Assessing the Impact of a Minimum Income Scheme: A Regional Case Study

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Abstract:

In this paper we evaluate the impact of a Minimum Income Scheme (MIS) in the Basque Country, one of Spain's autonomous regions. In particular, we assess whether the policy delays entry into employment for recipients, as well as the extent to which activating policies aimed at enabling recipients of the MIS to re-enter employment work. On average the Minimum Income Scheme does not delay entry into employment, although the impact differs from one demographic group to another. Furthermore, Active Labour Market Policies designed for this group, in particular training, have a strong positive impact on finding a new job.

Keywords: minimum income schemes; active labour market policies; poverty; inverse probability weighting; propensity score matching

JEL Classification: C14, C21, C52.

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1. Introduction

Most European Union Member States currently provide some form of Minimum Income Scheme so as to ensure a minimum standard of living for households when they lack other sources of financial support. The emergence of these schemes dates back to 1992, when a European Council recommendation assessed the need to develop last resort schemes which recognized the basic right of every individual to ensure a decent minimum standard of living. These programs were part of comprehensive, consistent plans to combat social exclusion. Since then, implementation of Minimum Income Schemes (MIS) across European Countries has varied in coverage and effectiveness. The most widely used are the so-called "simple and comprehensive schemes", which basically cover every person/household in need of support, without confining their effects to particular categories of people[1].

In 2008, The European Council endorsed the objective of combining adequate income support with labour market activation measures so as to facilitate re-entry of recipients into employment. Following the recommendations, Minimum Income Schemes are therefore a combination of passive and active policies.

Although the implementation of these schemes is progressing in most European countries, albeit heterogeneously, there is no sufficient assessment of their impact on aspects such as poverty and inequality reduction, labour market participation of recipients and/or the impact of activation measures on their recipients in terms of re-entry. Only some pilot projects and ex-ante or ex-post assessments around the world can be found. Examples of such studies include Gouveia and Rodrigues (2002), who assess the impact of particular MIS on poverty reduction in Portugal, and Gorjón (2017), where the impact of the studied in this paper Basque MIS on poverty is evaluated. According to these studies, the Portuguese policy measure has a modest effect on the reduction of the number of poor households, but a substantial effect on alleviating the intensity and severity of poverty. In the same line, the Basque MIS seems to be very effective at the time of reducing the intensity and the severity of poverty; however, the extreme poverty is far away to be eradicated. An ex-ante assessment of a Proposal in Québec is provided by Clavet, Duclos and Lacroix (2013). By predicting labour supply the result shows that the proposed scheme would have strong negative impacts on labour market participation rates, mostly among low-income workers. A different evaluation by Ayala and Rodríguez (2010) identifies what factors determine observed differences in the durations of the first off-welfare spell using an administrative data set for the a Minimum Income Program (*Ingreso*

[1] See Standing (2003) and Frazer and Marlier (2009) for extensive reviews on the Minimum Income Schemes in Europe.

Madrileño de Integración) of the Madrid Government. They find that experience of the first spell and, to a lesser extent, employability can contribute toward lengthening the time spent outside the program. The results also show that off-welfare spells of households leaving the program in periods of low economic growth will be longer than those that do so during economic expansions.

A more general review of the related literature pass through the debate of the impact of passive policies. A usual criticism is that cash transfers might reduce unemployed individuals' incentives to work (Ayala and Paniagua, 2016). An increase in the reserve salary of the unemployed workers can delay their exit into employment. Literature on passive policies has largely shown that unemployment insurances have negative effects in the transition from unemployment to employment. Rebollo-Sanz and García-Perez (2015) find that non-insured unemployed workers experience a greater rate of transition to employment than insured workers. Furthermore, Card and Levine (2000) and Meyer (1990) prove that the end of the unemployment benefits accelerates transitions towards to employment. In the same line, Lalive and Zweimuller (2004), Van Ours and Vodopivec (2006) and Roed and Zhang (2003) conclude that benefits strongly affects the duration of unemployment. Given that the MIS is indefinite by nature, its disincentive impact might be particularly strong.

In order to prevent MIS beneficiaries from perpetuating in an unemployment situation, compulsory activation measures are directed to them. Some activation measures have been proved to be more effective than others. Card, Kluve and Weber (2011) synthesize the main results in the Active Labour Market Policies (ALMP) literature. One of the main results they find is that the impact of the programmes varies over time: training programs, for example, have more positive impacts after two years than in the first one, while guidance services are specially helpful in the short-run. However, subsidized public sector jobs and for youth programmes are less successful than other types of activation measures.

Surprisingly, we are not aware of any study that assesses both potential impacts of the MIS, as a combination of passive and active policies. Our paper seeks to fill this gap. On the one hand, the MIS might delay recipients on their re-entry into work, the extended undesirable indirect effect of cash transferences. On the other hand, the activation programmes directed to the beneficiaries may have an accelerating effect into employment. According to Eichhorst and Konle-Seidl (2016), empirical evidence has influenced the design of labour market reforms themselves, not least in the area of active labour market policies and activation. This is precisely the ambitious goal of this paper.

Specifically, our study assesses the impact of a Minimum Income Scheme that operates in a northern Region of Spain - The Basque Country, called *Renta de Garantía de Ingresos*. This region pioneered the introduction of MIS in Spain in 1989. The Basque Country is currently the only Spanish region with a *Simple and Comprehensive MIS Scheme*[2]. We assess first whether the Basque MIS delays entry into labour market for its recipients. Then we test the efficacy of policies aimed at enabling its recipients to re-enter employment. We do this by using the Inverse Probability Weighting methodology, which enables MIS recipients to be compared with a similar, fictitious group created by weighting non-recipients. By doing so, the treatment is dissociated from individual characteristics and hence pseudo-randomised. Our results indicate that, on average, the Basque MIS does not, per se, delay entry into work for its recipients. Interestingly, however, the impact differs from one demographic group to another. Furthermore, Active Labour Market Policies designed for MIS recipients, in particular training, have a strong positive impact on re-entry into employment[3].

The rest of the paper is organised as follows: Section 2 reviews institutional aspects of the MIS implemented in the Basque Country. Section 3 gives a description of the data and the main descriptives of MIS recipients. Section 4 presents the methodological and analytical assessment methods and the empirical findings. Finally, Section 5 summarises and concludes.

2. The Minimum Income Scheme in the Basque Country

The Basque MIS was introduced in 1989, with the so-called *Integrated Plan to Combat Poverty*[4]. In the last few decades it has undergone several modifications. In 1998 it was given the rank of law, the concepts of “poverty” and “exclusion” were defined and employment incentives, penalties and infringements were established. The amounts provided and the requisites for recipients have also been modified several times. The latest modification was implemented in 2011 (Act 4/2011). We base the details of our description on that version.

Eligibility Requisites: The first important point to note is that the Basque MIS is household-based. To apply for the aid, applicants must comply with the following eligibility requisites: first, they must show that their household income is insufficient to meet basic needs, which means inability to access the goods and services classed as

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[2] The Basque Country is a small region in the northeast of Spain with a population of 2 million (5% of the Spanish population). The active labour force is over 1 million and the employment rate is 50%. The Basque Country is among the richest Regions in Spain, with the second highest GDP per capita and the third lowest unemployment rate (12.8%). The Basque Human Development Index is 0.924, the highest in the country, and at the same level as the Netherlands.

[3] A key unsettled question in the ALMP literature and in this paper is whether activation measures affect the outcomes of those who do not participate, via displacement or other general equilibrium effects (Card, Kluve and Weber, 2011).

