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Economic Recovery and Effectiveness of Active Labour Market Initiatives for the Unemployed in Spain: A Gender Perspective of the Valencian Region

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Received: 17 September 2018; Accepted: 5 October 2018; Published: 10 October 2018



Abstract: Macroeconomic indicators regarding employment have been gradually improved by southern European countries during recent years. However, the labour market still seems to be highly polarized across regions and some groups are persistently excluded from jobs recovery. This paper analyses the effectiveness of active labour market initiatives in the Valencian region, one of the worst-affected areas regarding unemployment in Spain. By using a large official database from the Valencian government, results of the probit model show that participating on active labour market initiatives have a positive impact on the probability of exiting unemployment, even after controlling for age, level of education and gender of candidates. The research also reveals that people aged 55 and older and females constitute the most vulnerable groups. Regarding women, only those with higher education increase their probability of finding a job.

Keywords: sustainable employment; active labour market policies; gender gap; probit model

1. Introduction

As a consequence of the recent financial crisis, Spain has registered the second highest unemployment rate between EU countries (only Greece reported a worse record). The unemployment rate in Spain before the financial crisis remained broadly stable at around 8.5% between 2005 and 2007. However, the loss of jobs sharply increased from 2008 until the end of 2012, when the unemployment rate reached a new historical maximum: 25.77%.

According to Grekousis [1], unemployment from the 2008 global economic crisis is highly polarized across the EU regions. In the case of Spain, one of the most affected regions regarding the unemployment was the Valencian region, a coastal area located on the east part of the country. During those years, the growth of the housing bubble in that region was facilitated by low-interest loans along the entire Mediterranean Spanish coast. However, the bursting of the real estate bubble restricted the lending capacity of the banking sector, house prices fell by up to 50% in some areas, the economy was seriously contracted and the labour market collapsed. The unemployment rate in Valencian region at the end of 2012 was 27.62%.

During the last several years, the Spanish national government has been committed to providing efforts and resources to alleviate the unemployment issue in coalition with regional governments.

Several national and regional public services are in charge of developing labour market policies to respond to problems raised by unemployment, considering that initiatives must be tailored to particular circumstances affecting each region. In this regard, Bassanini and Duval [2] analyse the impact of structural policies and institutions on aggregate unemployment in OECD countries. The research reveals that employment policies play a major role in shaping unemployment patterns. Changes in policies and institutions explain almost two thirds of non-cyclical unemployment changes. However,

macroeconomic conditions also matter: negative productivity shocks, deteriorations in the terms of trade, increases in long-term real interest rates and negative labour demand shocks are found to increase aggregate unemployment. Along with gender differences, Biagetti and Scicchitano [3] analyse how personal characteristics influence formal lifelong learning in 21 European countries. According to these authors, “formal lifelong learning incidence is significantly higher among young, better educated, part-time and temporary workers, and lower among those who changed current job in the last year, employed in small firms and having low-skilled occupations”. The research shows no gender differences regarding these facts. Arulampalam et al. [4] investigate gender differences in the European Union member states regarding training participation over the period 1994–1999. They conclude that women are no less likely than men to train, except in Spain where women are considerably more likely to undertake training. According to these authors, there is little correlation between the probability of starting formal training and women’s age, which provides some evidence of ‘lifelong learning’. However, there is a significant negative age effect for men in nine out of ten EU countries.

Focusing on labour market studies regarding the Spanish case, several authors have remarked the idiosyncratic particularities of this market (Table 1).

For example, Jimeno and Bentolila [5] show that regional wages, and relative unemployment and participation rates, are very persistent in Spain compared with the USA and the rest of European countries. Ahn and Ugidos-Olazabal [6] find that family connections in the labour market are important determinants of unemployment duration in Spain. Household heads are much faster in finding a job than non-heads. Long-term unemployment occurs more often among those who are eligible for unemployment benefit, those with less family responsibility, and those with low education.

Another interesting topic is the unemployed workers’ willingness to move for work. Ahn et al. [7] show that family responsibility, age and education are important in determining individuals’ migration willingness. However, the duration of unemployment does not show any significant effect on willingness to move. Silva and Vázquez-Grenno [8] examine transition rates in Spain, comparing the results with those reported in the UK and the USA. They show that transition rates from unemployment to employment and those that include unemployment and inactivity are lower in Spain.

Arranz and García-Serrano [9] document how recalls are playing a key role in the Spanish labour market. They show that the mean duration of the spells of unemployment ending in a recall tends to be shorter than the one corresponding to spells of unemployment ending in a new job. In the same vein, Jenkins and García-Serrano [10] report that increases in unemployment insurance benefit levels had a small disincentive effect on the re-employment hazard on average. The authors also state that the “unemployment assistance effect is a plausible explanation for the much lower re-employment hazards for men aged 52–59 years, as unemployed workers aged 52+ years who met all the requirements for retirement pension receipt were eligible to receive unemployment assistance until retirement age”. Rebollo-Sanz [11] also analyse the relationship between the unemployment insurance system and labour market turnover. These authors find that the Spanish public insurance system “reduce the time spent in employment throughout an individual’s working life by both directly increasing the probability of exit from employment and indirectly increasing unemployment duration”.

