

Appendix I. Sample Construction

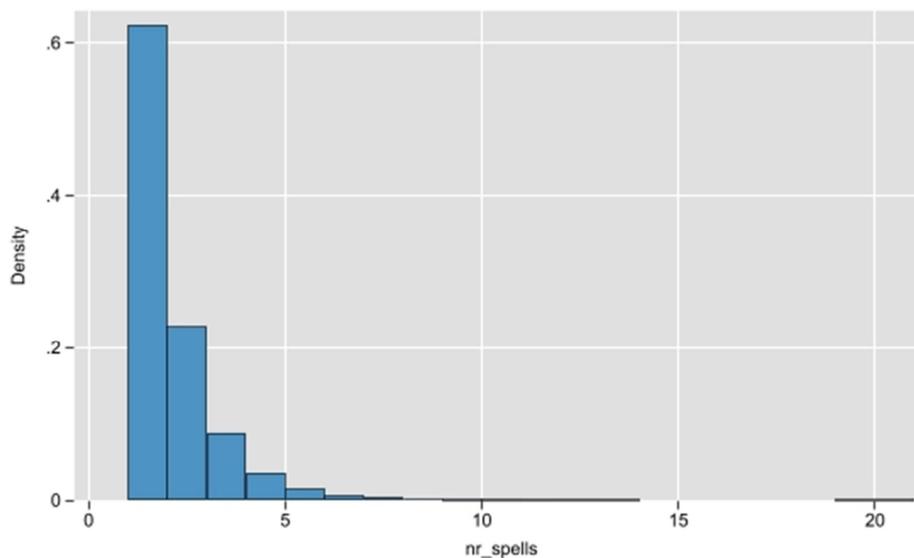


Figure A1. Histogram of number of spells before sample restriction.

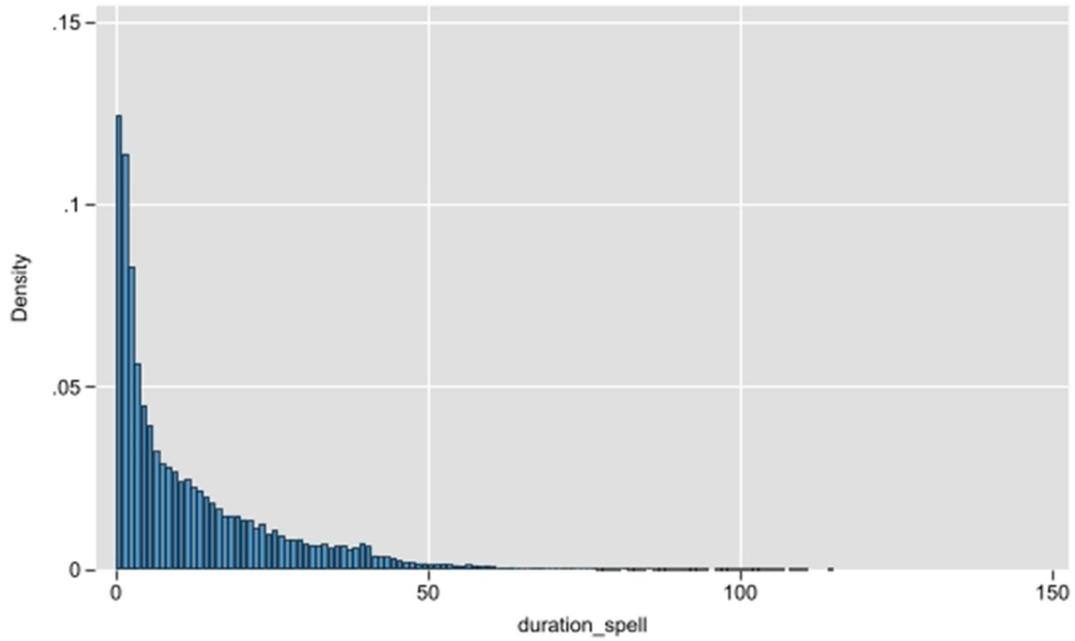


Figure A2. Histogram of first spell length.