[4] Different legislation can be found here: http://www.lanbide.euskadi.eus/rgi/-/informacion/rgi-legislacion-y-normativa/

necessary for minimum welfare in society according to the Basque Government criterion of poverty (which is outlined below). The second eligibility condition concerns residency in the Basque Country: in principle, the recipient of MIS in the household must be registered on the census and actually have resided in the Basque Country without interruption for the last three years. If applicants can prove five years of paid work in the Basque Country the residence requisite can be relaxed to one year instead of three. If none of the above requirements is met, applicants must have been registered for a continuous period of five years in the immediately preceding ten years[5].

Furthermore, the MIS is considered as a last resort scheme, so applicants must already have applied for all other income aids to which they are entitled. In principle, the scheme is compatible with other income aids or wages of family members, so long as they do not exceed the defined poverty line. In addition, applicants must own no property other than their habitual residence.

Coverage: MIS benefits are transferred to family units on a monthly basis. The amount set by the Basque Government to meet basic necessities varies depending on the minimum wage (MW), the number of people in the household, the number of retired persons and whether it is a single-parent household or not. Specifically, it is 88% of the MW for single-member households and can reach 125% of the MW for households with three or more members. In the case of households with at least one pensioner those figures rise to 100% and 135% respectively. Single-parent households receive a supplementary subsidy[6]. If there are other incomes in the household, the MIS covers the difference in that amount.

Household Labour Market Availability: Both holders and other members cohabiting in the same household who are able to work must commit to being available to do so and being registered in the Public Employment Service. In addition, they must participate in activities that increase their employability. In particular, the holder must sign an inclusion-oriented employment improvement agreement. However, although the spirit of the law is that every recipient should search actively for a job only around 40% are observed to receive any interventions from the public employment service or activating interventions[7]. We do not know what criteria the Public Employment Service uses to follow MIS recipients to monitor their activation, i.e.

[5] For particular groups, such as those who receive a public-sector pension or have been victims of domestic abuse, there is no need to prove work experience and only one year of residence in the Basque Country is required.

[6] Specifically, the amount in 2016 varied from €625.58 for a single member household to €959.70 for a household with three or more members and at least one pensioner. Single-parent families receive an additional €45.

[7] In particular, the activation rate is 41.7% for holders and 38.2% for non-holders.

whether individuals are self-selected into different activities or there is some kind of compulsory participation.

3. The Dataset and Descriptive Statistics

3.1. The Dataset

Our dataset consists of monthly longitudinal information on all individuals who were registered with the Basque Public Employment Service from February 2015 to January 2016. Data are collected on the last day of each month. Most of those registered are unemployed, but some may be employed and searching for another job. Their employment status is clearly stated. All MIS recipients and their cohabitants must register with the Basque Public Employment Service as a requisite for receiving income aid, independently of their employment status.

The database includes all the information provided by each individual when registering at the Employment Office, including standard demographic characteristics (gender, age, education level, nationality, postcode and residence, knowledge of other languages), as well as labour market information (previous employment experience, occupational and geographical searches, unemployment duration, etc.). The Basque Public Employment Service also provides exact information on whether individuals receive or have received unemployment benefits (entitled benefits, assistance benefits and/or MIS) and on the duration of entitlement. Finally, the database also records information on the assistance measures from the public employment services that unemployed workers have received in the last 12 years to enhance job access. Information such as the type of measure, number of hours and start and end dates are provided.

Basque Public Employment Service in Spain divides the pool of unemployed workers on their files into "Registered Unemployed" and "Other Unemployed Workers". The latter category, which accounts for around 22% of all unemployed workers, includes retirees and pensioners, those not immediately available for work, those registered in the current month, those who just seek particular kinds of work such as outwork and teleworking and those who seek work for under 20 hours a week. Students are also included in this category. We restrict our analysis to the “Registered Unemployed”, i.e. those without a job who are seeking work and immediately available for any "regular" job.

The Basque Country has records of around 60.000 MIS recipients each month, among them approximately 13.000 are employed and 38.000 are registered unemployed in the period under analysis, equivalent to 25% of all those registered as unemployed in the Basque Country.

In spite of the richness of information of the dataset, an important drawback is that there is no household identifier for MIS recipients. Hence, all we can assess is whether an individual is a MIS holder or not. Hence, although the MIS is provided at the household level, the whole analysis is conducted at individual level for data restriction reasons. An additional caveat of the data is the lack of information related to household income, and in particular, to the specific amount of any type of benefits received by the unemployed.

3.2. Statistical Distribution of MIS Recipients vs non-MIS Recipients

To give a precise idea of the differences between MIS recipients and other workers registered as unemployed, we present the distribution of each of the two groups under a total of four characteristics: gender, age (<30, 30-44 and >44), education level (primary at most, secondary and higher education) and duration of unemployment (<3 months, 3-6 months, 6-12 months, 12-24 and >24 months). Figures 1 and 2 show the distribution of MIS and non-MIS recipients, respectively, across the four characteristics. We do this for a particular month - October 2015 – to get a better idea in not only relative but also absolute terms. Any other month from the sample would give almost identical patterns.

[Insert Figures 1 and 2 here]

At first sight, the profile for education level and unemployment duration of MIS recipients is quite different from that of the rest of the unemployed. This is not surprising given that MIS is seen as a last resort scheme. In particular, 60% of MIS recipients have no secondary education qualifications and more than half have spent more than two years unemployed. The equivalent figures are barely one third and one fourth, respectively, for non-MIS recipients. More precisely, the biggest group among recipients is that of the very long-term unemployed aged over 30 with only primary education. This group accounts for a third of all MIS recipients. Among non-MIS recipients the equivalent group accounts for barely 10%. Furthermore, regardless of education level, MIS recipients over 30 who have spent more than two years looking for a job account for 50%. Focusing on the youngest group, it can be seen that more than half have spent more than two years seeking employment and 70% have only primary education. However, the pattern is very different among those who do not receive MIS: those who have been unemployed for a very short time are generally young people with secondary or higher education. It is important to note that many young people with higher education continue studying if they do not find a job and are not therefore considered as unemployed. This behaviour is not found among unemployed people with lower education levels, who are precisely the most common group among MIS recipients.

3.3. Monthly Exit Rates from Unemployment to Employment (Job Finding Rates)

We now describe the patterns of monthly job-finding rates for recipients and non-recipients of MIS, making use of the longitudinal nature of our dataset. We define “exit into employment” as a transition from “registered unemployed” in the current month to a labour status of “employed” in the next month[8]. Therefore, the characteristics of the unemployed people are fixed in the current month. Following the same structure as above, we characterise job-finding rates by comparing recipients with non-recipients of MIS using the same four characteristics, i.e. gender, age, education level and unemployment duration. Given that we observe unemployed people from February 2015 to December 2015 we compute job-finding rates from March 2015 to January 2016.

On average, the monthly job-finding rate for MIS recipients is 3%. This is significantly lower than the rate for non-MIS recipients, which is 9%. Figures 3 and 4 show job-finding rates for MIS and non-MIS recipients, respectively, for different profiles. It is immediately apparent that job-finding rates increase with education level and strongly decrease with unemployment duration for both groups. To give some numbers on the strong negative association between unemployment duration and job-finding rates, Figures 3 and 4 show that individuals unemployed for less than three months have an average exit rate of 11%, while the very long-term unemployed (over two years) have a rate of only 1%. Interestingly, 60% of MIS recipients belong to the group of very long-term unemployed. Another point to note is that although education level is relevant to understanding differences in access to jobs, it is far less significant than unemployment duration: the exit rate of MIS recipients with higher education averages 5%, compared to 2% among those with primary education only.

Figure 4 focuses on the comparison between MIS recipients and non-MIS recipients on job-finding rates. As mentioned above, there is a difference of 6 percentage points on average between the job-finding rates of the two groups. However, that difference varies markedly depending on individual profiles. For example, among the very short term unemployed there is a difference of 7.5 points, while among the very long term unemployed the difference is barely one percentage point.