Several papers have reported the effect of educational level and training on employment probabilities. Arellano [12] analyse the effect of the public training programme of the Spanish National Employment Institute for unemployed people. The reported results suggest that intermediate courses reduce unemployment duration more than lower level courses. The author also reports that women reduce their unemployment duration more than men, although “the differences are not high enough to reduce the gender gap in the labour market significantly”. Blázquez et al. [13] report a positive relation in the Spanish region of Madrid, and conclude that attending training courses improves the probability of employment. Furthermore, people attending these specific courses benefit from employments aligned with their skills. Finally, Núñez and Livanos [14] examine the effect of the educational level and the field of study on short and longterm unemployment for different European

countries. The authors show that an academic degree is more effective on reducing the likelihood of short-term than long-term unemployment. The rates of graduate unemployment are in most cases below 5%, but in the case of Spain this rate is significantly higher: 7%.

Table 1. Review of the literature on Spanish labour market.

Paper	Topic	Methodology	Sample	Countries
Ahn and Ugidos-Olazabal [6]	The effect of unemployment benefit and family characteristics on unemployment	Hazard model	4139 people	Spain
Jimeno and Bentolila [5]	Regional unemployment persistence	Augmented Dickey–Fuller (ADF) regression	Yearly unemployment rates, 1976–1994	Spain
Ahn et al. [7]	Unemployed workers' willingness to move for work	Logistic regression	3585 people	Spain
Jenkins and García-Serrano [10]	The effect of unemployment benefits on employment probabilities	Hazard model	329,947 people	Spain
Arellano [12]	The effect of public training programmes on unemployment	Probit regression	11,572 people	Spain
Núñez and Livanos [14]	The effect of education on employment	Logistic regression	775,700 people	EU15
blázquez et al. [13]	The effect of public training programmes on unemployment	Probit regression	73,098 people	Spain
Rebollo-Sanz [11]	The relationship between unemployment insurance system and job turnover	Hazard model	Not provided	Spain
Silva and Vázquez-Grenno [8]	The transition between employment and unemployment states	Transition rates analysis	180,000 people	Spain
Arranz and García-Serrano [9]	Recalls in labour market transitions	Hazard model	1,029,033 people	Spain

Public employment services are aimed to provide the unemployed a variety of active-labour market alternatives, which comprise a wide range of policies including training programs focused at improving the access of job-seekers to the labour market. Passive-labour market measures relates to spending on income transfers, namely unemployment benefits and early retirement pensions [15,16].

It is interesting to note that results about effectiveness of active labour market programs in terms of raising the employment of participants are mixed [16–21]. The success of these initiatives largely depends on the region, group and period analysed. However, in order to tackle the unemployment problem in OECD countries, some researches argue that governments should shift the balance of public spending on labour market policies towards active labour market measures [22]. Proponents of active labour market programs argue that they are the most direct instrument for dealing with unemployment and poverty among workers. On the other side, opponents counter that these initiatives are largely a waste of public funds, and that any observed benefits for participants are usually at the expense of other workers [23].

In addition, the commitment of policy makers, public institutions and private organizations must be aligned with the Sustainable Development Goals (SDGs) statements regarding the progress of Goal 8: promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all. In this regard, two targets highlight the relevance of promoting and facilitating employment from a sustainability perspective. Target 8.7 emphasizes full and productive employment for all women and men, while target 8.6 focuses on reducing the proportion of youth not in employment,

education or training. Despite the identification of a broad range of issues related to unemployment, Goal 8 does not point out older unemployed people as a group at risk of employment exclusion, although this group is shown to be the most vulnerable one in our research as we will remark later.

The United Nations has reported that women are more likely to be unemployed than men across all age groups, while youth are almost three times as likely as adults to be unemployed [24]. High youth unemployment forms the basis of the NEET phenomenon, a term used to describe young people neither in education, employment nor training [25]. According to United Nations, more than 1 in 10 youth are not in the educational system or working. However, statistics also confirm that older workers constitute a vulnerable group. According to Fournier et al. [26] “the loss of jobs among older workers is a highly worrisome situation, since it can be synonymous with long-term employment precariousness and definitive exclusion from the labour market.”

Government efforts to reduce unemployment must be evaluated systematically to ensure that this essential area of public policy is both effective and efficient [22]. Policy-makers need broad and accurate information about the characteristics of unemployed people to guide policies and practices in a successful way. A good starting point is to know what are the key characteristics of those job-seekers who succeed in finding a job.

This paper aims to estimate the relation between the individual’s employment probabilities and her/his participation in active-labour activities promoted by Valencian public employment services. The relation is examined after controlling by other factors, e.g., gender, age and level of education. We analyse the dichotomous variable ‘employed’ for each year in the period 2013–2015, considering as explanatory variables the participation in active-labour activities of the corresponding previous year and the abovementioned personal characteristics. The period analysed encompasses those years when the emerging economic recovery began and the unemployment trend in the Valencian region was reversed.

Our results are based on a large official database including almost 6 million of job contracts, and suggest that the probability of employment is significantly improved for those subjects participating in active-labour programs, even after controlling for personal characteristics. The employment probability decreases with age and also for those people without education (illiterates and people abandoning school prematurely), while being a woman still reduces the probability on working opportunities. From a political perspective, these results should have implications for regional political decision-makers, who could put forward new arguments to target public funds on certain particularly disadvantaged unemployed groups, or promoting tax benefits for employers aligned with the shared goals of sustainable employment and greater social cohesion.

