The Effect of Unemployment Insurance on Geographical Mobility

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Abstract

This paper investigates the effects of unemployment insurance generosity on workers' geographical mobility decisions. Identification is based on an unanticipated reform that reduced the unemployment insurance (UI) replacement rate (RR) in Spain for workers who were laid-off after July 14, 2012. Using administrative data from social security records and a regression discontinuity design, I find that the UI cut increased the probability to migrate to a different province by 4 percentage points, which represents a 25 percent increase with respect to the pre-reform mean. This result is driven by young educated men with no family responsibilities, and at the top 25 percent of the sample income distribution. The findings also suggest that the increase in mobility is due to actual changes in the province of residence, rather than to an increase in commuting distances.

Keywords: local labor markets, labor mobility, geographic mobility, unemployment insurance, natural experiment.

JEL Codes: J61, J65, J68

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1. Introduction

Unemployment rates vary widely across and within countries in the EU (see figure A2).[1][2] To adjust for such spatial disparities, geographical labor mobility is one of the most efficient equilibrating mechanisms (Blanchard and Katz, 1992). Yet, labor relocation is limited in the EU relative to other world regions, specially the U.S. (Decressin and Fatas, 1995).[3] Nickell (1997) or Bertola (1999) suggest that rigid labor market institutions (e.g. generous unemployment insurance) can help explain the low mobility rates in the EU.

But does the generosity of the unemployment insurance (UI) really deter labor geographical relocation? From economic theory, it is unclear in which direction changes in the UI benefit level affect mobility. On the one hand, generous UI can reduce geographic mobility and search effort by increasing reservation wages (Mortensen, 1977). On the other hand, generous UI can enhance productive job search and mobility by reducing the liquidity constraints (Ben-Horim and Zuckerman, 1987).

In this paper, I study the causal effect of reducing the UI benefit level on workers' mobility decisions using quasi-experimental evidence from a reform in Spain. More specifically, I exploit a plausible exogenous 10 percentage points cut in the UI replacement rate (RR) in the aftermath of the Great Recession. Before the policy implementation, the RR was set at 70 percent of the gross earnings during the first 180 days of unemployment, and 60 percent afterwards. On July 11, 2012, the Spanish government announced that workers who started an unemployment spell after

[1] The unemployment rate in the EU-28 was 7.6 percent (standard deviation of 4.01) in 2017, compared to 4.4 percent in the U.S. (standard deviation of 0.96).

[2] At the sub-national level, Italy and Belgium presented some of the largest disparities in unemployment in 2017. As an extreme example, the unemployment rates in Italy ranged from 3.1 percent in Provincia Autonoma di Bolzano to 21.6 percent in Calabria.

[3] In 2013, less than 5 percent of working-age EU citizens lived in a different EU country than the one where they were born. For the U.S., 30 percent of the working-age population lived in 2013 in a state different from their state of birth (Arpaia et al., 2016). Yet, the U.S. is one country, while the EU is the union of several countries with different culture, language, or labor market institutions. Comparing mobility within countries in the EU with mobility across states in the U.S., we observe that the annual rate of sub-national relocation in the EU is around 1 percent, compared to 3 percent in the U.S.

14 July 2012 would have their RR reduced to 50 percent after the sixth month of unemployment.

The Spanish context presents an interesting case to study. Spain's unemployment rate has been persistently high and very responsive to economic fluctuations. Over the course of the Great Recession, the unemployment rate spiked from 8.23 percent in 2007 to 26.09 percent in 2013.[4] Apart from large unemployment, Spain also presents high and stubborn disparities at the sub-national level (see figure A3). Yet, internal relocation has been persistently low after the 70s.[5] In fact, Jimeno and Bentolila (1998) argue that the lack of mobility in response to economic differentials in Spain explains part of the large asymmetries in the regional unemployment rates. In this scenario, it is very important to understand whether the Spanish UI system can be co-responsible for the low rates of internal mobility.

To conduct the empirical analysis I rely on administrative data from the Social Security records (Muestra Continua de Vidas Laborales, MCVL). To estimate the causal effect of the UI generosity, I use a regression discontinuity (RD) design and explore the mobility decisions of workers who start their unemployment spells around July 15, 2012. For the causal effect of the reform to be identified, workers who became displaced just above and just below the threshold must be comparable. I verify this assumption by showing that the density of the running variable is smooth at the discontinuity and that workers' features are balanced at baseline.

