



The impact of unemployment benefits on job finding in Spain

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Abstract

This paper provides new evidence of the impact of receiving contributive unemployment benefits on the exit rates to a job using an administrative database that includes the whole registered unemployed population in Spain. We estimate the causal impact of receiving unemployment benefits on job finding using a treatment effect framework. The analysis is carried out in five different exercises, which are designed to reduce the unobserved heterogeneity between the treatment (those who receive unemployment benefits) and control groups (those who do not). Our results show that receiving unemployment benefits delays the exit to a job, while the impact varies depending on the business cycle: there is a decrease of between 1.1 and 4.5 percentage points (12.1% and 21.8% in relative terms) in the probability of finding a job for those who receive unemployment benefit over those who do not, depending on the moment analyzed. We also find evidence of the existence of an exhaustion effect, i.e., the job finding rates accelerate when people exhaust their benefits. Our empirical exercises also denote the importance of properly specifying the treatment and control groups to account for unobserved heterogeneity.

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1. Introduction

During the economic recession of the last decade, unemployment rates and therefore, expenditure in unemployment insurance benefits in many countries have reached all-time highs. This has sparked new research on the effects of unemployment insurance benefits on the labor market and specifically, on the probability of finding a job (Schmieder and Von Wachter, 2016). Although it is widely acknowledged that unemployment insurance benefits provide –like its own name suggests– benefits to those who suffer from unemployment in the form of consumption smoothing and allowing more time to find a job and, theoretically, a better fit between employee and employer, it is also recognized that unemployment insurance benefits might distort the job search. Previous empirical research has shown that unemployment benefits can increase reservation wages and influence job search behavior (Krueger and Mueller, 2010, 2011).

This paper provides new evidence on the impact that receiving contributive unemployment insurance has on the probability of finding a job in Spain using administrative data from the Spanish Public Employment Service's database that includes the whole population of registered unemployed people in Spain and the labor contracts signed.

The effects of unemployment insurance (UI) on job search behavior and unemployment duration have been widely studied across different institutional settings. A broad body of empirical evidence, including Tatsiramos (2006) and Meyer and Mok (2014), shows that more generous UI systems tend to increase unemployment duration, though they may also improve subsequent job matches or employment stability. These effects, however, are context-dependent and often moderated by national labor market institutions (Bennmarker et al., 2005; Portugal & Addison, 1990). In this context, the Spanish UI system offers a particularly relevant case. Despite sharing some institutional features with countries like Portugal—such as strict job protection and centralized wage bargaining—Spain consistently displays higher unemployment rates (Bover et al., 1998, 2000, 2002). These differences have been attributed to both more generous unemployment benefits and distinct wage-setting dynamics. Additionally, Spain's system is marked by high firing costs in practice and broad coverage of contributory benefits (Toharia, 1997), making it a valuable setting to test the external validity of findings from other countries and to understand how UI effects interact with persistent structural unemployment.

A widely extended economic theory when analyzing the behavior of the unemployed and their job exit rates is the job search theory. Based on this theory first developed by McCall (1970), Mortensen (1970) and Stigler (1961), an individual faces multiple job offers and has to decide which one is the “best” for him or her. Typically, searching for another job offer has an associated marginal cost for the individual; but on the other hand, the individual has a reservation wage and will not accept any offer with a salary below such wage. This reservation wage is not constant and can vary depending on the time the individual has been searching for a job, the earnings the individual receives while being unemployed, his/her personal and family situation and also on the economic situation. Therefore, unemployment benefits play an important role on job search because they affect an individual's reservation wage, pushing it higher.

The exhaustion of unemployment benefits has also been found to affect the intensity of the job search and the exit rates to a job. Belzil (2000) used a multi-state duration model with state-specific unobserved heterogeneity to analyze the relationship between unemployment benefits' duration, unemployment duration and subsequent job duration in Canada. He found out that the exhaustion of benefits plays a role on the increase of the rate of transition to employment. However, these jobs tended to have a higher dissolution rate.

Although theory predicts that any type of unemployment benefits should decrease the exit rates to a job, empirical evidence suggests that this effect varies depending on the type of unemployment benefit actually received. Spiezia (2000) analyzed the effect of two types of benefits (contributive unemployment benefits and social assistance) on the exit rates to a job for various industrialized economies. He found out that social assistance tends to increase both the duration and the incidence of unemployment, while contributive unemployment benefits are likely to be without effect on the unemployment rate.

This difference in the effect obtained for those who receive one type of benefit over the other suggests that the people who receive each one of them are not necessarily of similar characteristics. In Spain, unemployed people that have previously worked for a minimum amount of time receive unemployment benefits (also known as unemployment insurance or contributive unemployment benefits). The duration and quantity of these benefits are based on (i) how long they worked for before becoming unemployed (ii) what their salary was while working. A cap on these benefits exists: unemployed individuals can receive contributive unemployment benefits for a maximum of two consecutive years. On the other hand, some unemployed people can receive social assistance, in addition to or instead of unemployment benefits. Social assistance is granted by the state based on a person's needs, after fulfilling some requirements typically related to guaranteeing a minimum income. They are in no way related to, nor based on, a previous job or salary; in fact, the person need not have previously worked in order to receive them. However, unemployed people that have already exhausted their unemployment benefits could also receive social assistance.