[Insert Figures 3 and 4 here]

[8] In particular, Basque Public Employment Service does not remove non-MIS recipients from the register once they became employed unless the individual specifically asks for it. In that way, we ensure we are capturing most re-entries into employment for non-MIS recipients. Note that for all MIS recipients its register is compulsory.

3.4. Determinants of the probability of finding a job: MIS recipients vs non-recipients

Finally, we estimate the probability of finding a job by the last day of each month for all those registered unemployed on the last day of the previous month. As above, we calculate the probability of finding a job from March 2015 to January 2016. The dependent variable, therefore, takes a value of 1 if the unemployed person gets a job in the consecutive month, and 0 otherwise.

To perform this exercise, we take into account all observable variables that may affect the employability of people registered with the Public Employment Service. In particular, we include demographic characteristics such as sex, age, nationality, disability, education and language skills; job characteristics such as requested occupations, experience, activity in the previous field of work, unemployment duration, geographical scope of the new job search, month(s) in which the individual is observed as unemployed, whether individuals are MIS holders or not[9], and province of registration.

We add a dummy indicating whether individuals have ever been referred to social services. The receipt of benefits in the current or in previous months is also included. We include in our estimation an indicator for whether individuals have received activation services at least once in the last six months. 40.7% of MIS recipients have received some kind of measure in the last six months, as compared to 13.75% of non-recipients[10]. We divide activation service into the following categories: guidance, monitoring, information on self-employment and training.

Table 1 presents the results of the estimation (marginal effects are shown) using a pooled probit model with month and province fixed effects[11]. The first column estimates the probability of finding a job for MIS recipients and the second does likewise for non-recipients. Note that this estimation does not account for unobserved heterogeneity. It should be taken as a preliminary view of the importance of the characteristics of unemployed people in the job search process.

[Insert Table 1 here]

The most noteworthy result has been already anticipated: unemployment duration is the variable that most affects the probability of exiting unemployment. The chances of entering employment decrease dramatically as the time for which a person remains unemployed increases. The largest decrease in the probability of getting a job occurs after the barrier of 3 months (reference group) with a reduction of 5

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[9] Note that the MIS is provided at household level, whereas the analysis is conducted at individual level. The data do not enable us to identify each of the household members and their labour market situation, only whether they are MIS holders or not.

[10] These figures are for October. Any other month from the sample would give percentages.

[11] Population average with a robust estimator of the variance is used.

percentage points when individuals are unemployed for between 3 and 6 months. Being unemployed for between 6 months and 1 year reduces the likelihood by one point (6.5 points less likely than for those unemployed for less than 3 months) and for those unemployed for between 1 and 2 years the probability falls by 1.6 points (8 points less likely). The negative impact increases to 9 points if the duration of unemployment goes beyond 4 years. A comparison of these results with the impact of the same variable on the total number of unemployed people who do not receive MIS (column 2) shows that the duration of unemployment also has the greatest negative impact in this group. In particular, being unemployed for more than 3 months reduces the exit probability by almost 8 percentage points. As occurs with the MIS group, the likelihood of exit continues to decrease as the duration of unemployment increases, with exit being 15.7 points less likely among those unemployed for more than 4 years. As can be seen, no other variable has a similar impact.

Considering education, in general the likelihood of finding a job can be seen to be correlated with the education level of each unemployed individual: having secondary education qualifications (compared with primary or no education) increases the probability midpoint; completing high school increases it by 0.8 points; medium level vocational training increases it by 1.2 points and higher level vocational training and higher university degrees raise it by 1.9. Notice that the impact of being unemployed for more than 3 months is double that of having university studies (as compared to primary or no education) for MIS recipients.

A separate section below is dedicated exclusively to a counterfactual assessment of the impact of Activation Services on the probability of finding a job, so here we present only a preliminary assessment of activation interventions. It is important to note that information on self-employment has a clearly differentiated nature, since people who use it are practically on their way towards self-employment. Thus, measuring its effectiveness via its impact on the probability of leaving for a job does not make much sense. From now on, we assess the effectiveness of only the other three interventions in exits into employment.

4. Assessing the Impact of the Basque Minimum Income Scheme on the Labour Market: A Counterfactual Assessment

Any Minimum Income Scheme is by nature a passive policy, as its main aim is to guarantee all individuals the resources required to meet their minimum needs. However, as mentioned above, the Basque MIS, following the dictates of the European Council since 2008, requires recipients to participate (in principle) in active policies to make their re-entry into employment as fast and successful as possible. In view of this two-fold scope of the MIS, with both passive and active aspects, our assessment of the policy is also two-fold.

Firstly, although the goal of any passive policy is not to accelerate the employability of the unemployed but to supplement their income so as to alleviate poverty, empirical evidence generally finds that most income transfers to the unemployed result in a delay in job-finding. Reservation wages increase for anyone who receives additional income, and this typically delays job entry, hence lowering job-finding rates. However, there are two aspects of the MIS which might accelerate rather than delay job access: one is that the MIS can also be received by employed workers with insufficient income to meet minimum needs, so MIS recipients might be willing to accept jobs with "low" wages compatible with retaining the transfer. The other is that recipients can lose their MIS if it is proved that they have rejected job offers. For these reasons, the typical "delay" effect of a passive transfer such as the MIS may be partially offset by some kind of “acceleration effect” for reasons other than the activation measures implemented.

Our first assessment with respect to the impact of the MIS in the Basque Country looks at whether the MIS causes a delay or an acceleration effect, and if so on what scale. This is the first objective addressed in this section.

Secondly, and perhaps more interestingly, we seek to assess whether active policies offered to MIS recipients make for better transitions towards employment. This is the second objective of the section.

4.1. Empirical Assessment Strategy

In both analyses the aim is to assess the impact either of the MIS itself or of the activation measures aimed at MIS recipients on the probability of exiting unemployment. As in previous estimations, the dependent variable (Y) takes a value of 1 if the unemployed individual gets a job in the next month and 0 otherwise. The treatment (D), which is a dummy variable, takes a value of 1 firstly when the individual is an MIS recipient and secondly if the individual receives activation measures[12]. The covariates included in our analyses are the same as in previous estimations (X).

The main problem that we face in both the analyses carried out in this paper is sample selection. In the first one unemployed people need to comply with strict requirements to receive MIS. In the second analysis, the profile of the unemployed people who receive activation measures differs broadly from that of non-activation measures recipients (as shown below). Consequently, given that individuals are not randomly chosen, a mean difference between the outcomes of treated and control group cannot be used to learn the causality in the corresponding treatment. Only when participation in the treatment depends on observable characteristics (X) can the

[12] We are unable to draw up a duration analysis because of data limitations. Our dataset includes only 2015 information and for MIS beneficiaries (more than 70% of whom have been unemployed for more than one year) we would need longer longitudinal information.

Average Treatment Effect on the Treated (ATT) be estimated by conditioning on these variables, rendering the counterfactual outcome independent of the treatment (*conditional independence assumption,* CIA). However, the probability of finding a job for recipients and non-recipients of MIS might be affected by confounding factors. Therefore, it is hard to justify the validity of CIA in this analysis. In the second analysis, our lack of understanding of the selection process for receiving activation measures means that we are unable to argue as to whether CIA is satisfied or not.