Appendix II. Descriptive Statistics

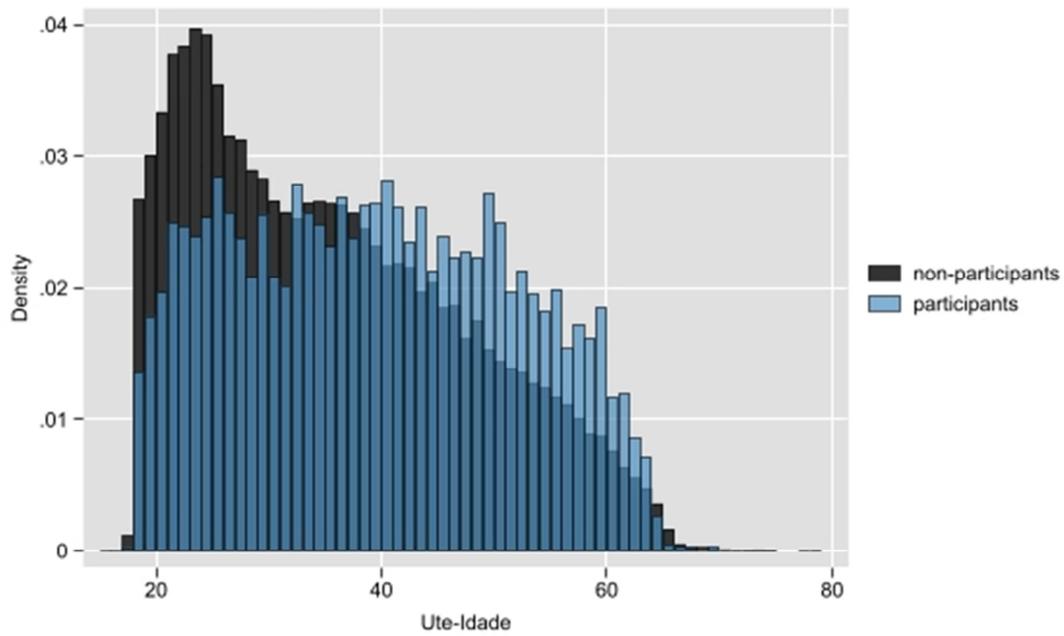


Figure A3. Histogram of Age (VA participants vs non-participants).

Table A1. Participants in VA Programme.

Participated in VA Programme in first spell	Frequency	Percent
No	51,239	86.83%
Yes	7,770	13.17%
Total	59,009	100%

Table A2. Employability of programme participants 12 month after finishing the training.

VA participants - Exited Unemployment in 12 Months	Frequency	Percent
No	1,459	18.78%
Yes	6,311	81.22%
Total	7,770	100%

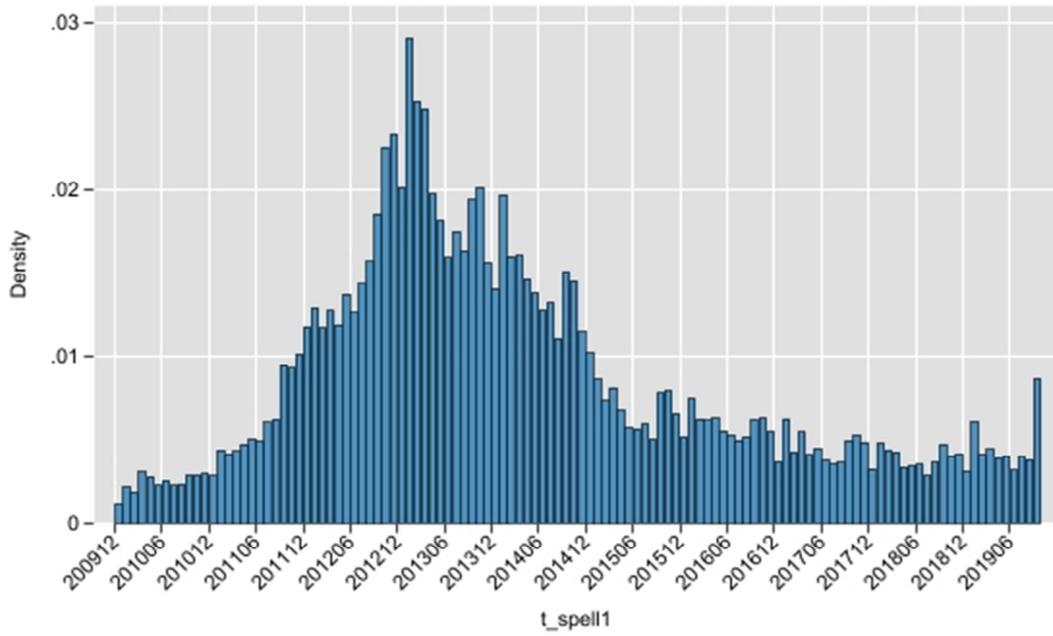


Figure A4. Histogram of the starting month of first unemployment spell.