Given that these two benefit types are different, people that receive them might also be different; therefore, we expect to find differences on the effect of the exit rates to a job for each benefit type. For the purposes of our analysis, and given the very specific characteristics of the social assistance benefits and those who receive them, we will focus on contributive unemployment benefits only (from now on simply “unemployment benefits”), and the effect that these have on the exit rates to a job.

In the case of Spain, Bover, Arellano, and Bentolila (2002) study the effects of unemployment benefits' duration and the business cycle on unemployment duration. To do so, they use duration models and a longitudinal sample of Spanish men between 1987 and 1994. They find that unemployment benefits delay the exit to a job, while favorable business conditions accelerate it. However, at sample-period magnitudes, the effect of the business cycle is significantly smaller. García-Pérez and Rebollo-Sanz (2015) also find that the exit rates to a job of the unemployed workers that do not receive unemployment benefits are higher than the rates of workers that do receive them when analyzing the dual labor market in Spain. The main contribution of this paper with respect to Bover, Arellano, and Bentolila (2002) is twofold: firstly, we will estimate the effect of unemployment benefits using a treatment effect framework that considers several different specifications to account for unobserved heterogeneity and confounding effects. Secondly, we will use a richer and more recent database that will serve to update their estimates for the time period between 2011 and 2016. To do so, this paper develops, firstly, the whole analysis for the year 2016¹ where the different treatment and control group specifications are discussed, and secondly, the analysis is extended for the previous years, so the impact of unemployment benefit along the business cycle can be evaluated as well.

The rest of the paper is structured as follows. In *Section 2* the data that has been used to analyze the impact of the contributive unemployment benefits are described, and some descriptive statistics and job exit rates are presented. *Section 3* is dedicated to the explanation of the estimation procedure and the strategy used to specify the treatment and control groups. In *Section 4* the main results are presented, first for the different treatment and control groups specifications in 2016, and then for the whole time period analyzed (2011–2016). Lastly, *Section 5* summarizes the main findings of the paper.

2. The Data

The data used for this analysis are two administrative data sets from the Spanish Public Employment Service's (SPES). The SPES is an autonomous agency (*organismo autónomo*) attached to the Employment and Social Security Ministry. This agency, together with the Public Employment Services of each Autonomous Community, forms the National Employment System. SPES's main activity is the creation, development and tracking of employment policies. The two administrative datasets used for our analysis will be (i) the SPES database that includes the whole population of registered unemployed people in Spain; and (ii) the SPES database that registers all the labor contracts signed in Spain. The combination of the two datasets allows us to identify the exit into employment for the unemployed individuals.

The first dataset contains monthly longitudinal information of all registered unemployed people in Spain from January 2011 to December 2016. Data is collected the last day of each month and includes all the information provided by each individual when registering at the employment office, including demographic characteristics (gender, age - under 30, 30 to 44, and 45 or older-, educational attainment, nationality, residence, knowledge of other languages), along with labor market information (previous employment experience, occupational and geographical preferences in their job search, unemployment duration, ...). The information can be updated when the unemployed individuals give new information. The SPES also provides precise information on the type of unemployment benefits or social subsidies that individuals are receiving or last received and the start and end dates of their entitlement (Gorjón, de la Rica, and Villar, 2019). Since the database is monthly, individuals may appear up to twelve times in the same year. For example, in 2016, the number of individuals which are at least once registered unemployed in the database is 6,119,778. However, as many of them are observed the maximum of twelve times, we are left with a total of 45,667,385 observations. This analysis is developed using a random sample of the 5% of the total population for each year analyzed. However, additional robustness checks have been performed with additional random draws and the results still hold².

¹ This time frame corresponds to the period for which we had access to administrative records through our agreement with the Spanish Public Employment Service (SEPE). In addition, it captures both the aftermath of the economic crisis and the early stages of recovery, providing variation along the business cycle that is key for our analysis.

² The decision of selecting a 5% responds to computational constraints associated with the high dimensionality and size of the dataset. Even after the sampling, we retain more than 2.7 million observations for 2016 alone, which ensures robust and representative estimation. This strategy is also in line with widely accepted practices when working with large-scale administrative data in Spain, such as the Continuous Sample of Working Lives, which is based on a 4% sample of the Social Security population.

In this random sample 341,160 unemployed people are included, leaving a total of 2,775,972 observations in 2016. The second dataset, which ranges from February 2011 to January 2017, includes all the labor contracts signed in Spain and their precise start date. This allows us to identify exits into employment for all the unemployed individuals.

The fact that data are available since 2011 until the end of 2016 allows to carry out an analysis of the effect of unemployment benefits along the business cycle, which we expect to vary since the economic recession was at a much higher point in 2012 than in 2016. For example, while the monthly average exit rate to a job for unemployment benefit recipients is 5.64% in 2012, this number much greater in 2016 and equal to 13.43%.

As mention in the introduction, first, the analysis will be developed for the year 2016. Thus, the results presented at first refer to this concrete year. In order to present some descriptive statistics of the unemployed individuals, figures 1 and 2 present the distribution of the unemployed population in October 2016 classified into three different groups: those who receive (contributive) unemployment benefits, those who receive social assistance-type benefits, and those who receive no benefits at all.