Propensity Score methods are useful for estimating treatment effects using observational data since they enable observational studies to be designed along lines similar to randomised experiments (Rubin, 2001)[13]. Rosenbaum and Rubin (1983) show that instead of conditioning on the covariates, conditioning on the probability of potential treatment conditional on observable covariates, the propensity score ($p(x) = P\ (D = 1/X)$), suffices to achieve a balance between the treatment and control groups as long as other requirements are met. Firstly, the covariates influencing assignment and outcome should not predict the treatment participation deterministically (*weak overlap,* $P\ (D = 1/X) < 1$for all X). Secondly, the participation in the treatment of one individual must not have an impact on the outcome of other treated or control individuals. Our two samples confirm the weak overlap. Furthermore, although there is a lack of evidence in the literature in this regard, it seems reasonable to think that being an MIS recipient or service recipient does not affect other people's probabilities of finding a job. For these reasons, we believe the use of Propensity Score techniques to be appropriate.

Different propensity score approaches have been suggested for estimating an adequate counterfactual outcome. The most widely used methods are matching and reweighting (Imbens, 2004). These methods seek to remove observed systematic differences between treated and control subjects. In our first analysis, Inverse Probability Weighting (IPW) makes the distribution of observable covariates similar in the treated and control groups.[14] Furthermore, as explained below, IPW is the only valid methodology in our first analysis due to the characteristics of the treatment. For the second part of our research, our lack of knowledge of the selection mechanism and the characteristics of the sample assessed leads us to calculate the treatment effect

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[13] Another alternative that has been suggested to us is the regression discontinuity approach, using as a control group those households that are close to fulfilling the total income requirements of the household to receive the MIS but do not comply. Unfortunately, this methodology cannot be used here for several reasons. Firstly, as previously mentioned, we do not have information on the total household income, therefore, we cannot measure how far individuals or households are to comply with the income requirement to receive MIS. Secondly, we are not able to identify those individuals belonging to the same household, thus, matching MIS households with non-MIS ones is not possible. Finally, the lack of other crucial household variables, such as the number of children or other dependents in the household is not available either.

[14] Table 2 below shows the distribution of the characteristics in the reweighted sample.

using two different methods: Inverse Probability Weighting (IPW) and Propensity Score Matching (PSM).

The idea behind Inverse Probability Weighting is the following: random assignment guarantees that the distribution of the covariates among units of observation in the treatment and control groups is probabilistically equivalent, i.e. all units are equally likely to be in the treatment or control groups. However, when the assignment is not random some individuals are more likely to be treated than others, depending on their particular characteristics. To account for these differences in the regression formulation observations must be weighted according to the inverse probability of receiving treatment. This gives a pseudo-random sample by weighting observations by the inverse of the probability of being treated. Therefore, the distribution of covariates between the groups would be probabilistically equivalent (Gardeazabal and Vega-Bayo, 2016). In short, weighting individuals by the inverse probability of treatment creates a synthetic sample where treatment assignment is independent of the observed covariates. Inverse Probability Weighting enables unbiased estimates of average treatment effects to be obtained. However, these estimates are only valid if there are no residual systematic differences in observed variables between the weighted treated and control groups (Austin and Stuart, 2015). We prove this to be the case here. It is thus assumed that when the observable differences are reduced, so too are the unobservable factors. For instance, unobservable variables such family income or motivation could be related with some observable factors, for example educational level or unemployment duration. Over representing control individuals with similar characteristics than treated individuals enables to reduce the differences in the unobservable factors between treated and control individuals.

It stands to reason that a more efficient estimator can be obtained if the regression of the reweighted sample includes all measured covariates as additional regressors. This other estimator is known as Augmented Inverse Probability Weighting (AIPW). AIPW estimator have the double-robust property, only one of the two models must be correctly specified to consistently estimate the treatment effects (Drukker, 2014).

The IPW estimator uses a two-step approach to estimate treatment effects. The specification for the Average Treatment Effect on the Treated (ATT) is as follows:

1) Estimate the probability of being treated based on the covariates by a probit[15] regression. Denote $p_i(x)$, i.e. the propensity score. Use the inverse probability weights to compute the new pseudo-random sample. Build regression weights (w_i) as:

$$w_i = 1 \quad if \;\; D_i = 1$$

[15] A logit model can be also used.

$$w_i = \frac{p_i(x)}{1 - p_i(x)} \quad if \;\; D_i = 0$$

The idea behind this reweighting procedure is quite straightforward. The objective is to approximate the distribution of the covariates of the control group to those of the treated group. For that reason all treated individuals have weights of 1. Control individuals with a 0.5 probability of being MIS recipients are assigned a weight of 1; those with a probability higher than 0.5 have weights of more than 1 with an increasing pattern and those with a probability lower than 0.5 have weights of less than 1 with a decreasing pattern. By doing this, the outcome of those control individuals with the highest probabilities of being MIS recipients would gradually weigh more and the outcome of those control individuals with the lowest probability of being MIS recipients would weigh exponentially less.

2) Calculate the ATT of the new sample, i.e. run a probit regression of the outcome on a constant and the treatment using the weights calculated. The coefficient of the binary treatment in the previous regression is a consistent estimation of ATT, provided that the propensity-score is correctly specified. Adding all confounders measured as additional covariates the Augmented Inverse Probability Weighting (AIPW) estimator is obtained.

In the second assessment, an additional Propensity Score approach is applied: Propensity Score Matching (PSM) here helps us also to estimate the impact of activation measures. This methodology entails matched sets of treated and untreated subjects who share similar propensity scores (Rosenbaum and Rubin, 1985), and it enables the ATT to be estimated (Imbens, 2004). The most common implementation is one-to-one pair matching, in which pairs of treated and control individuals are formed in such a way that they have similar propensity scores. Once a matched sample has been formed, the treatment effect can be estimated by directly comparing outcomes between matched treated and control individuals. Schafer and Kang (2008) suggest that treated and control subjects should be regarded as independent within matched samples. By contrast, Austin (2011) argues that the propensity score matched sample does not consist of independent observations. He maintains that in the presence of confounding factors covariates are related to outcomes, so matched subjects are more likely to have similar outcomes than randomly selected subjects.

Based on Austin’s argument, we reject the use of the Propensity Score Matching in the first analysis. Non-observed factors such as family income differ systematically between the treated and control individuals as they are crucial determinants for being selected for the treatment. However, the second assessment uses PSM, as we find it reasonable to argue that the unobservable factors of treated and control individuals resemble each other more (given the selected control group used) than in the first analysis.

4.2. Impact of MIS on job-finding rates - Does MIS delay the probability of finding a job?

As shown in previous sections, MIS recipients have a monthly job-finding rate of 3%, compared to 9% for the non-MIS unemployed group. However, as already stated, the composition of the group of MIS recipients differs notably from that of the rest of the unemployed, and those differences (mainly longer unemployment duration and lower education level) may be causing at least part of the differences observed in job-finding rates. To isolate compositional differences from the income scheme, we use the Inverse Probability Weighting Methodology as detailed above. This enables us to assess the extent to which the difference observed in job-finding rates are explained by (i) compositional differences between the two groups; and (ii) by the MIS.

To that end, we include in the treatment group all those individuals who are recipients of the MIS in the current month. Given that the observation unit is one individual per month, an individual may belong to the treatment group in some months (in which he/she receives the MIS) but not in others (in which he/she does not receive it). Hence, an individual may belong to the treated group in a given month and to the control group in another. To set up an adequate counterfactual, we must define the control group so that it provides the best possible simulation of job-finding rates for the group of MIS recipients if they had not received the benefit. According to the data, for 93% of MIS recipients MIS is the ONLY income aid received; a further 6% also receive other welfare benefits and the remaining 1% receive contributory benefits. In the last two situations, they receive both types of income aid because the other benefits received are still lower than what it is considered necessary to meet basic household necessities. We think that it makes sense to assume that if the income scheme did not exist the 93% currently receiving only MIS would not be getting any additional income aid and the remaining 7% would receive an insufficient amount. For this reason, we have chosen to include unemployed individuals who do not receive ANY benefit in the current month in the control group[16]. For this group, the observed monthly job-finding rate is 6.5%. Consequently, the outcome of the assessment must be interpreted as the differential impact of MIS on the job-finding rate compared to not receiving any benefit.