Before going to the main results, the first part of the empirical analysis studies the effect of the UI benefit drop on nonemployment duration and subsequent labor market outcomes. In a recent paper, Rebollo-Sanz and Rodríguez-Planas (2018) studies this

[4]Notice that the structural unemployment rate in Spain is very large. Even in the economic boom that preceded the Great Recession, unemployment rates were around 8 percent. To make clearer this magnitude, the unemployment rate in the peak of the Great Recession was 10 percent in the U.S., and 11 percent in the EU-28.

[5]Arpaia et al. (2016) shows that the annual flow of internal migration in 2013 in Spain was around 0.25 percent, compared to around 1 percent in the average of the EU-28 countries. In fact, just 21 percent of Spaniards were living in 2017 outside their province (territorial unit that have an average of 0.9 million inhabitants) of birth.

question using a difference-in-differences design and a different sample.[6] Rebollo-Sanz and Rodríguez-Planas (2018) shows that the 10 percentage points reduction in the UI decreased the expected nonemployment length by 5.7 weeks (or 14 percent) without affecting the job match quality. Using an RD design, I also find that the policy decreased the expected duration of nonemployment by 14 percent without affecting subsequent labor market outcomes.[7][8]

I then turn to the main objective of the paper. This is, I look at whether the UI cut has affected workers' geographical mobility decisions. The results show that the reform increased workers' relocation across provinces by 4 percentage points (a 25 percent of the pre-reform mean). This result is mostly driven by educated and young men, without family responsibilities, and at the top 25 percent of the sample income distribution. In addition, the results suggest that the increase in mobility is mainly towards the big cities, and it happens from the beginning of the unemployment spell.

This paper aims to contribute to two paths of literature: (1) the studies that analyse the effects of UI generosity on geographical mobility, and (2) the literature that seeks at understanding the mechanisms driving the positive relation between UI generosity and nonemployment length.

The empirical evidence on the relationship between UI generosity and mobility is very scarce and mixed. In their model, Hassler et al. (2005) argue that the large disparities in the generosity of unemployment benefits (UB) between Europe and the U.S. account for the different rates in geographical mobility, with Europe having more

[6] Rebollo-Sanz and Rodríguez-Planas (2018) uses the 2012 and 2013 waves of the MCVL, while this paper uses waves from 20012 to 2017.

[7] The positive effect of UI on nonemployment duration is one of the most robust empirical findings in economics. For a very complete review, see Schmieder and Von Wachter (2016).

[8] Because I have information up to 2017, I also study how the policy affected the probability of becoming a long-term unemployed (LTU) worker. The incidence of long-term unemployment has become very salient during the Great Recession, reaching record levels during its peak and remaining significantly high one decade after its starting (Abraham et al., 2019). In Spain, more than half of the unemployed workers in 2018 were LTU. The findings in this paper suggest that the UI reduction decreased the probability of becoming LTU by 10 percentage points. In terms of magnitude, this represents a 20 percent decrease with respect to the pre-reform mean. This is in line with Bentolila et al. (2017), who find that one of the factors that significantly contributes to the probability of becoming LTU is to be a recipient of unemployment benefits.

generous UB and lower relocation rates. Looking at European countries, Tatsiramos (2009) finds that among unemployed workers, UI's recipients exhibit higher mobility rates relatively to non-recipients in France, Denmark, and Spain. To the best of my knowledge, Nekoei and Weber (2017) is the only study that looks at the effect of the UI on geographical mobility using a quasi-experimental design and administrative data. More specifically, Nekoei and Weber (2017) exploits an age discontinuity in the UI system. In Austria, workers who start an unemployment spell after the age of 40 are entitled to a 9-week extension in the UI length. Using an RD design, they find a very precisely estimated zero effect of the UI extension on regional mobility.[9]

There have also been a number of previous studies examining the correlation between UB and labor mobility in Spain. Antolin and Bover (1997) or Bentolila (1997) argue that institutional factors such as the duration and coverage of unemployment benefits have a negative impact on inter-regional mobility. Jofre-Monseny (2014) analyses the effects of an increase in the agricultural unemployment assistance in two lagging regions in Spain. Using a border discontinuity design, the study shows a decrease in out-migration and an increase in in-migration in the treated areas, resulting in a 3 percentage points increase in the average municipal population growth between 1981 and 1991. Finally, De la Roca (2017) shows that the probability of migrating jumps by a factor of eight once the UI expires.