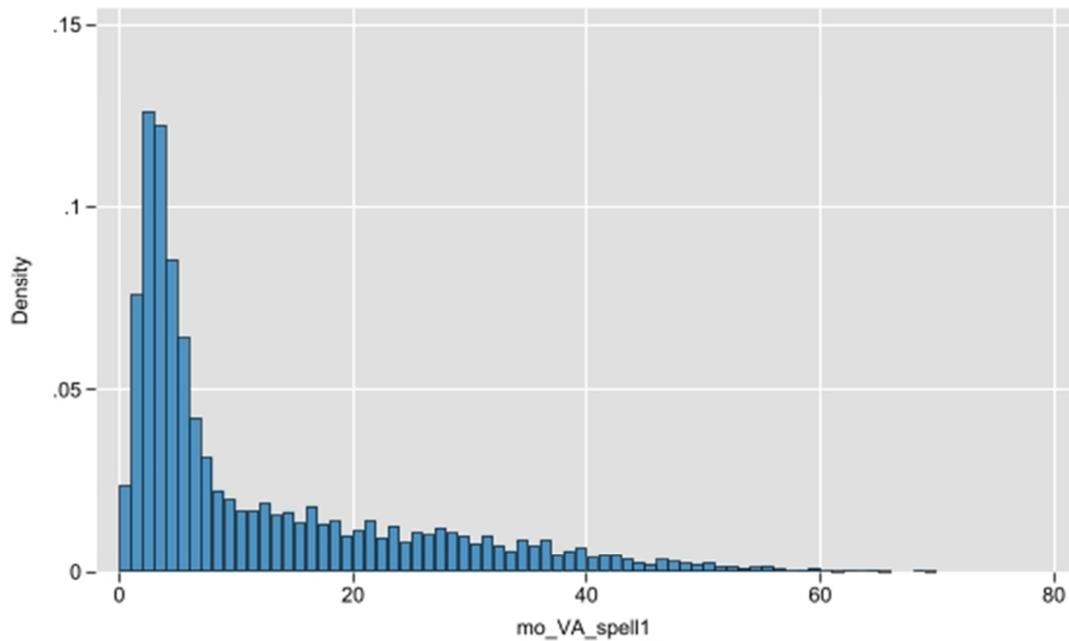


Figure A5. Histogram of the duration of the unemployment spell until programme participation (in months).

Appendix III. Regression Analysis

Table A3. Regression of VA participation in demographic and Job characteristics (controlling for time of unemployment spell start).

VARIABLES	VA_1
Fem	0.011*** (0.003)
Foreign	-0.028*** (0.003)
age_30_39	0.035*** (0.004)
age_40_49	0.071*** (0.004)
age_50_	0.103*** (0.004)

VARIABLES	VA 1
School	0.002*** (0.000)
Previous Job Area	-0.001** (0.001)
Period start spell	-0.000*** (0.000)
Constant	0.084*** (0.006)
Observations	59,009
R-squared	0.014

Table A4. OLS the effect of the programme in the remaining time of unemployment, if done in each month unemployed.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log_dur_spell1						
VA in month 1	0.258*** (0.080)						
VA in month 2		0.068* (0.038)					
VA in month 3			0.063*** (0.023)				
VA in month 4				0.031 (0.021)			
VA in month 5					-0.036 (0.023)		
VA in month 6						-0.036 (0.024)	
VA in month 7							-0.005 (0.030)
fem	0.039*** (0.008)	0.039*** (0.007)	0.036*** (0.007)	0.037*** (0.006)	0.037*** (0.006)	0.034*** (0.006)	0.032*** (0.006)
foreign	-0.190*** (0.010)	-0.156*** (0.009)	-0.131*** (0.008)	-0.127*** (0.008)	-0.119*** (0.008)	-0.107*** (0.007)	-0.105*** (0.007)
age_30_39	0.181*** (0.011)	0.163*** (0.010)	0.148*** (0.009)	0.143*** (0.008)	0.120*** (0.008)	0.116*** (0.007)	0.106*** (0.007)
age_40_49	0.343*** (0.012)	0.297*** (0.011)	0.265*** (0.010)	0.255*** (0.009)	0.228*** (0.009)	0.218*** (0.008)	0.211*** (0.008)
age_50_	0.557*** (0.014)	0.484*** (0.012)	0.429*** (0.011)	0.400*** (0.010)	0.360*** (0.010)	0.346*** (0.009)	0.334*** (0.009)
school	0.012*** (0.001)	0.005*** (0.001)	0.001 (0.001)	-0.002* (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)
Constant	3.445*** (0.039)	3.554*** (0.037)	3.594*** (0.035)	3.615*** (0.034)	2.454*** (0.020)	2.577*** (0.019)	3.691*** (0.032)
Previous Job Area	Yes						
Year Fixed Effects	Yes						
Observations	50,574	44,731	39,704	35,770	33,089	30,865	28,889
R-squared	0.389	0.391	0.381	0.369	0.364	0.361	0.358