However, the treatment (receiving MIS) is by no means random. As specified above, there are specific requirements. Some of them are observable in our dataset but others are non-observed confounder variables, such as total household income, that must be controlled for. To "correct" for these differences between the treatment and control groups we use the Inverse Probability Weighting method. Table 2 shows the distribution of the reweighted control group, which validates the use of the IPW

[16] In October this group consists of a total of 69,961 unemployed, compared with 38.345 unemployed MIS recipients.

methodology. This table shows that the differences in the main characteristics are eliminated by using the said weighting procedure.

[Insert Table 2 here]

The results of the Inverse Probability Weighting Estimation and of an extended version of it (the Augmented Inverse Probability Weighting Estimator) are presented in Table 3. Applying such methodology, we find that the impact of MIS is not significantly different from zero at any significance level. The result is the same for both the IPW and the AIPW estimators, which makes it more reliable[17]. This indicates that the monthly job-finding probability for MIS recipients would have been the same if they had not received any benefit. We can thus conclude that the MIS itself does not reduce the probability of finding a job. In other words, the differences observed in job-finding rates between the treatment and the control group are due solely to the difference in the compositions of the two groups and not to the effect of the policy.

[Insert Table 3 here]

As a second step, we analyse whether the MIS has different impacts on different demographic groups. Specifically, we assess the impact of MIS on men and women separately, on three age groups (< 30, 30-44 and > 45) and on three education groups (primary, secondary and higher)[18]. The results, presented in Table 4, confirm that the impact of MIS is not homogeneous across demographic groups. In particular, for women MIS delays exit to employment slightly (0.2 p.p) whereas it has no impact on men. According to the legislation, all members of the family MIS recipients must be registered in the Public Employment Service as unemployed. It may be the case that some women belonging to those households and registered as unemployed are actually inactive because of the traditional gender role attitudes. This would lead into an apparent delay of MIS beneficiaries women compared to non-MIS women. Second, the MIS accelerates job-finding for older workers (0.2 p.p) whereas for young workers (<30) it delays exit to employment (1 p.p). This remarkable delay among young individuals could not be explained in a similar way than before. In this case, students belong to the group of non-registered unemployed and, therefore, they are not included in the analysis. The observed delay for registered unemployed young MIS beneficiaries might be explained by the lack of motivation caused by the huge young unemployment rates and the insufficient labour demand. Finally, we find a delay as an impact of MIS for less educated workers (0.2 p.p), whereas it accelerates job entry for those with more than primary education (0.2 p.p for workers with secondary education and 0.5 p.p for those with higher education). As a possible explanation, MIS

[17] The assessment is also conducted using the Propensity Score Matching methodology. However, the results are divergent, corroborating the argument of Austin (2011).

[18] The same analysis is not carried out for duration of unemployment because of the endogeneity of the variable.

beneficiaries cannot reject job offers and it may be the case that medium or high-educated perceivers accept job offers that a non-MIS perceiver would not accept, in order not to lose the aid.

[Insert Table 4 here]

Our results coincide partially with the ex-ante assessment in Clavet, Duclos and Lacroix (2013) and with the findings (double and triple difference estimation strategy) in Chemin and Wasmer (2011). Both find a negative impact on labour market participation, particularly among specific groups such as low-skilled workers. However, their results are not directly comparable to ours as the methodology and the design of the policies in the regions that they examine are different. To our knowledge there is no comparable assessment of a similar policy.

The main conclusion of this exercise is as follows: by definition, the MIS reduces poverty and promotes social cohesion. Our analysis leads us to conclude that on average the MIS per se does not delay exit to employment. However, we do find differences in its impact on different demographic groups. In particular, it causes an undesired delay effect (also commonly found in other passive policies) for women, the less educated and young people, but accelerates entry into employment for medium and high-educated workers and for those aged over 45.

4.3. The Impact of Active Policies on job finding probability for MIS recipients

In this section we assess the effectiveness of the activation interventions received by MIS recipients. Such an assessment is highly recommended given that in general active policies are quite costly. It enables us to check and if necessary modify and improve the efficiency of the Basque Public Employment Service in providing recipients with the tools that they need to re-enter employment. This information can certainly highlight what actions should be strengthened, modified or even eliminated.

As mentioned before, we focus on three types of Active Policy: guidance, monitoring and training. Individuals are classed as users of activation services if they are observed to have received such measures at least once in the last six months (including the current month).

First, we present some descriptive statistics to show the extent of activation for the MIS group. As in the descriptive section, we focus (in order to present the characteristics of the unemployed) on a particular month (October 2015) so as to avoid overrepresentation of the long-term unemployed. Of the 38.345 unemployed people registered as MIS recipients in that month, 15.630 had received some kind of active policy in the form of guidance, monitoring or training at some time in the previous 6 months. This amounts to 40.8% of the total. As regards the types of services received, 15,106 people (39,4% of all unemployed MIS recipients) received guidance services, 265 (0.7%) monitoring services and 881 (2.3%) training courses. This means that 728 individuals received more than one type of service. Given the low figure for monitoring, from here on we focus our results on activation through guidance or training interventions.

A brief profile is given below of how individuals involved in each of these two policies compare to individuals who receive no activation measures. Table 5 shows the distribution of the four main characteristics (sex, age, education and unemployment duration) depending on the type of active policy received.

[Insert Table 5 here]

In general men receive more activation than women: around 65% of those who received training were men. The age range varies depending on the type of service. Guidance and training predominate in the 30-45-age range (their relative incidence among MIS receivers is 46%). In general, young people tend to receive fewer activation interventions. There are also substantial differences between education levels: 60% of MIS recipients have at most primary education, 27% secondary and 13% higher education, which means that on average fewer activation measures are received by highly educated MIS recipients. In addition, activation measures decrease as unemployment duration increases.

Furthermore, we find distributional differences per type of activation measure. Guidance measures are distributed similarly across education levels, but we find significant differences in training measures, as recipients with secondary or higher education levels receive more training measures than those with at most primary education.

To assess the impact of each of these activation interventions, we place those MIS recipients who have received each particular activation policy being assessed (either individual guidance or training) in the last six months in the treatment group. As before, we measure the impact of receiving the activation measures on monthly job-finding rates. As a control group we use MIS recipients who have not participated in ANY activation measures from the Public Employment Service in the last six months so as to get a cleaner impact of each specific activation measure[19]. The results must therefore be interpreted as the impact of the intervention on the probability of finding a job compared to not receiving any activation service in the last six months.

As shown in Table 5, the treatment and control groups differ in important characteristics such as the duration of unemployment and education level. We assess each intervention following the IPW methodology described above. The interventions

[19] As robustness check an alternative control group has been used, i.e., those who did not participate in any activation measures in the last year. The results show that the impact of both services are very similar or even more accentuated.

are thus "pseudo-randomised", so the distribution of the covariates between the two groups is balanced and the treatment is probabilistically equivalent. Therefore, the impact of each type of intervention can be properly assessed without the results being biased by differences in composition.

In addition to the IPW (and AIPW) method, we also use a Propensity Score Matching technique to enhance robustness. Given that the control group now consists of MIS-recipients (although they do not receive activation measures), we find it reasonable to assume that unobserved confounding factors of treated and control individuals do not differ substantially from one group to the other. This assumption is essential to validate the use of the Propensity Score Matching technique.