This study also contributes to the understanding of the mechanisms that explain the positive relation between UI generosity and nonemployment duration. A fundamental question regarding unemployment benefits is whether they are subsidizing unproductive leisure (Goss and Paul, 1990) or productive job search (Nekoei and

[9] Nekoei and Weber (2017) is closely related to this paper. However, there are several dimensions that separate both studies: First, the Spanish reform affected at the UI benefit level, rather than at the UI duration. According to Schmieder and Von Wachter (2016), agents react more to the former than to the latter. Second, the distribution of the unemployment rates across regions is more uniform in Austria than in Spain. Thus, mobility may be less important as a mechanism to alleviate local labor market shocks in Austria. Finally, Nekoei and Weber (2017) studies the behavioural responses in terms of mobility (among other outcomes) by people who are around 40 years old. For this subgroup of the population, I do not find any effect either. These results go in line with the migration literature, which shows that younger workers are more prone to geographically relocate.

Weber, 2017). Overall, the results point towards the former. Namely, the findings suggest that lessen unemployment protection increases job search effort, and geographical mobility can be a possible mechanism.

The remainder of the paper is organized as follows. Section 2 provides institutional details on the Spanish unemployment benefit system and the reform. Section 3 outlines the empirical strategy used to identify the effect of interest. Section 4 describes the data used in this paper and the constraints imposed on the original sample. Section 5 discusses the results of the econometric analysis and presents some robustness checks. Section 6 concludes.

2. Institutional Setting

2.1 Unemployment Insurance in Spain

To be eligible for UI in Spain, individuals need to have worked for at least 360 days in the six years prior to the displacement.[10][11] For entitled unemployed workers, the UI duration ranges from 120 to 720 days, depending on the length of the prior contribution periods in employment (details in table A1).

The UI benefit amount results from multiplying the RR -which is time variant- by the average salary in the 180 working days preceding the unemployment. However, this amount is censored to a floor and a ceiling that depend on the Monthly Public Income Index (IPREM), and on the family circumstances (see figure 1).[12]

In comparative terms, the UI benefit duration in Spain is larger than the OECD

[10] If the worker has received another unemployment benefit during these six years, the period that is considered for the computation of the new UI is the one that elapses between the last day the worker has received the previous unemployment benefit and today's new request for UI.

[11] UI beneficiaries who take a new job before exhausting their previous UI and then return to the unemployment can choose between renewing the original entitlement for the remaining length of time or receiving a benefit based on the new contributions. If the worker chooses to recover the previous UI, the contributions that led to the new benefit will be lost.

[12] Dependants are defined as descendants who are younger than 26 or with a disability greater than 33 percent.

average, while the UI replacement rate is similar (Esser et al., 2013).

Claimants who have not accumulated enough contributions to be eligible for UI or who have exhausted their entitlement can apply for unemployment assistance (UA). The eligibility and duration depend on the length of the previous contributions and on the family responsibilities. The benefit amount for the UA has no relation with the previous earnings, and it has been recently set at 80 percent of the IPREM.

2.2 The 2012 change in the Replacement Rate: Law 20/2012

On 11 July 2012, the former Spanish President Mariano Rajoy reported a package of austerity measures aimed to reduce the fiscal deficit in Spain. One of the most controversial announcements was the reduction of the UI benefit replacement rate.[13] The main purpose of such reform was to encourage the active search for employment of unemployed workers. Despite the social discontent, the announcement become law on July 13, 2012 (Law 20/2012).[14]

Before the policy implementation, the RR was 70 percent during the first 180 days of unemployment, and 60 percent afterwards. The reform reduced the RR from 60 to 50 percent from the 181^{st} day of unemployment for workers who started their unemployment spells after July 14, 2012 (see figure A4 to get an idea on how the policy affected the average worker in the sample).

The policy was sudden and unanticipated: the announcement of the reform happened two days before its approval, and four days before its implementation.[15]

[13]None of the other additional measures changed other aspects related to the UI generosity or duration.