Appendix III. 2 OLS restrictions dur

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A5. OLS the effect of the programme in the remaining time of unemployment, if done in each extra month unemployed (continuation).

VARIABLES	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1
VA in month 8	0.002 (0.030)						
VA in month 9		0.006 (0.036)					
VA in month 10			-0.046 (0.032)				
VA in month 11				-0.033 (0.035)			
VA in month 12					-0.020 (0.030)		
VA in month 13						-0.039 (0.033)	

VARIABLES	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	log dur spell1						
VA in month 14							-0.020 (0.032)
fem	0.032*** (0.005)	0.026*** (0.005)	0.023*** (0.005)	0.018*** (0.005)	0.014*** (0.005)	0.012** (0.005)	0.011** (0.005)
foreign	-0.096*** (0.007)	-0.091*** (0.007)	-0.084*** (0.007)	-0.079*** (0.006)	-0.075*** (0.006)	-0.074*** (0.006)	-0.070*** (0.006)
age_30_39	0.110*** (0.007)	0.112*** (0.007)	0.107*** (0.007)	0.099*** (0.007)	0.093*** (0.007)	0.090*** (0.007)	0.079*** (0.007)
age_40_49	0.216*** (0.008)	0.216*** (0.008)	0.212*** (0.008)	0.207*** (0.007)	0.196*** (0.007)	0.196*** (0.007)	0.184*** (0.007)
age_50_	0.329*** (0.009)	0.326*** (0.009)	0.319*** (0.008)	0.306*** (0.008)	0.294*** (0.008)	0.288*** (0.008)	0.274*** (0.008)
school	-0.006*** (0.001)	-0.006*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
Constant	3.701*** (0.032)	2.822*** (0.018)	2.890*** (0.017)	2.957*** (0.017)	3.745*** (0.031)	3.076*** (0.017)	3.119*** (0.017)
Previous Job Area	Yes						
Year Fixed Effects	Yes						
Observations	27,290	25,835	24,425	23,127	21,900	20,597	19,410
R-squared	0.355	0.352	0.347	0.339	0.329	0.323	0.310

Appendix III. 3 OLS restrictions Dur (cont)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A6. OLS the effect of the programme in the probability of recurrence, if done in each extra month unemployed (continuation).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	spell2	spell2	spell2	spell2	spell2	spell2
VA_month1	-0.073** (0.037)					
VA_month2		0.012 (0.022)				
VA_month3			0.014 (0.017)			
VA_month4				0.042** (0.017)		
VA_month5					-0.013 (0.020)	
VA_month6						0.020 (0.023)
fem	0.025*** (0.004)	0.025*** (0.004)	0.027*** (0.005)	0.026*** (0.005)	0.025*** (0.005)	0.025*** (0.005)
foreign	0.066*** (0.005)	0.073*** (0.006)	0.082*** (0.006)	0.088*** (0.007)	0.092*** (0.007)	0.095*** (0.007)
age_30_39	-0.024*** (0.005)	-0.020*** (0.006)	-0.015** (0.006)	-0.020*** (0.007)	-0.023*** (0.007)	-0.024*** (0.007)
age_40_49	-0.045*** (0.006)	-0.044*** (0.006)	-0.041*** (0.007)	-0.047*** (0.007)	-0.049*** (0.008)	-0.050*** (0.008)
age_50_	-0.121*** (0.007)	-0.120*** (0.007)	-0.122*** (0.008)	-0.129*** (0.008)	-0.134*** (0.008)	-0.138*** (0.009)
school	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)
Constant	0.309*** (0.014)	0.422*** (0.054)	0.417*** (0.054)	0.280*** (0.023)	0.301*** (0.027)	0.437*** (0.055)
Previous Job Area	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,507	47,742	41,628	37,100	34,068	31,594
R-squared	0.034	0.034	0.034	0.034	0.035	0.035

Appendix III. 4 restrictions spell2

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A7. OLS Main regressions without the retrospective data (only including spells started in December 2012 or after).