The results of the assessment of each active policy for MIS recipients (guidance and training) are shown in Table 6. Inverse Probability Weighting (IPW), Augmented Inverse Probability Weighting (AIPW) and the Propensity Score Matching (PSM)[20] estimators are presented. The first three columns correspond to the three specifications for the impact of guidance service. It can be seen that guidance has a positive impact on exit into employment. This impact is statistically significant for all three approaches, although its magnitude differs slightly from one to the other. As a general result, we conclude that guidance increases the probability of getting a job by about half a percentage point over not receiving any activation intervention in the last six months[21].

The last three columns in Table 6 show the impact of training programmes on job-finding rates. Unfortunately, we have no information on the type of training provided or on whether there is any selection process prior to participating in a training programme. Given this information limitation, all that we can assert is whether participating in any kind of training programme helps individuals find a job. What we find is that training is undoubtedly the factor with greatest impact on the probability of finding a job for the MIS group. Individuals who use these programmes increase their likelihood of finding a job by around 3 percentage points. Given that the average job-finding rate for MIS recipients is 3%, the probability of finding a job increases by around 100% when an unemployed MIS recipient attends a training course. Due to their potential for job-finding, it would be most helpful to have more detailed information regarding training programmes so as to assess in the future more precisely which types of training programme seem to work best.

[Insert Table 6 here]

[20] One-to-one pair matching implementation is presented. However, the results barely changes when different number of matches per observation are used in both analysis.

[21] The impact of guidance is also addressed for the population subgroups. The results are not shown here as all profiles have similar results, so they are deemed to be of little interest. Training programmes are not assessed for the different population groups for reasons of sample size.

In line with the literature on Active Labour Market Policies, we also find that an adequate design of activation policies accelerates re-entry into employment[22]. In short, active policies significantly accelerate the probability of finding a job for MIS recipients. However, only around 40% of them use such measures, even though participation in them is supposedly compulsory. Specifically, training is the most effective policy: those who undergo it are twice as likely to find a job. This conclusion emphasises the importance of linking passive policies with active policies, because those MIS recipients who use active policies enhance their chances of finding a job compared to similar unemployed people who do not receive any aid.

5. Summary and Conclusions

In the Basque Country (a region in north-eastern Spain) a Minimum Income Scheme has been in place continuously since 1989. Its main objective is to guarantee all individuals the resources required to cover their basic necessities, and at the same time to provide for their progressive integration into society and employment. Furthermore, in line with European Council recommendations, the Basque MIS has an interesting feature: recipients are in principle required to participate in active measures to make their re-entry into employment as fast and successful as possible.

In 2015 there were about 62,000 MIS recipients, 60% of whom belonged to the group denoted as “registered-unemployed” at the Public Employment Service. The rest are workers, retired recipients and non-working persons who for different reasons do not fit into the category of those registered as unemployed. MIS recipients account for 25% of all the registered unemployed in the Basque Country.

Given that the Basque MIS is a last resort scheme, individuals with low education levels and the (very) long-term unemployed are prevalent among recipients. Specifically, 60% of MIS recipients have at most primary education and 52% have been looking for a job for more than two years. Unsurprisingly, low education levels and particularly long unemployment durations are the main determinants that delay job-finding. Indeed, MIS recipients have an average monthly job-finding rate of 3%, while for unemployed people who do not receive the MIS, the rate stands at 9%.

The first empirical strategy in this paper is to measure whether this difference is solely due to the different composition of the unemployed or, whether the MIS delays entry into employment as empirical evidence has proven that passive policies do in general.

The second aim of the paper is to measure the effectiveness of active policies on MIS recipients in terms of their impact on the probability of finding a job. Even

[22] Unfortunately, we are not able to measure the impact of the programmes in the long-term due to sample restrictions.

though all MIS recipients are supposed to engage in activation measures, the fact is that only around 40% of them (16,000 out of 38,000 unemployed recipients) have done so at any time in the last six months. Guidance is the most common service: it is received by 39% of all unemployed MIS recipients. It is followed at some distance by training (received by only 2.3%). The profiles of the participants differ from one kind of activation measure to another and also with respect to those who do not participate in such services.

Propensity Score methods are applied in both assessments. In both analyses we follow an Inverse Probability Weighting methodology. In the second exercise we also supplement our assessment with a Propensity Score Matching. Both methodologies help us deal with confounding effects and differences in composition between the treated and control groups in the most suitable way according to the characteristics of the corresponding sample.

Our results confirm that on average the MIS does not delay entry into employment, so the difference in the job-finding rates observed are due solely to the different compositions of the treated and control groups. If the analysis is conducted for specific population groups, we find that its impact differs. The undesired delay effect commonly found in passive policies is observed among less educated and younger MIS recipients, but the MIS accelerates entry into employment for medium and high-educated people and for the over 45s. To the best of our knowledge there are no other assessments of similar policy implementations that we could compare our results with.

The second finding is that all types of public employment activation services have positive impacts on job-finding rates, but the extent of that impact varies from one measure to another: the most effective services are training programmes (which double the probability of finding a new job), followed by guidance services (which increase the probability by around 20%). Hence, as a policy device, this study supports the conclusion that training services for MIS recipients should be enforced, as they help recipients to re-enter employment, which is the ultimate aim of activation measures. Moreover, it is essential to emphasise the importance of linking passive policies with activation measures for recipients.

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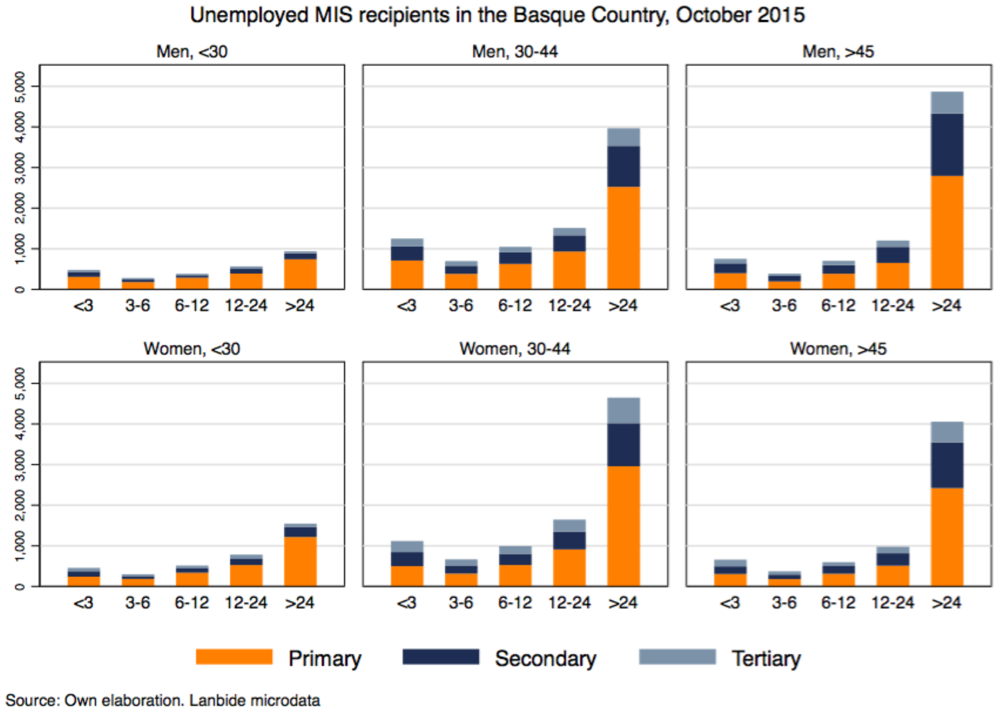
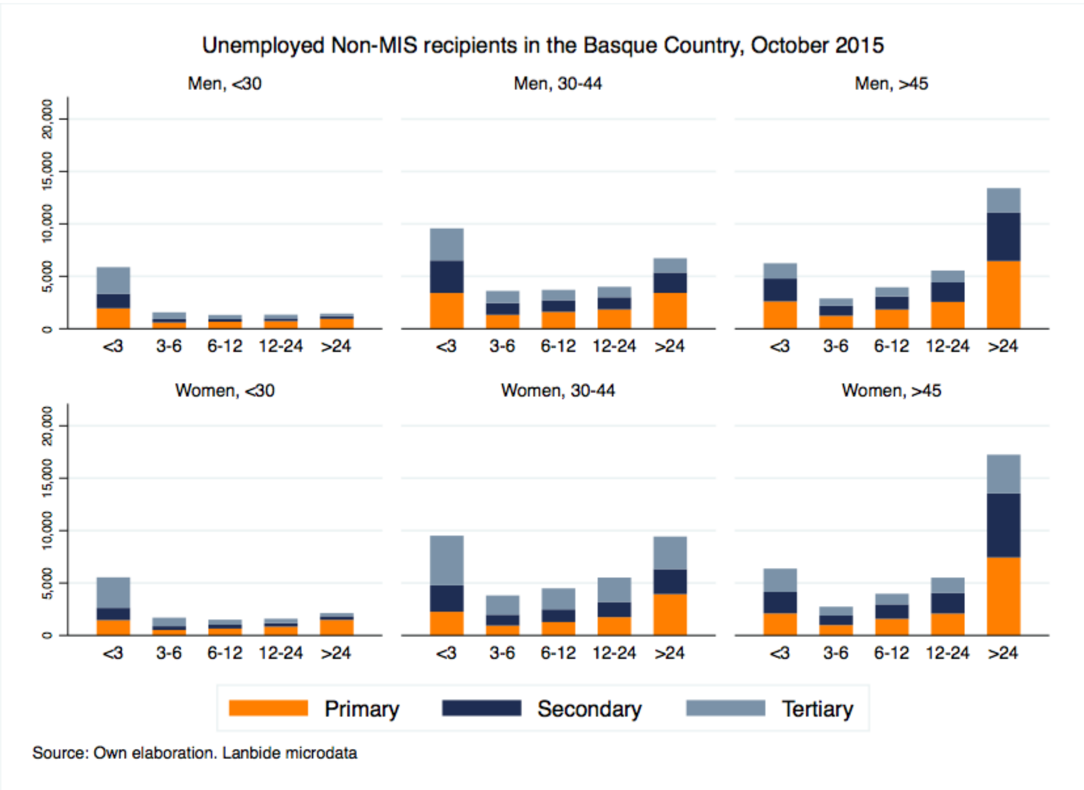
Figures