[14]This reform was approved by means of a law-decree. A law-decree is a form of legislation limited (in theory) to cases of extraordinary and urgent need. This type of law can be effective the following day after its publication in the State Official Bulletin (BOE) and it needs the approval of the Congress or Senate within 30 days after its publication. In this case, the law was published in the BOE on July 13, 2012. Regarding the need for approval, the conservative party had absolute majority in both chambers at the moment.

[15]Behavioural responses to the 10 percentage points reduction on the RR can just happen if the public is informed. Albeit the introduction of this policy was sudden and unanticipated, the media has extensively covered its characteristics and consequences. In fact, in the same day of the

In addition, the reduction in the benefit replacement rate was introduced in the aftermath of the economic crisis, with a large and growing unemployment rate (see figure A5). The week after the approval of the law there were important demonstrations against the cuts in different cities of the Spanish geography (see El País). Nonetheless, the unemployment insurance RR is still regulated by law 20/2012.

3. Methodology

The main contribution of this paper is the identification of the causal effect of the reduction in the UI generosity on workers' mobility decisions. To do so, the empirical analysis uses a regression discontinuity (RD) design. This approach exploits the sudden and unanticipated change in the UI benefit amount for those workers who become unemployed after July 14, 2012.

In the baseline specification, I estimate a local linear regression (Gelman and Imbens, 2018) of the form

$$Y_i = \alpha + \beta T_i + \gamma_1 (c_i - c') + \theta X_i + \epsilon_i \tag{1}$$

where Y denotes the outcome variable for individual i. In the main specification, Y_i is an indicator variable that takes the value 1 if individual i changes of geographical area during the time the worker is entitled to receive UI, 0 otherwise.[16] The treatment assignment T_i is a deterministic function of the day in which the worker starts the unemployment spell c_i and the cutoff date c'. In particular, T_i is defined as follows: $T_i = \mathbb{1}\{c_i \geq c'\}$ where $\mathbb{1}\{\cdot\}$ is the indicator function that denotes that those

announcement, all main newspapers and TV channels echoed the news. (See El País, ABC, or La Vanguardia). In addition, if you write *prestación de desempleo (UI) or recortes paro (UI cuts)* in Google trends, the results show that the popularity of these terms in Spain during the year 2012 jumped in the week the law was passed. Thus, it seems plausible to assume that the individuals were well aware of the reduction in the RR and its implications.

[16] I mainly look at mobility across provinces. However, I also estimate the effect of the reduction in the UI on mobility across urban areas and states. Furthermore, I look at the effect of the policy on the nonemployment duration and on the probability of becoming a long term unemployed.

workers who become unemployed before c' are not affected by the reduction in the benefit amount and are the control group ($T_i = 0$), while those who became displaced afterwards are affected by the policy and form the treatment group ($T_i = 1$). In this scenario, the cutoff date is July 15, 2012.

The model also includes a liner trend $c_i - c'$ that consists on the date each person enters in the unemployment minus July 15, 2012.[17] X_i is a vector of observable characteristics. It includes a set of worker traits (e.g., sex, age, amount of under-age people sharing the house with the sampled worker, three educational dummies, years of experience prior to the displacement, and earnings during the year before the unemployment), and a set of employment pre-displacement characteristics (e.g., categorical variables for open-ended contract, for private job, 13 dummies for the different types of sectors, and four skill dummies). I also control for the potential duration of the UI entitlement, and the unemployment rate in the province of last employment[18] ϵ_i captures unobservable variables.

In the main specifications, I estimate equation 1 using local linear regression with the MSE optimal bandwidth (Calonico et al., 2014) and a triangular kernel density function (Porter, 2003).[19] Standard errors are clustered on the day of entry at unemployment in order to account for potential correlation in date of entry unobservable (Lee and Card, 2008). To assess robustness I also consider alternative bandwidths and different orders of the polynomial in the running variable.

The main advantage of the RD design is that, as long as individuals do not have precise control on the day they become unemployed, the variation in the treatment is *as good as random* in a neighbourhood around the discontinuity threshold (Lee and

[17] $c_i - c'$ takes the value of 0 for workers who begin their unemployment spell on July 15, 2012. For individuals with an unemployment spell starting on July 14, 2012 the variable takes the value of -1, and so on and so forth.

[18] Albeit in the RD context conditioning for observable characteristics is not required for consistency, it improves precision.