The rest of the paper is structured as follows. Section 2 gives some stylised facts on Valencian unemployment and describes the main characteristics of the database used in the research. Section 3 presents the results of applying a probit model for explaining the probability of leaving unemployment for Valencian jobseekers, and analyses the impact of age, level of education, gender and level of participation in initiatives organized by the Valencian employment service. Section 4 discusses some political implications regarding the results obtained. The paper ends with the main conclusions and future lines of research.

2. Materials and Methods

As depicted in Figure 1, official statistics regarding unemployment in the Valencian region confirm that women have been systematically discriminated from the employment recovery of the last years. The unemployment crisis essentially reduced the employment figures of men, while women continued to be excluded from the labour market before, during, and after the economic crisis. During the most critical period of the crisis, the unemployment rate between women and men was almost the same. However, before this period and, more interestingly, after it, the gap regarding unemployment between women and men remained approximately at 5 points.

However, women is not the most victimised group according to these statistics. The crisis mainly focused on youth employment with devastating effects. The unemployment rate for people under 25 years of age reached a peak of 58.69% in 2013. Unlike women, the beginning of the economic recovery has enabled young people to reduce the gap regarding other groups, although they continue to be the most vulnerable one by far. According to 2017 figures, about 40 per cent of people under 25 years old remained unemployed in the Valencian region, even taking into account that the youngest generation is the best educated.

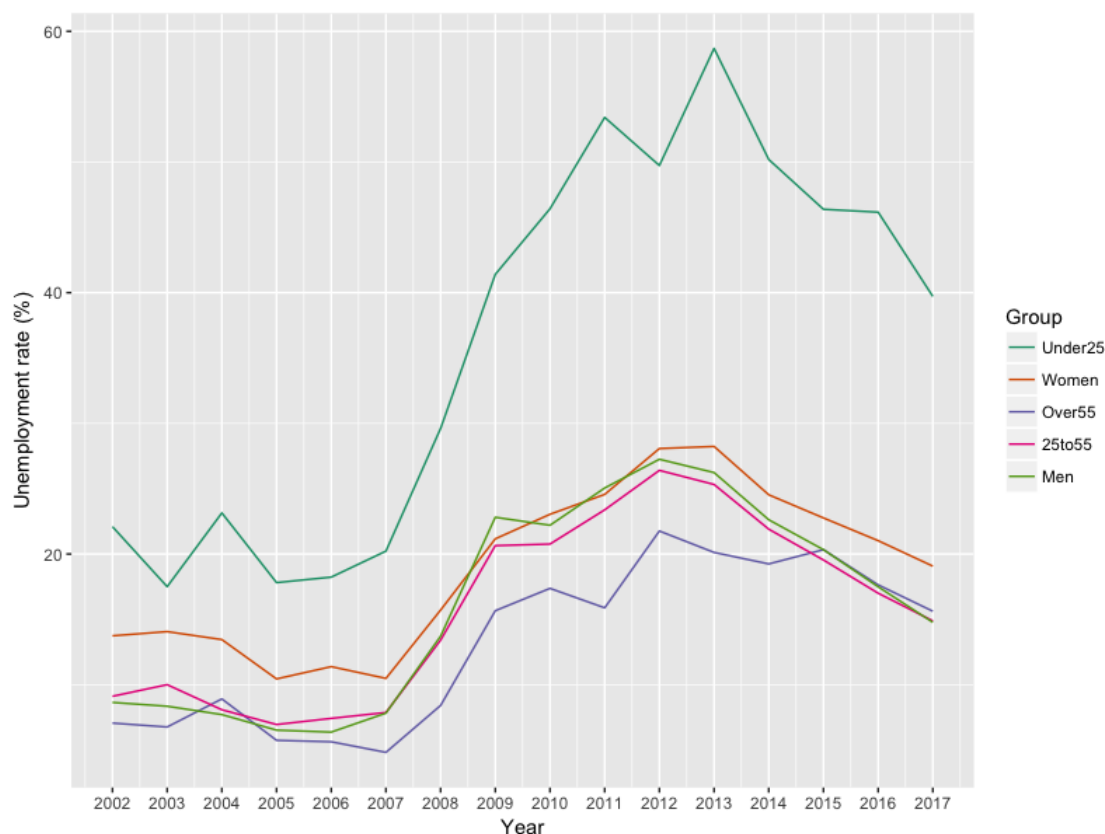


Figure 1. Evolution of the unemployment rate in the Valencian region (Spain). Differences regarding gender and age.

We have gathered information from different databases provided by SERVEF (*Servicio Valenciano de Empleo y Formación*, Valencian Service of Employment and Training), the public Valencian government institution with competence in jobseeking and training for unemployed people registered in the Valencian region. Variables covered the period 2012–2015, with 2,564,422 people registered in the system as unemployed, and 1,367,294 people involved in 5,824,603 employment contracts. Therefore, each employed person during this period signed 4.26 contracts on average. This depicts the situation where most contracts signed in Spain and Valencia were temporary contracts.