VARIABLES	(1)	(2)	(3)	(4)	(5)
	log dur spell1	log dur spell1	log dur spell1	spell2	spell2
VA_1	1.093*** (0.011)		1.289*** (0.039)	-0.045*** (0.007)	-0.067*** (0.024)
VA_month1		0.282*** (0.066)			
VA_fem			0.071*** (0.022)		-0.001 (0.013)
VA_foreign			0.031 (0.026)		0.073*** (0.017)
VA_30_39			0.032 (0.028)		-0.006 (0.017)
VA_40_49			0.047 (0.030)		0.003 (0.019)
VA_50			0.025 (0.034)		-0.036* (0.020)
VA_school			-0.028*** (0.003)		0.002 (0.002)
fem	0.030*** (0.010)	0.046*** (0.011)	0.020* (0.011)	0.028*** (0.005)	0.028*** (0.005)
foreign	-0.195*** (0.011)	-0.227*** (0.012)	-0.197*** (0.013)	0.048*** (0.006)	0.039*** (0.006)
age_30_39	0.159*** (0.012)	0.199*** (0.013)	0.158*** (0.014)	-0.016*** (0.006)	-0.015** (0.006)
age_40_49	0.275*** (0.014)	0.347*** (0.015)	0.270*** (0.016)	-0.021*** (0.007)	-0.021*** (0.007)
age_50_	0.500*** (0.016)	0.605*** (0.018)	0.498*** (0.019)	-0.074*** (0.008)	-0.066*** (0.008)
school	0.016*** (0.001)	0.016*** (0.002)	0.021*** (0.002)	-0.010*** (0.001)	-0.010*** (0.001)
Constant	1.203*** (0.026)	1.269*** (0.028)	1.168*** (0.027)	0.301*** (0.014)	0.305*** (0.015)
Previous Job Area	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	40,571	40,571	40,571	44,912	44,912
R-squared	0.188	0.059	0.190	0.036	0.036

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A8. OLS the effect of the programme in the remaining time of unemployment, if done in each extra month unemployed, without the retrospective data (only including spells started in December 2012 or after).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	log dur spell1					
VA_month1	0.282*** (0.066)					
VA_month2		0.091*** (0.033)				
VA_month3			0.058*** (0.020)			
VA_month4				0.042** (0.019)		
VA_month5					-0.022 (0.021)	
VA_month6						-0.029 (0.022)
fem	0.046*** (0.011)	0.048*** (0.009)	0.050*** (0.009)	0.056*** (0.009)	0.052*** (0.008)	0.048*** (0.008)
foreign	-0.227*** (0.012)	-0.183*** (0.011)	-0.151*** (0.011)	-0.150*** (0.011)	-0.136*** (0.010)	-0.118*** (0.010)
age_30_39	0.199*** (0.013)	0.170*** (0.012)	0.146*** (0.011)	0.137*** (0.011)	0.112*** (0.010)	0.113*** (0.010)
age_40_49	0.347*** (0.015)	0.280*** (0.014)	0.232*** (0.013)	0.221*** (0.012)	0.191*** (0.012)	0.184*** (0.012)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1	log_dur_spell1
age_50_	0.605*** (0.018)	0.499*** (0.016)	0.417*** (0.015)	0.376*** (0.015)	0.328*** (0.014)	0.312*** (0.014)
school	0.016*** (0.002)	0.008*** (0.001)	0.004*** (0.001)	0.001 (0.001)	-0.002 (0.001)	-0.003** (0.001)
Constant	1.269*** (0.028)	2.040*** (0.033)	2.157*** (0.032)	2.366*** (0.030)	2.571*** (0.028)	2.555*** (0.023)
Previous Job Area	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,571	33,665	27,805	23,331	20,449	18,230
R-squared	0.059	0.070	0.075	0.070	0.065	0.063

Appendix III. 5

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix IV. Institutional Aspects

In the period after the 2008 financial crisis, the unemployment rate in Portugal was high, and above the EU average. In the framework of the Portuguese Public Employment Services (PES) the Instituto do Emprego e Formação Profissional (IEFP) is responsible to implement the Active Labour Market Policies (ALMP). In the last decade, Portugal invested between 1.25% of GDP in 2010 and 2.33% in 2013 [39] in executing these policies. The average annual expenditure in ALMP was €651 million between 2011 and 2015, a period in which PES's users increased by 45% [22]. Training programmes represent an important share of ALMP investment. According [24], more than 50% of PES spending in labour market programme was for professional training. Furthermore, training programmes have high dropout rates (15.2% in our dataset), which increase the training cost per capita.