With respect to gender, we observe that there are no remarkable differences in the distribution between the three groups. However, when it comes to age, it can be clearly seen that social assistance recipients are older, and that the proportion of young people within the no benefit group is the greatest. With respect to educational level, the unemployed group with the highest educational level is the contributive benefits group, whereas social assistance recipients have, on average, a lower educational level.

Lastly, unemployment duration varies considerably among the three groups. Unemployment duration is lowest for recipients of contributive benefits, since these benefits are capped at two years. Most of these unemployed workers are entrants to unemployment (they have been unemployed for six months or less). The social assistance group is the group with the longest unemployment duration, since more than half of the unemployed have been in that situation longer one year.

Figure 1: Descriptive Statistics by Unemployment Benefit Type, Spain, October 2016 (I)

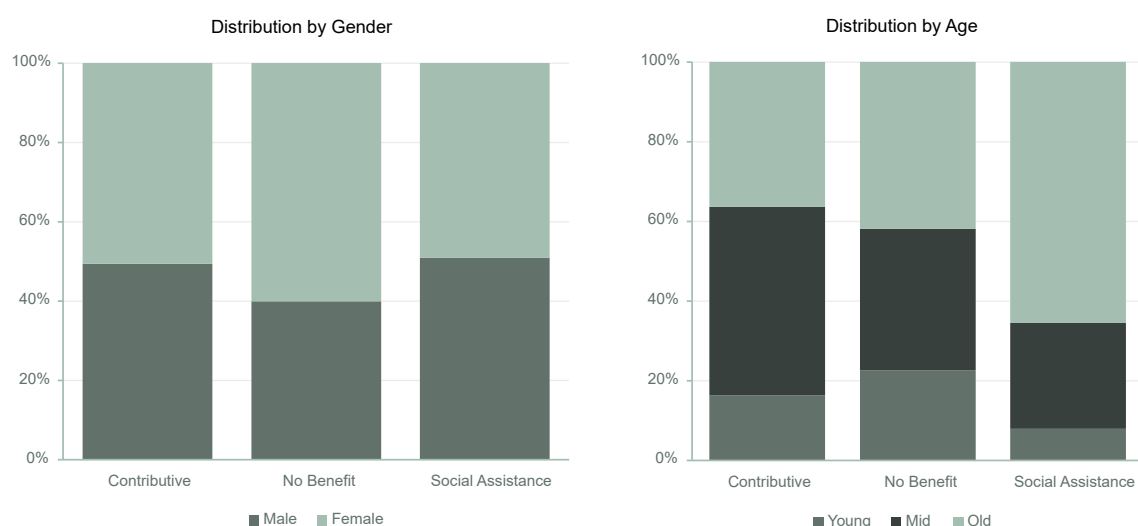


Figure 2: Descriptive Statistics by Unemployment Benefit Type, Spain, October 2016 (II)

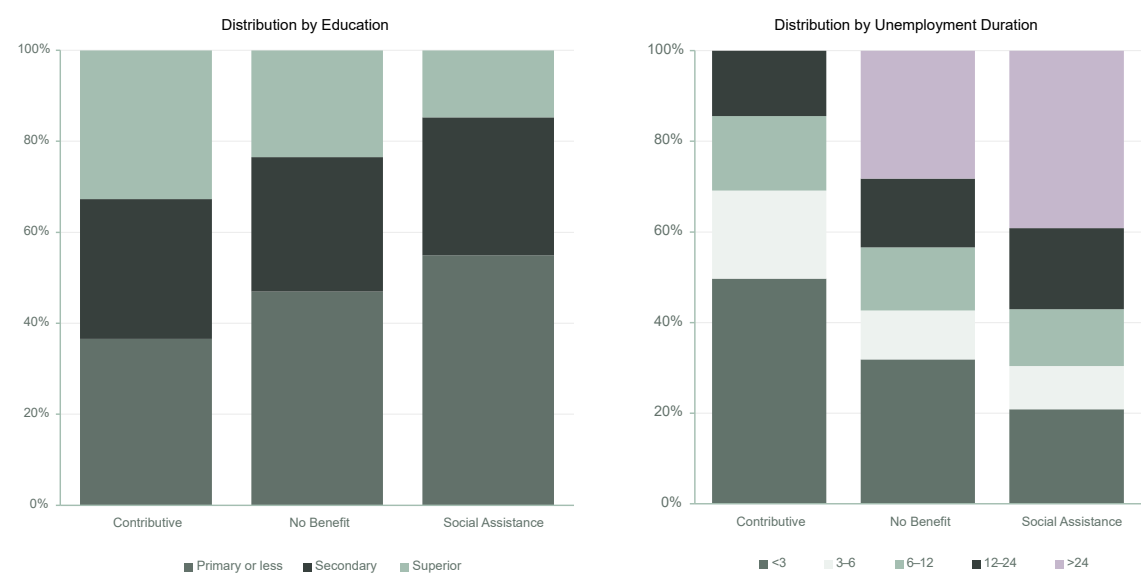


Figure 3 shows the average monthly exit rates to a job for each group, i.e. the percentage of people that transitions from unemployment to employment in each month, per benefit type. The lowest exit rates are for the beneficiaries of the social assistance benefit, which is on average older, with a lower educational level and longer unemployment spells. However, there is also a very large difference in the exit rates between those who receive (contributive) unemployment benefits and those who receive no benefits at all. This descriptive evidence seemingly goes against traditional economic theory that unemployment benefits delay unemployment exit to a job; but it is very likely that this result is influenced at least in part by differences in the socio-demographic composition of the two groups. In particular, among those that do not receive any benefits, there is a high proportion of long-term unemployed workers. Figure 4 displays the average monthly exit rates by unemployment duration, and shows that the average monthly exit rate decreases as the unemployment duration increases.