SERVEF collects personal information for people registered as unemployed in the system. Once the subject is registered, a wide range of alternatives or ‘actions’ are offered to improve the chance of finding a job. Jobseekers can attend short individual interviews to design a customized curriculum, learn about how to approach a job interview, use Internet extensively to search employment opportunities, or improve her/his communication skills and self-esteem. SERVEF also offers training and updating long courses focused on improving specific skills, such as foreign languages, administrative assistance, computerised accounting, etc.

We have computed the number of actions undertaken by registered unemployed people in years 2012, 2013 and 2014. This way we can measure how active is a person on searching for employment.

Personal information about gender, age and level of education for each subject was also included in the analysis. All these variables were collected to explain the ‘employed’ dichotomous variable, which takes the value 1 for those subjects who signed an employment contract in the following year (action undertaken in 2012, contract signed in 2013, and so on), and 0 otherwise. This way, we can measure the short-term effectiveness of SERVEF initiatives’ attendance of year t on the employment success of year $t + 1$, with $t \in \{2012, 2013, 2014\}$. Certainly, we could also consider a longer gap (more than one year) between the attendance and the employment success, namely attendance on year t and employment on year $t + 2$; but this should necessarily include the actions undertaken by unemployed people during year $t + 1$. Consequently, we have decided to follow the same short-term approach as McGuinness et al. [22]. Andrén et al. [27], Kelly et al. [28].

Summary statistics for the involved variables in our sample can be found in Table 2. Here, we can analyse the distribution of people considered in our dataset concerning their employment condition, age, gender, level of education and number of actions that unemployed people have attended to.

Table 2. Summary statistics. Values are expressed in percentage.

Year	2013	2014	2015
Employment rate:			
Employed	34.14	37.40	38.92
Age:			
Age < 25	9.70	10.00	12.94
Age 25–34	30.24	25.63	24.29
Age 35–44	30.33	29.39	27.09
Age 45–54	21.02	25.43	23.64
Age >= 55	8.71	9.55	12.04
Gender:			
Female	53.48	52.74	50.98
Male	46.52	47.26	49.02
Education:			
No education	2.90	2.19	2.31
Primary	67.47	66.05	63.35
Secondary	12.65	13.62	14.49
Bachelor degree	16.19	17.07	18.58
Master degree	0.69	0.95	1.13
Doctoral degree	0.10	0.12	0.14
Actions:			
No active	51.44	52.95	53.67
Moderately active	34.56	35.92	39.09
Highly active	14.00	11.13	7.24

We can observe a slight improvement in the employment rate during the period 2013–2015. Only 34.14% of ‘active’ people in 2012 (those subjects who participated in at least one action offered by SERVEF) was able to find a job in 2013. This percentage was improved the following two years: 37.40% and 38.92%, respectively. Following previous literature [22,28,29], we have decided to distribute the age of subjects in different groups: under 25, 25–34, 35–44, 45–54 and 55 years or older. This simplifies the non-linear analysis of the relationship between leaving unemployment and age.

The education level of people registered in SERVEF was coded in 6 different groups: No education, Primary school, Secondary school, Bachelor degree, Master degree and Doctoral degree. This way we can measure the individual effect of these levels on leaving unemployment. Table 2 shows that 2 out of 3 people have compulsory primary education. However, this percentage has gradually decreased during the analysed period from 67.47% in 2013 to 63.35% in 2015. On the contrary, unemployed people with higher education have slightly risen during the same period. This reveals how difficult is

to find a job for people with technical skills and high education in Valencia, a region where particularly young people are the best educated generation.

Finally, the number of actions undertaken by unemployed people were also classified in three different groups. Any person registered in SERVEF must necessarily attend one action at least. Otherwise she/he cannot be included in SERVEF databases. Therefore, the lower bound for the number of activities is 1, corresponding with those *stricto sensu* not active people in the activities promoted by SERVEF. The second level is for people attending 2 to 5 activities (moderately active), while those participating in more than 5 activities (highly active) were classified in the third group.

The explanation of leaving unemployment (binary variable) was performed for the years 2013, 2014 and 2015, by estimating a probit model and using variables included in Table 2 as explanatory variables. Probit regression models are a special type of the Generalized Linear Models to explain dichotomous or binary outcome variables. The independent variable Y has a Bernoulli distribution with parameter p . The expected value $E[Y]$ measures the success probability p . The inverse standard normal distribution of the probability is modeled as a linear combination of the predictors following Equation (1).

$$\text{probit}(E[Y]) = \Phi^{-1}(p) = \Phi^{-1}(P[Y = 1]). \quad (1)$$

The probit function is modeled as a linear combination of the regressors X as indicated in Equation (2), where β is a vector of unknown parameters.

$$\text{probit}(E[Y]) = X\beta. \quad (2)$$

Finally, the predicted probability \hat{P} can be obtained by the inverse probit transformation (Equation (3)).

$$\hat{P}[Y_i = 1] = \Phi(X_i, \hat{\beta}). \quad (3)$$

Further information about probit models can be found in aldrich et al. [30], hosmer et al. [31].

3. Results

This section presents the results obtained with the probit model. Econometrical models were computed using R software [32]. Figures and tables were also designed using R and the *ggplot* library [33].