Despite the financially significant spending, ALMP in Portugal are only object of evaluation in few studies. The main available studies were published by Costa Dias *et al.* [11], and another one by OECD [37]. Hence, this research about the short run VA programme is new and important to the literature, as it contributes to a limited evidence base, regarding labour market policies impact on the long run.

This article draws on IEFP data from Amadora Employment Centre (AEC), one of the IEFP's employment centre national network, and one of the biggest. In December 2019 it was the third leading centre in professional training provision, following Porto and Lisbon centers, covering 4.5% of the total number of jobseekers covered in Portugal [24].

Finally, the rich dataset used, has a large amount of information about the employment and unemployment history of registered users at this centre. This sort of dataset, in Portugal, has been barely analyzed. The main two studies found using similar data, were the 2012 evaluation, by Costa Dias *et al.* [11], already referred, and Martins *et al.* [32].

References

- [1] Arellano, F. A. (2010). Do Training Programmes Get the Unemployed Back To Work? A Look at The Spanish Experience. *Revista de Economía Aplicada Número*. Vol. 53.
- [2] Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of political economy*, 70(5, Part 2), 9-49.
- [3] Becker, G. S. (1975). Investment in human capital: effects on earnings. In *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, Second Edition (pp. 13-44). NBER.
- [4] Betcherman, G., Olivas, K. & Dar, A. (2004) Social Protection Discussion Paper Series Impacts of Active Labor Market Programs: New Evidence from Evaluations with Particular Attention to Developing and Transition Countries. *Social Protection Discussion Paper Series - The World Bank*.
- [5] Brodtkin, E. Z. & Larsen, F. (2013). Changing boundaries: The policies of workfare in the US and Europe. *Poverty & Public Policy*, 5(1), 37-47.
- [6] Brown, A. J. G., & Koettl, J. (2012). Active Labor Market Programs: Employment Gain or Fiscal Drain? *IZA Journal of Labor Economics* (2015) 4: 12. DOI 10.1186/s40172-015-0025-5.
- [7] Caliendo, M., Kunn, S. & Schmidl, R. (2011). Fighting Youth Unemployment: The Effects of Active Labor Market Policies. *IZA Discussion Paper No. 6222*.
- [8] Caliendo, M. & Schmidl, R. (2016). Youth unemployment and active labor market policies in Europe. *IZA Journal of Labor Policy*, 5(1), 1-30.
- [9] Card, D., Kluve, J. & Weber, A. (2010). Active Labour Market Policy Evaluations: A Meta-Analysis. *The Economic Journal* 120 (548). <https://doi.org/10.1111/j.1468-0297.2010.02387.x>
- [10] Card, D., Kluve, J. & Andrea, A. (2015). What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations. *Institute for the Study of Labor (IZA)*.
- [11] Costa Dias, M. & Varejão, J. (2012). *Estudo De Avaliação Das Políticas Ativas De Emprego*. FEP - Faculdade de Economia Da Universidade Do Porto.