Figure 3: Monthly Average Exit Rates by Benefit Type, Spain 2016

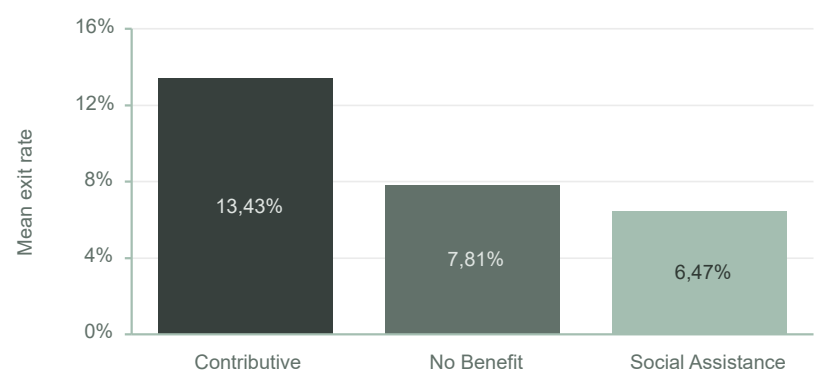
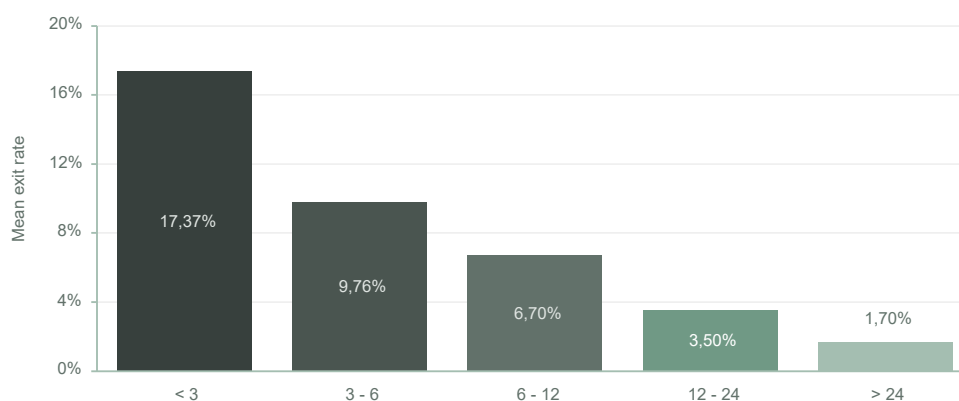


Figure 4: Monthly Average Exit Rates by Unemployment Duration, Spain 2016

Given the heterogeneity between the three groups, but especially of those who receive social assistance, for the remainder of this paper we will focus on those who receive unemployment benefits and on those who do not receive any type of benefit. This will allow us to properly address the question of whether receiving unemployment benefits, all else equal, delays or not the exit to a job, compared to not receiving any benefits at all.

3. Methods

Let us define the variable “unemployment benefits”, UB_{it} , as a dummy variable that indicates whether an individual i receives unemployment benefits (the treatment) in month t or not:

$$UB_{it} = \pi \begin{cases} 1 & \text{if individual } i \text{ receives unemployment benefits at time } t \\ 0 & \text{otherwise.} \end{cases}$$

If the assignment of unemployment benefits were random, calculating the treatment effect (the effect of receiving unemployment benefits) would simply entail obtaining the difference in the outcome (probability of exit to a job) means between the treatment and control groups. In this case, however, treatment is not randomly assigned, since such benefits are given based on the individual's past working history.

We check whether the characteristics of the individuals are indeed related to the treatment status (i.e. whether covariate imbalance exists) using proportion tests reported in Table 1, which contains a proportion test for two covariates. This test is run on the unemployed (less than two years' duration) that receive contributive benefits ($T = 1$) and the unemployed (less than two years' duration) that do not receive any benefit at all ($T = 0$). It can be observed that the difference between both groups for the two covariates is statistically significant³. Therefore, to deal with this lack of covariate overlap, Propensity Score Matching (Abadie and Imbens, 2006) and Inverse Probability Weighting (Robins, Rotnitzky, and Zhao, 1994) techniques have been used in order to rebalance the covariates⁴. Both techniques are based on the assumption of common support. This assumption ensures that, for given values of the covariates, the probability of receiving treatment (also known as propensity score, $D_i = 1|X_i$) is

³ Differences for the rest of the covariates and years, although not reported, have also been tested, and the differences have been found to be significant.