We have explained the employment success during years 2013, 2014 and 2015 for people attending initiatives from SERVEF. The dependent variable is a binary variable, indicating that the person was able (value 1) or unable (value 0) to sign at least one contract during the corresponding year. Regarding the independent variables, we have considered gender, age, level of education, and the number of activities that the unemployed person attended the previous year. All these variables were transformed to binary variables to code the levels showed in Table 2. The variable associated with gender was coded as 0 for males and 1 for women. We have decided variables corresponding to people under 25, males, without education and only 1 action to remain as reference categories, and hence they have been excluded of the analysis.

Model A includes the above-mentioned independent variables, while Model B also controls for interaction terms between gender and the remainder independent variables. Interaction terms are estimated to infer how the effect of one independent variable on the dependent variable depends on the magnitude of another independent variable [34]. This way, we can closely measure how gender interacts with other personal characteristics in our research.

The specification for Model A is given in Equation (4), where $P(\text{employed} = 1|x)$ is the probability of being employed conditional on x ; and x includes variables related to age, gender, educational level and participation in SERVEF activities. All independent terms are binary variables, so levels for age

under 25, no education and no active were omitted. Consequently, the reference subject for Model A is a man below 25 years, without school-leaving certificate and only 1 action recorded in SERVEF.

$$P(\text{employed} = 1|x) = F(\beta_0 + \beta_1 \text{age}_{25-34} + \beta_2 \text{age}_{35-44} + \beta_3 \text{age}_{45-54} + \beta_4 \text{age}_{55+} + \beta_5 \text{primary} + \beta_6 \text{secondary} + \beta_7 \text{bachelor} + \beta_8 \text{master} + \beta_9 \text{doctoral} + \beta_{10} \text{moderately_active} + \beta_{11} \text{highly_active} + \beta_{12} \text{gender}). \quad (4)$$

Table 3 presents the marginal effects of the probit model to better understand how the above-mentioned variables can impact on getting out of unemployment. The number of observations fluctuates from 142,177 in 2014 to 387,067 in 2015, which consequently improves the statistical significance of the results. Notwithstanding the dataset consists of 1,367,294 observations, we must remark that the sample size was eventually reduced because of the design of the experiment. We must note that the proposed econometric model explores the effect of actions performed on year t over the employment results on year $t + 1$. This way, we have matched actions of year 2012 with employment of year 2013; actions of year 2013 with employment of year 2014; and, finally, actions of year 2014 with employment of year 2015. Therefore, Table 3 reports the results obtained with 3 different regressions. We are losing the regression which explains the employment result for the year 2012, because we do not have information regarding actions of the year 2011. This is why we have 1,367,294 people in the dataset, but the sample size reported in Table 3 is lower.

According to the reported coefficients, we observe that people aged 55 and older show the worst situation across all ages considered in the research. If we focus on year 2013, the probability of exiting unemployment for people 55 and older is 25.4% lower compared to the reference subject (a person under 25 years of age). A similar behaviour is observed for people in the age range 45–55 years old: 14.8%. These results remain quite stable regardless of the year considered (2013 to 2015). Also for any of the years, people aged between 25 and 34 exhibited a higher probability of leaving unemployment than people under 25: 1.9% in 2013, 1.8% in 2014 and 3.7% in 2015. Compared to the rest of groups, we can conclude that people in the range 25–34 were the most benefited regarding employment probability.

Table 3 also exhibits significant coefficients for all educational levels except for doctoral degree, what could be explained by the low percentage of people with a PhD in the sample. Unlike the age variable, percentage differences in the probability of exiting unemployment compared with the reference subject (no education) are much lower. Furthermore, we observe that ranking between educational levels according to its coefficients vary from year to year, while in the case of age the order remains constant. On average, we can confirm that people with a master degree are more likely to leave unemployment. As expected, positive and significant coefficients for all variables indicate that people with no educational level are at the worst position to find a job.

Results confirm a positive effect of the number of actions accomplished by unemployed people. The probability of exiting unemployment for highly active people—those concluding more than 5 actions in SERVEF—is between 2.3% (2014) and 5.5% (2015) higher than in the case of inactive unemployed—concluding only 1 compulsory action—However, the sign of the coefficient for moderately active people—those accomplishing between 2 and 5 actions—vary during the period analysed. According to the absolute coefficients observed for other variables, we can state that participating in active labour market activities presents the lower net effect on leaving unemployment; although the impact is positive and statistically significant.

Based on these results, we can conclude a positive relation between attending active labour market initiatives and finding a job for Valencian people, but only when participation is actually active. Those subjects attending a small number of actions of SERVEF do not show a significant improvement in their chance of getting a job. We must also remark that this statistical relationship does not necessarily imply a causal association. In other words, another point to research is which variable is actually causing the other one, since present work only confirms the existence of a relationship between both variables.

Table 3. Probit model estimating the probability of leaving unemployment (marginal effects).