- [12] Damaske, S., Frech, A., & Wething, H. (2023). The Life Course of Unemployment: The Timing and Relative Degree of Risk. *Work and Occupations*, 0(0). <https://doi.org/10.1177/07308884231162949>
- [13] Crépon, B., Ferracci, M. & Fougère, D. (2007). Training the Unemployed in France: How Does It Affect Unemployment Duration and Recurrence? *IZA Discussion Paper No. 3215*. DOI: 10.2307/23646576.
- [14] Esping-Andersen, G. (1994). After the Golden Age: The future of the welfare state in the new global order, *UNRISD Occasional Paper: World Summit for Social Development, No. 7*, United Nations Research Institute for Social Development (UNRISD), Geneva
- [15] Fitzenberger, B., Osikominu, A. & Völter, R. (2008). Get Training or Wait? Long-Run Employment Effects of Training Programs for the Unemployed in West Germany. *Annales d'Économie et de Statistique*, No. 91/92, 321-355.
- [16] Gambetta, D. (2011). Signaling. In Bearman P and Hedström P (eds) *The Oxford Handbook of Analytical Sociology*, Oxford Handbooks. online edn. 168–194. <https://doi.org/10.1093/oxfordhb/9780199215362.013.8>,
- [17] Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology*, Vol. 91, No. 3 (Nov., 1985). 481-510.
- [18] Heath, A. & Swann, T. (1999). Reservation Wages and the Duration of Unemployment. *Research Discussion paper 1999-02*. Economic Research Department. Reserve Bank of Australia. <https://www.rba.gov.au/publications/rdp/1999/pdf/rdp1999-02.pdf>
- [19] Hemerijck, A. (2018). Social investment as a policy paradigm. *Journal of European public policy*, 25(6), 810-827.
- [20] IEFP (2011). Síntese da Execução dos Programas e Medidas de Emprego e Formação Profissional. <https://www.iefp.pt/documents/10181/277125/SinteseEF+dezembro+2011.pdf/ca1e887b-9837-4043-9ebd-28877972482a>
- [21] IEFP (2013). *Vida Ativa - Regulamento Específico*. Available at: <https://www.iefp.pt/documents/10181/10763895/Ficha+s%C3%ADntese+Medida+Vida+Ativa.pdf/e9cae134-a55a-4e1b-a2e0-0d8dbcf6d2de>
- [22] IEFP (2015). *Políticas Ativas do Mercado de Trabalho em Portugal - Relatório 2011-2015*. Available at: https://www.etf.europa.eu/sites/default/files/event/IEFP_Active%20Employment%20Measures2_14112017_PT.pdf
- [23] IEFP (2018). *Vida Ativa - Regulamento Específico. 4ª Revisão*. Available at: <https://www.iefp.pt/documents/10181/7942815/Regulamento+Espe%C3%ADfico+Vida+Ativa+4%C2%AA%20Revis%C3%A3o>
- [24] IEFP (2019). *Relatório de Execução Física e Financeira 2019*. Available at: <https://www.iefp.pt/documents/10181/9300317/Relatorio+de+Execu%C3%A7%C3%A3o+Financeira+dezembro+2019.pdf/df8bd1ae-f327-439e-9c69-9ea1efe5c837>
- [25] IEFP (2022). *IEFP - Instituição 2022*. Available at: <https://www.iefp.pt/instituicao>
- [26] ILO (2018). *Decent Work in Portugal 2008–18: From Crisis to Recovery*. Available at: www.ilo.org/publns.
- [27] Jenkins, A. (2004). *Women, lifelong learning and employment*. (No. 39). Centre for the Economics of Education, London School of Economics and Political Science.
- [28] Kluge, J. (2010). The Effectiveness of European Active Labor Market Programs. *Labour Economics* 17 (6): 904–18.
- [29] Lalive, R., van Ours, J. C. & Zweimüller, J. (2008). The Impact of Active Labour Market Programmes on the Duration of Unemployment in Switzerland. *Economic Journal* 118 (525): 235–57.
- [30] Lechner, M., & Conny, W. (2009). Are Training Programs More Effective When Unemployment Is High? *Journal of Labor Economics*, 27, 653-692.
- [31] Martin, J. P. & Grubb, D. (2001). *What Works and for Whom: A Review of OECD Countries' Experiences With Active Labour Market*. Working Paper, No. 2001: 14. Institute for Labour Market Policy Evaluation (IFAU), Uppsala
- [32] Martins, P. S. & Pessoa e Costa, S. (2014). *Reemployment and Substitution Effects from Increased Activation: Evidence from Times of Crisis*. Discussion Paper No 8600, Institute for the Study of Labor (IZA).
- [33] McTier, A. & McGregor, A. (2018). Influence of work-welfare cycling and labour market segmentation on employment histories of young long-term unemployed. *Work, Employment and Society*, 32(1), 20-37.
- [34] Meghnagi, M. & Tuccio, M. (2022). The recognition of prior learning: Validating general competences, OECD Social, Employment and Migration Working Papers, No. 270, OECD Publishing, Paris, <https://doi.org/10.1787/2d9fb06a-en>.
- [35] Mincer J (1958) Investment in human capital and personal income distribution. *Journal of political economy*, 66(4), 281-302.
- [36] OECD (2010). *Economic Outlook No 88*. OECF. Paris.
- [37] OECD (2017). *Labour Market Reforms In Portugal 2011-2015 A Preliminary Assessment*. Available at: <https://doi.org/10.1787/9789264269576-en>
- [38] OECD (2022a). Short-Term Labour Market Statistics - 2022. Available at: <https://stats.oecd.org/Index.aspx?DatasetCode=STLABOUR#>.
- [39] OECD (2022b). *Public Spending on Labour Markets (Indicator) - 2022*. Available at: <https://data.oecd.org/chart/6Uml>.
- [40] Pedroso, P. (2014). *Portugal and the Global Crisis: The Impact of Austerity on the Economy, the Social Model and the Performance of the State*. Ed. Friedrich-Ebert-Stiftung | Western Europe /North America. Available at: <https://library.fes.de/pdf-files/id/10722-20220207.pdf>
- [41] Schultz, T. W. (1961). Investment in Human Capital: Reply. *The American Economic Review*, 51(5), 1035–1039. Available at: <http://www.jstor.org/stable/1813848>
- [42] Segurança Social (2022). *Coordenação Internacional de Legislações - 2021*. Available at: <https://www.seg-social.pt/coordenacao-internacional-de-legislacoes>
- [43] Smelser, N. J. (2013). *The sociology of economic life*. Reprint. Quid Pro Books.