⁴ We have conducted the treatment effect analysis using both Propensity Score Matching and the Augmented Inverse Probability Weighting (AIPW) estimator. Since both methods yield very similar results, we present the AIPW estimates in the main text. AIPW is preferred because of its double robustness property—it provides consistent estimates if either the treatment assignment model or the outcome model is correctly specified. Moreover, AIPW has been shown to outperform PSM in terms of efficiency and robustness, particularly in settings with moderate covariate imbalance or misspecification risks. For an overview, see Scharfstein et al. (1999), Wooldridge (2010), Fan et al. (2020), and Zhao & Li (2020).

greater than zero and smaller than one. In practice, this forces us to restrict the pool of unemployed workers not receiving any benefits to those who have been unemployed less than two years, given that this is a requisite for receiving unemployment benefits in Spain.

Table 1: Covariates Proportion Tests, Spain 2016

Variable	T	Mean	SD	z	P > z
Women	0	0.5687	0.0005	—	—
	1	0.4949	0.0008	2014	—
Diff.	—	0.0739	0.0009	75.29	0.000
Spanish	0	0.854	0.0003	—	—
	1	0.8989	0.0005	—	—
Diff.	—	-0.0449	0.0006	-66.77	0.000

Based on the AIPW Estimator, a first approach to specifying the treatment and control groups is the following:

- **Treatment:** Unemployed (for less than two years) that receive unemployment benefits.
- **Control:** Unemployed (for less than two years) that do not receive any benefit.

The average (observed) monthly exit rate for the treatment group is 13.6%, while for the control group is 10.13%. We observe a positive difference between the two groups, that is, receiving unemployment benefits is positively correlated with the exit from unemployment. This positive result seems contrary to the economic theory. The next step is calculating the AIPW estimation of the Average Treatment Effect on the Treated (from now on ATT). The results are displayed in Table 2. As it can be observed in Table 2, the estimated difference in the probability of exiting to a job is considerably smaller than the value of the observed difference. This may be because the estimation procedure is capturing the observed differences that have to do with the values of the covariates. Nevertheless, the effect is still positive, which does not come up with the standard prediction that benefits delay exit to a job. The most reasonable explanation is that treatment and control groups are still very heterogeneous in unobserved composition. This could be due to several reasons, for example, they might have different intangible characteristics that make beneficiaries more susceptible to be employed or they might be better informed about the labor market demand. We must also consider that in order to receive benefits, one must have worked before; whereas those who are not receiving any benefits might have never worked before or have worked only in short-duration jobs and therefore are more unlikely to find a job.

Table 2: AIPW Estimation for the First Exercise, Spain 2016

Value	ATT	Base Prob	SD
Coef.	0.01088***	0.13049	0.0008
SD	0.00072		0.0006

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

In order to deal with this unobserved heterogeneity, we have tried to obtain a better specification of both the treatment and control groups. To do so, five exercises have been carried out. On each exercise, we restrict the treatment and control groups in order to obtain more homogeneous groups. The different exercises are the following:

1. The treatment group is defined as unemployed people that have been unemployed for less than two years (from now on simply unemployed) and that receive unemployment benefits in 2016. For the control group, we will choose those unemployed workers (also unemployed for less than two years) who do not receive any benefit at all in 2016. Note that in this exercise we are including in the control group unemployed people that may have never generated contributive benefits. Hence, there are likely to exist notable differences in composition effects between individuals belonging to the treatment and control group, both observed and not observed in the data.
2. In this second exercise, we take into consideration the fact that those who have never generated unemployment benefits (and therefore have never worked before) are more than likely inherently different to those who are receiving benefits. Hence, the treatment group remains the same as in Exercise 1; the control group, however, now only includes unemployed people who did not receive contributive benefits in 2016, but did receive them for at least one month between 2010 and 2015. This means that they generated benefits during the recession, as the treated group did. Doing so, we get rid of the unobserved differences between those that did and did not work in the recession period.
3. In the third exercise we take into consideration that exit rates to a job fall considerably after six months of unemployment. Hence, the treatment group is now defined as those entrants to unemployment (those with an unemployment duration smaller than six months) who receive benefits in 2016. The control group is entrants to unemployment who did not receive benefits in 2016 (the year of analysis) but did receive them in the past. This allows us to compare individuals close to the labor market and with a higher probability of exiting to a job, therefore, more similar in unobserved confounding. It is important to note that this implies that, from this exercise on, we are not measuring the impact of the unemployment benefit as a whole but only for a group of unemployed individuals, the entrants.
4. Fourthly, we take into account the fact that the business cycle has varied to a great extent during the years analyzed and that exit to a job may be affected by this. The treatment group is defined as in the third exercise, but the control group is specified as entrants to unemployment who did not receive benefits in the specific year analyzed but did receive them in the immediately previous year (i.e. for the case of 2016, this means that we consider entrants to unemployment who did not receive benefits in 2016, but did receive them in 2015). The year previous to our analysis is precisely when the treated individuals generated at least part of their own benefits. In this fourth exercise, therefore, more similar unemployed individuals are compared since both have generated benefits (i.e., have been working for a long enough period) relatively at the same time, which undoubtedly reduces the unobserved heterogeneity.
5. The final exercise deals with potential differences between the treatment and control group due to the so-called “exhaustion effect” discussed in the introduction (i.e. exit rates to a job increase in the period immediately prior to and right after exhausting the benefit, probably because when facing the exhaustion of their benefits, individuals increase the intensity of their job search). In order to avoid this effect, we specify the treatment group as the unemployed entrants whose benefits will end between 6 and 12 months in the future, and the control group as the unemployed entrants whose benefits ended between 6 and 12 months ago. Therefore, we exclude those who are about to exhaust their benefits or who recently exhausted them, in order to avoid the exhaustion effect⁵.