[19] All results presented in Section 5 are robust to (1) non controlling for covariates, (2) the use of a CER-optimal bandwidth instead of MSE optimal bandwidth, and (3) the use of a uniform rather than a triangular kernel density function.

Lemieux, 2010). In this scenario, the parameter of interest β measures the causal impact of the reform.

4. Data

Data: This study uses the Continuous Sample of Working Histories (*Muestra Continua de Vidas Laborales*, or MCVL). The MCVL is a microlevel data set provided by the Spanish Ministry of Employment and Social Security since 2004. It is based on administrative records compiled from social security, income tax, and census registers. Each wave contains a 4 percent non-stratified random sample of all individuals who have any contact with the Social Security Administration (including both workers and recipients of contributory pensions -such as unemployment insurance-) during at least one day in the year the sample is selected.

The MCVL has a longitudinal design, meaning that if a person is selected in a given wave and remains in contact with the Social Security Administration, such person continues as a sample member in the subsequent editions. The data also contain complete individuals' employment histories back to the moment they have entered in the labor market (or 1967 for earlier entrants).

For each employment spell, the data include its exact start and end dates, the type of contract (fixed-term or open-ended; part-time or full-time), the social security contribution group (a proxy for occupation) and regime, an anonymized employer identifier, the type of firm (public or private), and its location, as well as monthly earnings. When the relationship with the firm ends, there is information on whether it is a voluntary or an involuntary termination. The MCVL also includes personal characteristics such as age, sex, nationality, province of birth, educational attainment, and individual's household composition.

The Estimation Sample: For the analysis, I use waves 2005-2017, and limit the sample to workers who start receiving UI at some point between 2011-2013.[20] In addition, I exclude workers whose benefit amount does not drop after the reform because (1) they are entitled to receive UI for less than 181 days, or (2) their benefit amount is above the maximum or below the minimum under both RR (see figure 1). As in previous studies, I just consider individuals who are aged between 25 and 50 at the moment they start receiving UI and who have been working in full-time jobs belonging to the general regime of the social security in the six months before the displacement.[21][22][23] Finally, I do not include those individuals who cannot be followed during the time they are entitled to receive UI. This group represents a 4 percent of the restricted sample. Albeit it is not a large amount, this creates some risks of sample selection, as the probability of leaving the sample is not equally distributed over observable characteristics. In particular, foreign born workers are remarkably overrepresented in this group.[24] Thus, I limit the analysis to workers who were born in Spain and who have Spanish nationality.

The MCVL has three crucial characteristics for the purposes of this analysis. First, unemployment spells in which workers receive UI are clearly identified. Second, the longitudinal design of the data allows to calculate the UI entitlement of each worker, both in terms of duration and benefit level. This permits to recognize those workers who are actually affected by the drop in the RR. Finally, there is information on the

[20] For those individuals who start receiving UI several times during this period, I keep the first UI spell. The analysis focuses on unemployed workers who have been working and without taking up UB for at least 720 days during the 6 years prior the unemployment. Thus, if I change the criteria and keep the last UI, I will lose an important part of the sample. Anyhow, this criterion may seem potentially arbitrary. Yet, the results are robust to keep only those workers who start receiving UI just once during the period of analysis.

[21] For very young individuals, there may be a problem of representativeness (see García-Pérez et al. (2016)). In addition, I limit the age to 50 years because there is a policy at the same time that changes the minimum age to be entitled to a particular retirement pension from 52 to 55 years.

[22] Wages and hours of work are not reliable in jobs that are not included in the general regime. In addition, those workers can have different rules regarding the UI.

[23] The way of computing the RR for part-time workers changed at the same time this policy was passed.

[24] There are two main reasons that explain why people dissapear from the MCVL: they die or they move to another country. Izquierdo et al. (2016) show that there was an increase in out-migration during the Great Recession, driven by immigrants leaving Spain.

workplace location, which allows to track individuals across space.[25]

Descriptive Statistics: Table 1 reports the summary statistics. The main outcome variable is the change of province. This is a binary variable taking the value 1 if the UI recipient has changed of province during the period the person is entitled to receive UI, and 0 otherwise (the "baseline" province is where the worker was working before the displacement). Table 1 shows that the average mobility among UI beneficiaries is 16 percent. It is relevant to indicate that this changes of province do not necessary imply a change in the province of residence. Instead, they reflect a change in the province where workers have their relationship with the social security administration -in terms of working, receiving unemployment benefits, or receiving a contributory pension-.