	Model A			Model B		
Year	2013	2014	2015	2013	2014	2015
Age:						
Age 25–34	0.019 *** (0.004)	0.018 *** (0.005)	0.037 *** (0.003)	0.047 *** (0.005)	0.040 *** (0.007)	0.067 *** (0.004)
Age 35–44	−0.047 *** (0.004)	−0.037 *** (0.004)	−0.026 *** (0.003)	−0.010 * (0.005)	0.001 (0.006)	0.017 *** (0.004)
Age 45–54	−0.148 *** (0.003)	−0.150 *** (0.004)	−0.125 *** (0.002)	−0.112 *** (0.005)	−0.114 *** (0.006)	−0.083 *** (0.003)
Age >= 55	−0.254 *** (0.003)	−0.262 *** (0.004)	−0.282 *** (0.002)	−0.224 *** (0.005)	−0.241 *** (0.006)	−0.251 *** (0.003)
Education:						
Primary	0.044 *** (0.007)	0.051 *** (0.009)	0.029 *** (0.006)	0.035 *** (0.009)	0.054 *** (0.012)	0.024 *** (0.007)
Secondary	0.064 *** (0.008)	0.072 *** (0.010)	0.045 *** (0.006)	0.036 *** (0.010)	0.060 *** (0.013)	0.011 (0.008)
Bachelor degree	0.053 *** (0.008)	0.063 *** (0.010)	0.029 *** (0.006)	0.006 (0.010)	0.021 (0.013)	−0.020 ** (0.007)
Master degree	0.061 *** (0.015)	0.097 *** (0.017)	0.043 *** (0.010)	−0.015 (0.023)	0.045 (0.025)	−0.013 (0.013)
Doctoral degree	−0.021 (0.037)	−0.061 (0.038)	−0.047 * (0.021)	−0.107 (0.055)	−0.102 * (0.050)	−0.107 *** (0.030)
Actions:						
Moderately active	0.010 *** (0.002)	−0.006 * (0.003)	0.035 *** (0.002)	0.003 (0.003)	−0.016 *** (0.004)	0.039 *** (0.002)
Highly active	0.055 *** (0.003)	0.023 *** (0.004)	0.054 *** (0.003)	0.041 *** (0.004)	0.012* (0.006)	0.060 *** (0.004)
Gender:						
Female	−0.061 *** (0.002)	−0.079 *** (0.003)	−0.085 *** (0.002)	−0.044 ** (0.016)	−0.038 * (0.020)	−0.049 *** (0.012)
Interaction effects:						
Gender * Age 25–34				−0.060 *** (0.007)	−0.047 *** (0.009)	−0.060 *** (0.005)
Gender * Age 35–44				−0.078 *** (0.007)	−0.079 *** (0.009)	−0.090 *** (0.005)
Gender * Age 45–54				−0.084 *** (0.008)	−0.081 *** (0.009)	−0.091 *** (0.005)
Gender * Age >= 55				−0.098 *** (0.010)	−0.066 *** (0.012)	−0.094 *** (0.006)
Gender * Primary				0.027 (0.014)	−0.008 (0.019)	0.018 (0.011)
Gender * Secondary				0.063 *** (0.016)	0.026 (0.021)	0.077 *** (0.012)
Gender * Bachelor degree				0.094 *** (0.016)	0.073 *** (0.021)	0.100 *** (0.012)
Gender * Master degree				0.137 *** (0.033)	0.081 * (0.035)	0.108 *** (0.020)
Gender * Doctoral degree				0.171 (0.089)	0.097 (0.085)	0.134 ** (0.047)
Gender * Moderately active				0.016 ** (0.005)	0.020 *** (0.006)	−0.010 ** (0.003)
Gender * Highly active				0.031 *** (0.007)	0.023 ** (0.009)	−0.014 * (0.006)
Pseudo R ²	0.086	0.082	0.096	0.090	0.085	0.101
Observations	193,150	142,177	387,067	193,150	142,177	387,067

Standard errors in parentheses; *** Significant at $p < 0.01$; ** Significant at $p < 0.05$; * Significant at $p < 0.1$.

The last explanatory variable in model A of Table 3 refers to gender. Coefficients are significant for all years, and indicate that women are on average less likely to find a job than men during the analysed period. The situation is even worsening during the last years: -6.1% in 2013, -7.9% in 2014 and -8.5% in 2015. This highlights that women are not profiting from the employment recovery, and gives new arguments for the long debate about gender exclusion from a sustainable employment perspective [35–39]. These results are aligned both with Spanish national statistics and Valencian figures given in Table 2. As previously stated, the financial crisis has certainly served to balance female and male unemployment. However, once the economic recovery was initiated, the historical gender gap returned to unemployment figures.

The second estimated model, Model B, serves to account for interaction effects between gender and the rest of variables. It captures how gender interacts with other explanatory variables, and the results can serve to focus government initiatives to those exposed groups that face the biggest difficulties to climb out of unemployment. The model is presented in Equation (5), which adds interaction terms to the variables already considered in Equation (4).