Table 3 summarizes the discussed treatment and control groups for each exercise, and Table 4 shows information on the number of unemployed people on each group within the five exercises. The AIPW Estimator is obtained in the analysis using the following control variables: standard demographic characteristics such as, gender, age, education

⁵ Note that from Exercises 1 to 4 the treatment and the control groups are becoming more restricted, however, this is not the case for the control group in Exercise 5, since some individuals can belong to the control groups in Exercise 5 and might not belong to the control groups in Exercise 4.

level, nationality, province of residence and knowledge of other languages; and labor market information: previous employment experience, occupational and geographical searches and unemployment duration.

Table 3: Summary of the Five Exercises

Exercise	Treatment	Control
1	Unemployed	Unemployed
	UB	NB
2	Unemployed	Unemployed
	UB	NB, received UB after 2009
3	Entrants	Entrants
	UB	NB, received UB after 2009
4	Entrants	Entrants
	UB	NB, received UB last year
5	Entrants	Entrants
	UB, exhaustion in between 6 and 12 months	NB, exhausted UB in between 6 and 12 months

After carrying out the estimation of the treatment effect for each of the five specifications using the AIPW Estimator, we conduct a placebo analysis that enables us to show evidence that the empirical results found for the impact of unemployment benefits are not spurious. We randomly re-assign the treatment between the treatment and control groups, and obtain the differences in the estimated probability of finding a job between both groups. In order to illustrate this procedure, let us focus on exercise one.

As it can be observed in Table 4, in the first exercise 26.3% of the unemployed receive unemployment benefits. Therefore, for placebo analysis of exercise 1, in the randomization of the treatment, 26.3% of the total of 1,318,337 unemployed in this exercise will be randomly assigned to the treatment group, and the remainder 73.7% to the control group. After that, the ATT estimation will be obtained for this randomized placebo treatment. Proportions in Table 4 have been also used for the rest of the exercises. Each estimation of the ATT has been replicated 100 times to ensure that results for the placebo analysis are consistent. If, with the randomized treatment, we were to obtain a null treatment effect, our main result would be validated, meaning that there is indeed an effect on exit rates to a job caused by receiving unemployment benefits⁶.

⁶This placebo analysis is consistent with validation strategies commonly used in the treatment effects literature to ensure that estimated effects are not driven by spurious correlations or data structure. Similar falsification approaches have been proposed by Hartman and Hidalgo (2015) and Fer- man and Pinto (2017), among others.

Table 4: Number of Unemployed People on Each Treatment and Control Group

Exercise	Treatment	Control	Total
1	345,998	972,339	1,318,337
	26.3%	73.7%	100%
2	345,998	201,459	547,457
	63.2%	36.8%	100%
3	232,959	124,849	357,808
	65.1%	34.9%	100%
4	232,959	58,803	291,762
	79.9%	20.1%	100%
5	44,286	13,576	57,862
	76.5%	23.5%	100%

4. Empirical Results

This section presents the results obtained for the treatment effect estimation with the five different treatment and control groups specifications as well as the placebo analysis. For all estimations, as explained previously, we control for a set of individual and labor market characteristics, including gender, age, education level, nationality, province of residence, language knowledge, previous employment experience, occupational and geographical search preferences, and unemployment duration. The treatment effect has been obtained, in each case, using the Augmented Inverse Probability Weighting technique⁷.

Table 5 shows the estimation results for the ATT and the mean probability of finding a job for the control group (Base Prob) using AIPW for each of the specified five exercises. Figure 5 presents the same ATT estimation results measured in percentage points (p.p.) together with the results of the corresponding placebo analysis.

In the first exercise, the result shows an impact of the benefit of almost 1 percentage point (p.p.) in the probability of exiting to a job. As it was stated before, this positive effect of the treatment on the monthly exit rates does not coincide with the economic prediction that unemployment benefits delay exit to a job. This result is likely due to the fact that the control group in Exercise 1 includes individuals who might have never worked before. In the second exercise, however, unemployed people with little experience or any experience at all are not considered in the control group, since they have never generated unemployment benefits. It can be seen how this first improvement on the specification of both treatment and control groups makes the treatment effect be negative, which is in line with economic theory, with an ATT close to -3 p.p.

⁷ Results using Propensity Score Matching, although not shown, are also consistent.