Figure 1



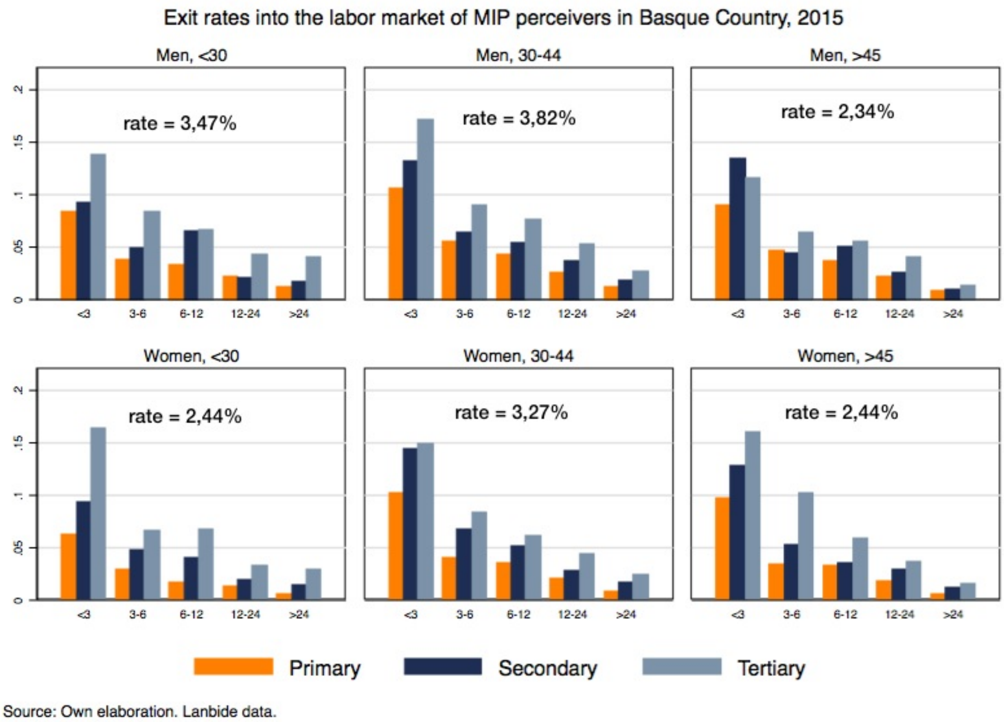
Axes: gender, age, unemployment duration (months), educational level

Figure 2



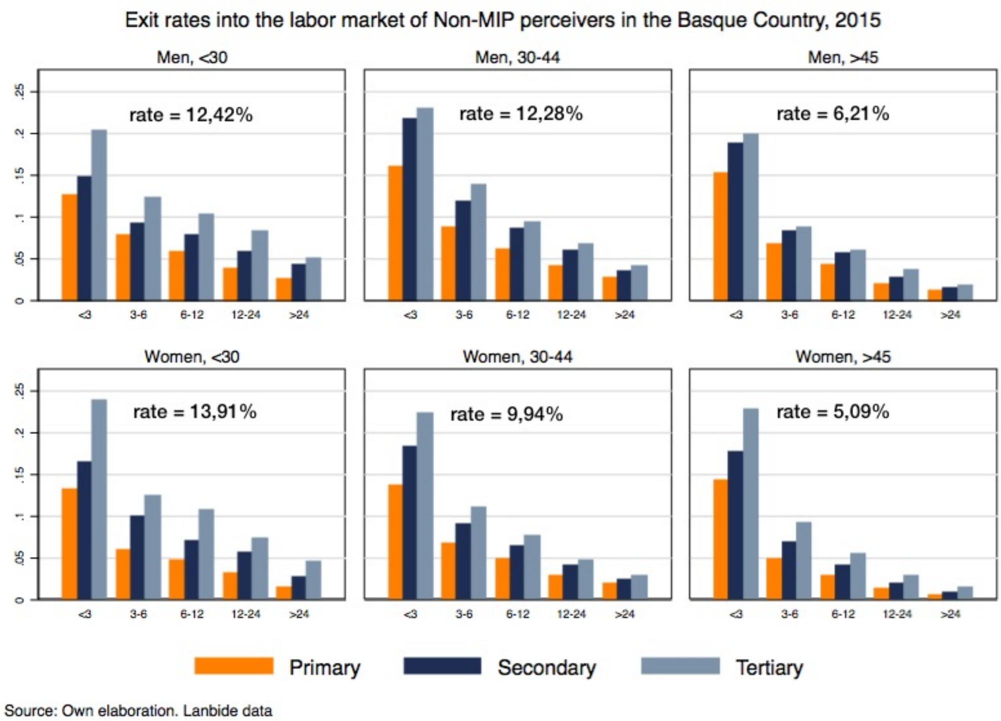
Axes: gender, age, unemployment duration (months), educational level

Figure 3



Axes: gender, age, unemployment duration (months), educational level

Figure 4



Axes: gender, age, unemployment duration (months), educational level

Tables

Table 1. Probability of finding a job.