- [44] Spence, M. (1973). Job Market Signalling. *Quarterly Journal of Economics*, No 87, pp. 355–374.
- [45] Taylor, P. & Urwin, P. (2001). Age and Participation in Vocational Education and Training. *Work, Employment and Society*, 15(4), 763–779. <https://doi.org/10.1177/095001701400438198>
- [46] Vooren, M., Haelermans, C., Groot, W., & van den Brink, H. M. (2019). The effectiveness of active labor market policies: a meta - analysis. *Journal of Economic Surveys*, 33(1), 125-149. Available at: <https://doi.org/10.1111/joes.12269>
- [47] Wunsch, C. (2016). How to minimize lock-in effects of programs for unemployed workers. *IZA World of Labor* 2016: 288. DOI: 10.15185/izawol.288.

1 The raw database (before it was simplified) had 1,153,883 lines, representing 88,726 people. To calculate the impact of VA programme on the outcomes of interest, the data had to be cleaned further. Although registrations available start in December 2012, some unemployment spells started before that date. People whose unemployment spell started more than three years (the maximum duration of unemployment benefits) before December 2012 were removed (as these may be individuals with very particular profiles), while the remaining cases were kept. Furthermore, people with more than 10 unemployment spells were excluded (Table A1.) as well as those with training courses done before being registered at the employment centre (or without contemporaneous registration). Finally, there is the possibility to be employed, but registered in IEF, being “actively looking for another job” - these observations are excluded, since the analysis is focused on the unemployed.

2 The spell’s duration reflects a highly skewed distribution, hence, for statistical robustness the logarithms of the variable will be used (`log_dur_spell1`). This will change the interpretation of results, as the exponential of the coefficients will represent percentage change in spell length motivated by unit changes in the regressors.

3 The outcome variable will be a dummy variable representing if the individual had second spell of unemployment or not (`spell2`).

4 Average duration of first spell for non-program participants is 11.46 months, hence the VA would increase its length to around 22 months.

5 average VA length is 1.51 months

6 This inference considers no endogeneity. Analysis of later months should represent more similar individuals, as the sample is restricted to longer spells.

7 Following the reasoning of people who have longer spells are more similar in unobserved characteristics, the regression on the probability of re-employment was calculated sequentially, restricting the sample for longer first spells (Table A6.), which decreased the significance of VA in decreasing the probability of recurrence, if the program is taken after the first month.

8 These results are built using the sample described in the Data section (including the “retrospective” data of people who were still unemployed in December 2012 but started the unemployment spell before that date).

The same analysis was made, but without that data (Table A7). The control for fixed effects of the year when spell started, motivated me to maintain the retrospective data. Furthermore, this “retrospective” data would represent individuals more similar among them, as their unemployment spells are longer, contributing to the accuracy of the results.

9 During this study an attempt was made to build an approximation of classes, joining people who entered in the same date to the same course area. However, the approach was not taken further, since true information on classes was needed to surpass problems of late application to the courses, or more than one class in the same day (since the class sizes are not pre-determined). If class sizes are pre-determined, or there is a known limit, it would allow to infer possible exogenously determined variability in participating month or course area of the courses that would help to analyse heterogeneity of effects in these settings, discarding endogeneity issues.