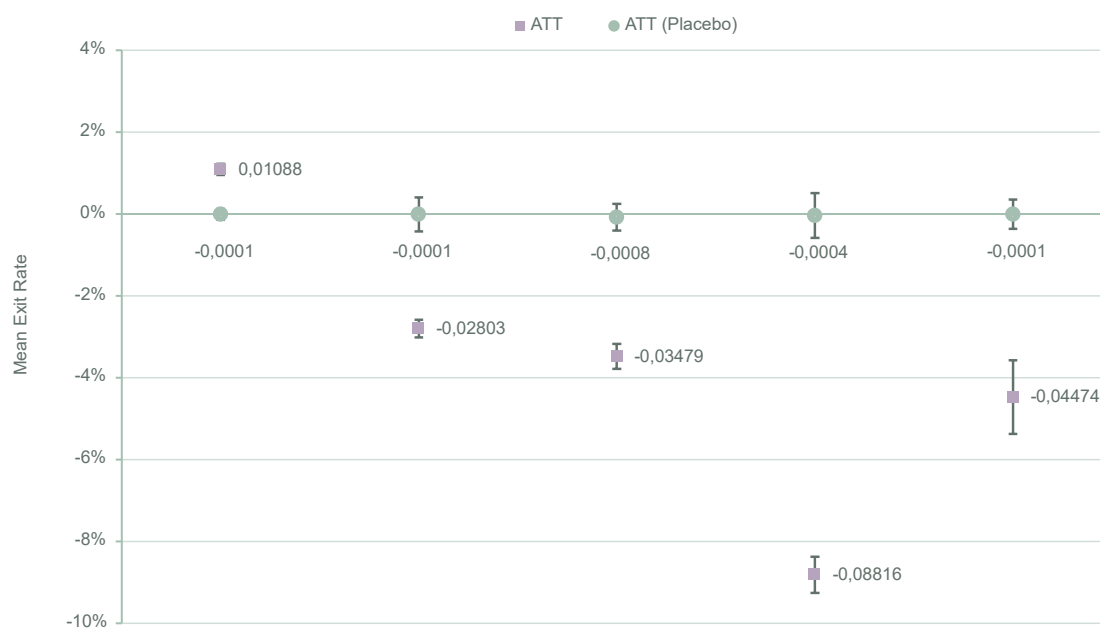
Table 5: AIPW estimation results, Spain 2016

Exercise	Value	ATT	Base Prob
1	Coef.	0.01088***	0.13049
	SD	0.00072	
2	Coef.	-0.02803***	0.15083
	SD	0.00110	
3	Coef.	-0.03479***	0.19558
	SD	0.00154	
4	Coef.	-0.08816***	0.22227
	SD	0.00224	
5	Coef.	-0.04474***	0.20508
	SD	0.00458	

Note: Exercises 1 to 5 refer to those defined in section 3.* p < 0.1, ** p < 0.05, *** p < 0.01

For the third exercise, given that the observed exit rate drops after six months of unemployment, the new restriction leaves out all the unemployed which have been unemployed for more than 6 months and we focus only on those more connected to the labor market. It is possible that in this exercise the estimated effect of the treatment is greater in absolute value since the exit rates of entrants are higher. Note that from now on, we are not measuring the impact of the unemployment benefit on all the unemployed but only on the group of entrants to unemployment. As it can be observed in Figure 5, the absolute value of the ATT is greater for this exercise compared to the previous one (-3.5 p.p. compared to -2.8 p.p.). However, the average exit probability is quite higher for the entrants (19.6%) compared to the previous set of unemployed individuals (15.1%), as it can be observed in Table 5. In consequence, the estimated impact of the unemployment benefit in delaying exit into the labor market is larger in absolute value but smaller in relative terms (17.8% compared to 18.6%) for the entrants than for all the beneficiaries.

In the fourth exercise, the control group only includes the unemployed that generated their benefits in approximately the same time period in which the treated did, therefore allowing us to compare individuals which have worked (and generated benefits) roughly at the same time and, thus, account for unobserved heterogeneity related to business cycles. This specification results in a huge increase in absolute value in the ATT (- 8.82 p.p.). Our suspicion is that we may now be overestimating the magnitude of the treatment effect due to the exhaustion effect. Since some of the unemployed in both groups see that their benefits are about to end (or just ended, in the case of the control group), the exit rates to a job increase because they boost (boosted) the intensity of their job search.

Figure 5: Estimation Results by Exercise, Spain 2016

Note: Error bars represent 95% confidence interval.

To study whether this potential overestimation of the treatment effect in exercise four exists, exercise five has been carried out accounting for the exhaustion effect by eliminating from the analysis those unemployed individuals whose benefit is about to end (or just ended). In this case, as we can observe on Figure 5, the absolute value of the ATT is smaller than in the previous exercise; and so is the average exit probability presented in Table 5. This is in line with our suspicion that the exhaustion effect is biasing the treatment effect in Exercise 4. The absolute value of the impact of the UB is still larger than in Exercise 3, where we only consider the entrants into unemployment no matter when in the recession period, they had generated the benefit; and therefore, the treatment and control groups were more heterogeneous.

We believe the treatment effect estimated in this fifth exercise, with an estimated effect value that is between the values obtained in exercises three and four to be the most precise, since individuals in both the treatment and control groups are as similar as possible, while also accounting for the exhaustion effect. To sum up, in this last exercise we are left with treatment and control groups formed by people that are entrants into unemployment, have generated their benefits in very similar periods of time (one year apart), and whose benefits are not about to end (or not just ended). This value therefore indicates that receiving unemployment benefits delays the exit to a job, because after having controlled for all the observed differences in the composition and having defined treated and control groups most similar in unobservable characteristics, the UB delays the entry into the labor market in 4.47 p.p., with an average exit probability for the non-receivers of 20.5%. In other words, the UB delays exit into the labor market by more than 20% in relative terms.

The results of the placebo analysis confirm this result since, under random assignment of the treatment, the values of the ATT are very close to zero for all the exercises, as one can also observe in Figure 5.