$$\begin{aligned}
 P(\text{employed} = 1|x) = & F(\beta_0 + \beta_1 \text{age}_{25-34} + \beta_2 \text{age}_{35-44} + \beta_3 \text{age}_{45-54} + \beta_4 \text{age}_{55} + \\
 & \beta_5 \text{primary} + \beta_6 \text{secondary} + \beta_7 \text{bachelor} + \beta_8 \text{master} + \beta_9 \text{doctoral} + \\
 & \beta_{10} \text{moderately_active} + \beta_{11} \text{highly_active} + \beta_{12} \text{gender} + \\
 & \beta_{13} \text{gender} \times \text{age}_{25-34} + \beta_{14} \text{gender} \times \text{age}_{35-44} + \beta_{15} \text{gender} \times \text{age}_{45-54} + \quad (5) \\
 & \beta_{16} \text{gender} \times \text{age}_{55} + \beta_{17} \text{gender} \times \text{primary} + \beta_{18} \text{gender} \times \text{secondary} + \\
 & \beta_{19} \text{gender} \times \text{bachelor} + \beta_{20} \text{gender} \times \text{master} + \beta_{21} \text{gender} \times \text{doctoral} + \\
 & \beta_{22} \text{gender} \times \text{moderately_active} + \beta_{23} \text{gender} \times \text{highly_active}).
 \end{aligned}$$

Results are summarized in Table 3 and confirm that women are negatively affected by unemployment regardless of age. For all three years considered in our research, most coefficients of the gender variable and interactions variables between gender and age are negative and statistically significant. Although the magnitude of the gender variable in Model B is slightly lower than the one observed in Model A, it is compensated with the values reported for interaction effects. Focusing on the age variables of Model B, we can conclude that significance of coefficients is lower in Model B than in Model A. However, interaction effects show a greater gender significance in Model B, and this is due to the fact that difference in the probability of employment are partially explained by age, but better explained when age is jointly considered with gender (thought interaction effects).

Another interesting point is related with the educational level. We observe a significant positive sign for the interaction between gender and bachelor and master degree. This translates into a higher probability of finding a job for those women with higher education. Again, the model suggests that education is relevant for explaining employment opportunities, but once gender differences have been accounted for.

The pseudo R^2 confirms that Model B fits better than Model A in all 3 years considered. The best result is obtained for Model B with data corresponding to year 2015. Results confirm that the model can predict probabilities that are 0.10 (10%) better than a model using only constants. Although the values reported for pseudo R^2 might seem low, they are actually in line with those obtained in recent literature references. For example, the value of pseudo R^2 reported by McGuinness et al. (2014) [29] in their most accurate model is 0.083, while models by McGuinness et al. (2011) [22] are around 0.10 and models by Kelly et al. (2012) [28] vary between 0.05 and 0.15. The highest reported pseudo R^2 was obtained in Andrén and Andrén [27], where the Swedish unemployment rate is explained with a pseudo R^2 value of 0.35.

As stated by McFadden ([40], pp. 34–35), “while the R^2 index is a more familiar concept to planners who are experienced in ordinary regression analysis, it is not as well-behave as the pseudo R^2 measure, for maximum likelihood estimation. Those unfamiliar with the pseudo R^2 index should

be forewarned that its values tend to be considerably lower than those of the R^2 index and should not be judged by the standards for a good fit in ordinary regression analysis. For example, values of 0.2 to 0.4 for pseudo Rs represent an excellent fit.”.

As previously stated, Table 3 shows the marginal effects of independent variables, where we can observe that some coefficients corresponding to different levels in one variable are quite similar. Tables 4–9 include the results of testing differences in coefficients, including interaction effects. We present significance levels for pairwise comparisons between reported levels of age, educational level and participation in active-labour activities.

For example, the difference between all reported coefficients for age are significant at the 0.01 level of significance in year 2013 (Table 4). This way we can conclude that employment probability is statistically different for each group we have analysed, i.e., people aged between 25 and 34 are 4.7% less likely to get out of unemployment than people under 25; people aged between 35 and 44 are 14.8% less likely to get out of unemployment than people under 25; and these two percentages are statistically different on each other. We can see that differences on age coefficients remain significant for 2014 (Table 6) and 2015 (Table 8).

The same applies to the level of activity in SERVEF actions: differences between coefficients for levels “moderately active” and “highly active” are statistically significant. We can conclude that employment opportunities increase in attending more than 5 activities more than in the case of attending between 2 and 5 activities.

However, results are heterogeneous with regard to the level of education. For example, primary and master coefficients are statistically different for 2013 and 2015, but not in 2014.

Tables 5, 7 and 9 present significance for differences between interaction effects.

Table 4. Wald Test for testing differences in coefficients, year 2013.

	25–34	35–44	45–54	Primary	Secondary	Bachelor	Master	Moderately Active
35–44	***		***					
45–54	***	***						
>=55	***	***	***					
Secondary						***	**	
Bachelor				***	***			
Master				**	**			
Doctoral				**	**			
Highly active								***

*** Significance at $p < 0.01$; ** Significant at $p < 0.05$.

Table 5. Wald Test for testing differences in coefficients of interaction effects, year 2013.

	25–34	35–44	45–54	Primary	Secondary	Bachelor	Master	Moderately Active
35–44	***							
45–54	***							
>=55	***	***	***					
Secondary				***		***	**	
Bachelor				***	***			
Master				***	**			
Doctoral								
Highly active								**

*** Significance at $p < 0.01$; ** Significant at $p < 0.05$.

Table 6. Wald Test for testing differences in coefficients, year 2014.