		Dependent variable: exit probability	
		Unemployed MIS recipients	Unemployed Non-MIS recipients
	Women	-0.0008	-0.0014**
		(0.00067)	(.0006315)
	Foreign nationals	0.0002	-0.0106**
		(0.00076)	(0.00107)
	Disabled persons	-0.0074***	-0.0173***
		(0.00197)	(0.00243)
	MIS recipients	0.0013*	-
		(0.0007)	-
	Social services derivation	-0.0227***	-0.0554***
		(0.00505)	(0.01238)
Benefits	contributory	0.0104***	.0292***
		(0.00151)	(0.00089)
	attendance	0.0091***	0.0245**
		(0.00080)	(0.00112)
	ex-contributory	-	0.0406***
		-	(0.00090)
	ex-attendance	-	0.0207***
		-	(0.00105)
Activation services	guidance	0.0056***	0.0054***
		(0.00056)	(0.00082)
	monitoring	0.0068***	0.0048
		(0.00176)	(0.00504)
	self-employment info	0.0164***	0.0237***
		(0.00358)	(0.00426)
	training	0.0195***	0.0403***
		(0.00126)	(0.000148)
Age	25-30	0.0018	0.0001
		(0.00151)	(0.00152)
	30-35	0.0022	-0.0144***
		(0.0015)	(0.00154)
	35-40	0.0012	-0.0206***
		(0.00144)	(0.00153)
	40-45	0.0015	-0.0200***
		(0.00146)	(0.00154)
	45-50	-0.0006	-0.0208***
		(0.00148)	(0.00156)
	50-55	-0.0028*	0.0265*
		(0.00153)	(0.00158)
	55-60	-0.0083***	-0.0473***
		(0.00159)	(0.00159)
	60-65	-0.0178***	-0.0785***
		(0.00166)	(0.00159)

Education	primary	0.0026***	0.0025*
		(0.00098)	(0.00144)
	uncompleted secondary	0.0001	0.0041***
		(0.00095)	(0.00141)
	secondary	0.0053***	0.0151
		(0.00102)	(0.00140)
	high school	0.0080***	0.0157***
		(0.00135)	(0.00155)
	Medium-level vocational training	0.0111***	0.0289***
		(0.00148)	(0.00158)
	High-level vocational training	0.0175***	0.0284***
		(0.00177)	(0.00158)
	Undergraduate	0.0253***	0.0301***
		(0.00317)	(0.00187)
	Bachelor's degree or higher	0.0176***	0.0300***
		(0.00230)	(0.00170)
Unemployment duration	3-6 months	-0.0524***	-0.0796***
		(0.00189)	(0.00091)
	6-12 months	-0.0662***	-0.1045***
		(0.00172)	(0.00087)
	1-2 years	-0.0819***	-0.1297***
		(0.00163)	(0.00084)
	2-3 years	-0.0857***	-0.1392***
		(0.00164)	(0.00091)
	3-4 years	-0.0891***	-0.1480***
		(0.00164)	(0.00092)
	4 years or more	-0.0943***	-0.1566***
		(0.00160)	(0.00081)
	baseline prob.	0.0291	0.0617
	average pred. prob.	0.0304	0.0750
	Observations	431,773	1,297,683

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Additional variables are included in the estimation: experience in requested occupations, activity in previous field of work, language skills, geographical scope of job search, province of registration and months in which the individual is observed as unemployed.
Baseline profile: men, native, no disabilities, not referred to social services, under 25, illiterate, unemployed for less than 3 months.

Table 2. Composition of the treated, non-weighted and weighted control groups in the analysis of the impact of MIS on the probability of finding a job (%)

	Treatment	Non-weighted Control	Weighted control
Gender			
Men	49.6	42.19	48.3
Women	50.4	57.81	51.7
Age			
< 30	16.27	20.13	14.1
30-44	45.73	39.32	50.5
> 44	37.99	40.55	35.4
Education			
Primary	59.82	32.7	61.3
Secondary	26.83	29.72	26.3
Tertiary	13.35	37.58	12.4
Unemployment duration			
< 3 months	12.29	33.73	11.5
3-6 months	7.04	10.8	6.2
6-12 months	11.03	11.98	11.3
1-2 years	17.42	13.55	18.8
> 2 years	52.21	29.94	52.1

Treated group: Unemployed MIS recipients.
Control group: Unemployed people without benefits.

Table 3. Assessment results: impact of MIS on the probability of finding a job.

	IPW	AIPW
ATT	0.000135	-0.000690
	(0.000823)	(0.000510)
N. Observations	724,144	724,144
Treated individual	42,606	42,606
Treated individual-month	431,776	431,776
Control individual	55,487	55,487
Control individual-month	292,368	292,368

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
IPW: Inverse Probability Weighting. AIPW: Augmented Inverse Probability Weighting.
Treated group: Unemployed MIS recipients.
Control group: Unemployed people without benefits.

Table 4. Assessment results: impact of MIS on the probability of finding a job per group.

		Gender		Age			Education		
		Men	Women	< 30	30-44	>44	Primary	Secondary	Tertiary
ATT	IPW	0.00305**	-0.00163**	-0.0128***	0.00343***	0.00228**	-0.00144*	0.00368***	0.00641***
		(0.00120)	(0.000681)	(0.00124)	(0.00122)	(0.00102)	(0.000804)	(0.00119)	(0.00180)
	AIPW	0.000726	-0.00189***	-0.0108***	0.00127	0.00223***	-0.00202***	0.00276***	0.00545***
		(0.000834)	(0.000506)	(0.00109)	(0.000883)	(0.000598)	(0.000592)	(0.000895)	(0.00129)
N. Observations		324,751	399,393	190,570	272,115	261,456	371,111	196,226	156,807
Treated	Individual	21,314	21,312	7,673	20,210	16,477	25,345	12,162	6,027
	Ind-month	214,539	217,237	73,366	197,729	160,681	256,299	117,251	58,226
Control	Individual	23,186	32,329	28,565	13,546	14,309	20,958	14,783	20,785
	Ind-month	110,212	182,156	117,204	74,386	100,775	114,812	78,975	98,581

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

IPW: Inverse Probability Weighting. AIPW: Augmented Inverse Probability Weighting

Treated group: Unemployed MIS recipients belonging to the specific group.

Control group: Unemployed people without benefits belonging to the specific group.

Table 5. Composition of MIS recipients per type of activation (%)

		No activation	Guidance	Training
Gender				
	Men	48.0	51.7	64.5
	Women	52.0	48.3	35.5
Age				
	< 30	18.6	12.9	16.0
	30-44	43.1	49.4	54.3
	> 44	38.3	37.7	29.7
Education				
	Primary	60.8	59.1	41.1
	Secondary	26.6	27.0	36.4
	Tertiary	12.6	13.9	22.5
Unemployment duration				
	< 3 months	13.2	10.7	18.2
	3-6 months	7.9	5.8	4.5
	6-12 months	11.3	10.6	11.0
	1-2 years	16.7	18.5	19.5
	> 2 years	50.9	54.4	46.8

Table 6. Assessment results: impact of activation on the probability of finding a job.

	Guidance			Training		
	IPW	AIPW	PSM	IPW	AIPW	PSM
ATT	0.00543***	0.00475***	0.00760***	0.0297***	0.0258***	0.0298***
	(0.000601)	(0.000453)	(0.000772)	(0.00233)	(0.00204)	(0.00292)
N. Observations	431,773	431,773	420,482	431,773	431,773	292,816
Treated individual	9,436	9,436	-	1,484	1,484	-
Treated ind-month	139,554	139,554	-	11,888	11,888	-
Control individual	42,309	42,309	-	50,270	50,270	-
Control ind-month	292,219	292,219	-	419,885	419,885	-

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
IPW: Inverse Probability Weighting. AIPW: Augmented Inverse Probability Weighting. PSM: Propensity Score Matching
Treated group: Unemployed MIS recipients who have received activation services in the last six months.
Control group: Unemployed MIS recipients who have not received any activation services in the last six months