Lastly, we repeat the analysis of exercise 5 year by year between 2011 and 2016. ATT results in percentage points are shown in Figure 6 together with the average exit probability rate for the control group (baseline probability, in percentage terms)⁸.

⁸ Table A.1 in Appendix I presents the AIPW estimation results for Exercise 5 along the business cycle.

Figure 6: Estimation Results for Exercise 5 by year, Spain



The period 2011–2016 not only reflects the span of available data, but also captures meaningful variation in macroeconomic conditions, which allows us to observe how the effect of unemployment benefits evolves across the business cycle. We can observe that the ATT in absolute value increases over the considered time frame, from -1.7 p.p. to -4.5 p.p.; so, does the average exit probability rate, in this case from 9.5% to 20.5%. There is also a slight increase of the effect in relative terms (i.e. ATT over the average exit rate): in 2011, the relative effect on entrants’ exit rates of receiving unemployment benefits is a delay of approximately 18%; in 2016, it is around 22%. In 2012, when the recession was at its peak, the absolute effect was 1.1 p.p. and the relative effect 12% (both the lowest effects of the analyzed period). This seems to suggest that the more pronounced the economic recession is, the delaying effect of unemployment benefits is smaller; perhaps because unemployed people do not expect to get “better” job offers and accept, with a higher probability, the first chances they have. When the economy is under recovery from the recession, however, the delaying effect of receiving unemployment benefits is larger. These results are consistent with those obtained by Bover, Arellano, and Bentolila (2002), given that we also find that unemployment benefits delay exit to a job and favorable business conditions accelerate it. According to official data from the Spanish Labor Force Survey (EPA), the unemployment rate in Spain reached its peak in 2012 and gradually declined until 2016. This trajectory matches the year-by-year variation in our estimated ATT: the smaller delaying effect observed in 2012 aligns with the period of most limited job opportunities, while the increase in the magnitude of the effect over time corresponds to the improving labor market. Thus, our results not only capture individual behavior but also reflect broader macroeconomic dynamics.

5. Conclusions

This paper analyzes the effect of receiving unemployment benefits on job finding. Using a treatment effects framework and a rich administrative database, our results confirm and update previous results in the literature suggesting that receiving unemployment benefits delays exit to a job. However, the size of the effect depends largely on the treatment and control groups, as well as the moment of the business cycle analyzed.

Furthermore, the present evaluation exercise highlights the importance of properly defining the treatment and control groups when measuring the impact of a specific policy, such as the unemployment benefit. This paper develops five different exercises so as to eliminate the unobserved heterogeneity between treated and the control groups and shows that different specifications of both groups results in different estimations of the treatment effect. Therefore, clearly stating the treatment effect that we want to measure and the individuals on whom the effect is to be measured is extremely important.

More precisely, we find that in Spain in 2016, the estimated difference in the probability of exiting a job between those entrants to unemployment who receive unemployment benefits and those who do not (but did receive benefits in the previous year), accounting for the exhaustion effect, is -4.47 p.p., a delay of more than 20% in relative terms. However, this estimate changes if the effect to be measured is over all entrants to unemployment (-2.8 p.p.) and if we do not take into account the exhaustion effect (-8.82 p.p.). Furthermore, even when estimating the same treatment effect (i.e. the estimated difference in the probability of exiting a job between those entrants to unemployment who receive unemployment benefits and those who do not, but did receive benefits in the previous year accounting for the exhaustion effect), the size varies along the business cycle: in the case of Spain, the delaying effect is at its lowest coinciding with the height of the economic recession, in 2012, and it is equal to -1.1 p.p. (-12% in relative terms).

One potential limitation of our analysis is that other labor market policies may have influenced the outcomes observed. However, during the period 2011–2016, there were no major reforms to either the eligibility criteria or the replacement rates of contributive unemployment benefits in Spain. Regarding active labor market policies (ALMPs), while they may affect job search behavior, they are implemented at the regional level and only reach a small share of the unemployed population⁹.

In summary, this study confirms, on the one hand, that unemployment benefits do appear to delay exit to a job; however, this effect is dependent on the business cycle as well as the duration of unemployment and time left until the exhaustion of the benefits. On the other, it also highlights the importance of properly specifying the treatment for which we want to measure the effect, as well as the correct control group, when using the treatment effects framework.

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Conflict of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Lucía Gorjón: Conceptualization, Supervision, Writing – review & editing

Ainhoa Vega Bayo: Conceptualization, Supervision, Writing – review & editing

Ander Galian: Data curation, Formal analysis, Writing - original draft.

⁹ Moreover, our dataset excludes individuals participating in ALMPs from our analysis, since they are not considered “registered unemployed”. Although we cannot completely rule out the influence of these programmes, we believe they do not significantly alter the main findings of our study.

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APPENDIX I

Table A.1: AIPW estimation results for Exercise 5, years 2011-2016, Spain

Exercise	Value	ATT	Base Prob
2011	Coef.	-0.01735***	0.09452
	SD	0.00272	
2012	Coef.	-0.01105***	0.09102
	SD	0.00238	
2013	Coef.	-0.02787***	0.14999
	SD	0.00318	
2014	Coef.	-0.02514***	0.16976
	SD	0.00364	
2015	Coef.	-0.03287***	0.18825
	SD	0.00407	
2016	Coef.	-0.04474***	0.20508
	SD	0.00458	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01