	25–34	35–44	45–54	Primary	Secondary	Bachelor	Master	Moderately Active
35–44	***		***					
45–54	***	***						
>=55	***	***	***					
Secondary						***		
Bachelor				***	***			
Master								
Doctoral				***	***	**	**	
Highly active								***

*** Significance at $p < 0.01$; ** Significant at $p < 0.05$.**Table 7.** Wald Test for testing differences in coefficients of interaction effects, year 2014.

	25–34	35–44	45–54	Primary	Secondary	Bachelor	Master	Moderately Active
35–44	***							
45–54	***							
>=55	***							
Secondary				***		***	*	
Bachelor				***	***			
Master				***	*			
Doctoral								
Highly active								

*** Significance at $p < 0.01$; ** Significant at $p < 0.05$; * Significant at $p < 0.1$.**Table 8.** Wald Test for testing differences in coefficients, year 2015.

	25–34	35–44	45–54	Primary	Secondary	Bachelor	Master	Moderately Active
35–44	***		***					
45–54	***	***						
>=55	***	***	***					
Secondary				***		***	**	
Bachelor				***	***			
Master				***	**			
Doctoral				***	***	***	***	
Highly active								***

*** Significance at $p < 0.01$; ** Significant at $p < 0.05$.**Table 9.** Wald Test for testing differences in coefficients of interaction effects, year 2015.

	25–34	35–44	45–54	Primary	Secondary	Bachelor	Master	Moderately Active
35–44	***							
45–54	***							
>=55	***	***	**					
Secondary				***		***	*	
Bachelor				***	***			
Master				***	*			
Doctoral				**				
Highly active								

*** Significance at $p < 0.01$; ** Significant at $p < 0.05$; * Significant at $p < 0.1$.

4. Discussion

Although young people show the worst unemployment figures according to official Valencian statistics, women constitute the core of structural unemployment.

According to labour statistics for 2017 published by the Spanish National Statistics Institute (*Instituto Nacional de Estadística, INE*), 44% of temporary contracts were signed by women. In absolute terms, the difference between women and men regarding temporary contracts is approximately two million contracts. However, women represented a higher proportion in the period we have analyzed: by 2014 women involved in temporary contracts reached a 47% of the total. Regarding permanent contracts, 63% of contracts were signed by women in 2012, while currently this percentage is balanced between women and men.

An explanation for the slow recovery of female employment is related to sectors that are supporting the current economic recovery. For the last years, the brick and construction industries are engaging those construction workers who were unemployed after the financial crisis. In Spain, these jobs have been traditionally linked to the men. Some harmful prejudices about women involved in construction jobs still exists, indicating that there are significant pockets of bias to overcome in the future. A visible gap in gender role and employment opportunities regarding other EU countries should encourage Valencian and Spanish government institutions to focus their labour market policies on reducing significantly such differences. This way, public initiatives could be aligned with the “no-one left behind” principle supported by the Sustainable Development Goals and the European Commission.

Furthermore, our work suggests that older people face the worst situation to exit from unemployment. Job prospects for older people are aggravated because of their inability to easily adapt to new working environments and new technology-intensive jobs, where technology management and foreign language skills are crucial.

Another point that must be closely analysed is the effectiveness of current labor market initiatives. This research shows a positive relation between the individual’s employment probabilities and participation in active-labour activities promoted by Valencian SERVEF during the emerging economic recovery period. Although the relation was statistically significant, other variables show to be more relevant in the success of finding a job. This should encourage political decision-makers to reconsider the way these initiatives are implemented, to avoid the usual situation where unemployed are seated at training desks without any hope of finding a job. Further research must be performed to analyse the active-market labour activities from an efficient perspective, providing key clues to improve the results of employment policies.

5. Conclusions

This paper analyses the effectiveness of active labour market initiatives in the Valencian region, one of the worst affected areas regarding unemployment in Spain. We have run a probit model on a large official database from the Valencian government, with information regarding nearly 6 million contracts signed by 1,367,294 people. This database has enabled us to analyse the relationship between exiting unemployment and several critical variables: level of activity of unemployed in active-labour market activities, gender, age and level of education. The period analysed include those years when the emergent economic recovery favoured a trend reversal in Spanish and Valencian unemployment rate figures.

Results of the probit model show that participating on active labour market initiatives have a positive impact on the probability of exiting unemployment, even after controlling for other variables. However, the most significant percentage is related to older people. Those unemployed aged 55 and older constitute the most discriminated group.

Furthermore, our research reveals a significant gap between women and men regarding employment probability, even after controlling for age and education level. Only those women with higher education improve their probabilities of finding a job according to our results.

A future research line is to analyse how these variables relate with the quality of employment, i.e., the dichotomy between temporary and permanent contracts. A variable that could also be included in the analysis, when possible, is the salary of the first occupation. A low salary may determine a longer period of unemployment, and analysing the relation between this variable and the other ones

considered in the paper could give researchers new insights on the subject. Further analysis on the cost of public employment initiatives should be also addressed to analyse the efficiency of active-labour market policies.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EU	European Union
INE	<i>Instituto Nacional de Estadística</i> , Spanish National Statistics Institute
NEET	Not in Education, Employment or Training
OECD	Organisation for Economic Cooperation and Development
SERVEF	<i>Servicio Valenciano de Empleo y Formación</i> , Valencian Service of Employment and Training
SDGs	Sustainable Development Goals

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