Regarding the covariates included in the analysis, 60 percent of individuals in the sample are men. The average person is around 36 years old, and has no dependent. 14.5 percent of them have tertiary education, and 29 percent have completed secondary education. The other 56 percent have less than secondary education. The average time of experience is 13 years, and the average earnings during the year prior to the unemployment (wages are deflated to 2009 Euro using the CPI) is €16,391. Regarding the characteristics of their previous employment, 12 percent worked in a job that requires a high level of skills, 21.4 (44.8) percent of workers had a job that implied a medium-high (medium-low) level of skills, and 21.6 percent had a low skilled occupation. In addition, 67 percent of the sample had an open-ended contract, and 93 percent of the sample worked in the private sector. The average unemployment in the last province of employment and in the term they got displaced was 23 percent. In addition, they are entitled (on average) to 20 months of UI benefits.

[25] The dataset provides information on firm location at a municipal level. In particular, the variable that identifies firm location is composed by 5 digits, two of them that identify the province and three more that correspond to the municipality. However, the three digits that allow for the identification of the municipality are just informative when it has more than 40,000 inhabitants. Therefore, desegregating the location to less than a provincial level implies a high cost in terms of losing information, especially because more than half of the population in Spain reside in municipalities with less than 40,000 inhabitants.

5. Results

The main aim of this paper is to estimate the causal effect of the UI generosity on workers' mobility decisions. The identification strategy -RD design- relies on comparing the behavior of workers who become unemployed around the date of the policy change. Before moving to the RD results, I present the standard validity checks (Cattaneo et al., 2018a).

5.1 Validity of the RD Approach

The main threat to validity of the RD design is the possibility that workers or employers manipulate the date of the layoffs to land below the threshold. However, I find stratification unlikely in this scenario. First, workers have no control on the timing of their dismissals.[26] Second, the reform was implemented three days after its announcement. This leaves no room for manipulation to employers, who are obliged to give a 15-day written notice to the employees who are being laid off.[27] Anyhow, whether sorting around the cutoff affects the analysis is an empirical question. To solve it, I examine both the density of observations and the balance in covariates around July 15, 2012.

Figure A6 shows the number of UI entries before and after the UI benefit amount cut. There is no graphical evidence of manipulation on the timing of the layoffs around the cutoff date. This visual impression of continuity is supported by the results of implementing the density test of the running variable proposed by Cattaneo et al. (2018b), which indicates that the discontinuity at the cutoff is equal to 0.1615 (p-value 0.8717).[28]

In order to test whether there is endogenous sorting around the threshold I esti-

[26] Recall that workers who voluntarily quit their jobs are not eligible for UI.

[27] In addition, there is no reason to think that firms are interested in strategically move the date of dismissals so that their employees can land on the control group.

[28] Figure A6 also indicates that the number of entries in the UI is noisy, with special peaks at the beginning of each month.

mate equation 1 using as dependent variables the background covariates I include in the analysis as controls. The results (see table A2) show that there are no systematic differences in any of the observable characteristics between those workers who became unemployed just before and just after July 15, 2012.

Overall, these checks support the validity of the RD approach.

5.2 The effect of the UI reduction on unemployment duration

Before moving to the main results, this section analyzes the effect of the UI benefit cut on nonemployment duration and subsequent labor market outcomes. The positive effect of UI on nonemployment length is among the most robust empirical findings in economics (Nekoei and Weber, 2017). For the Spanish scenario, Rebollo-Sanz and Rodríguez-Planas (2018) uses a difference-in-differences (DiD) strategy to study the causal effect of the 10 percentage points cut in the UI replacement rate on the nonemployment duration. In particular, they compare workers who become unemployed in 2012, before and after the 15 July 2012, to similar workers who got displaced at the same time but who were entitled to less than 180 days of UI. Rebollo-Sanz and Rodríguez-Planas (2018) shows that reducing the RR by 10 percentage points increases workers' probability of finding a job by 41 percent relative to similar workers who were not affected by the reform (i.e., the reform reduced the mean expected duration of the unemployment spell by 5.7 weeks). In this section, I aim to replicate the findings by Rebollo-Sanz and Rodríguez-Planas (2018) using a different empirical strategy and sample. I therefore estimate equation 1 using as outcome variable the time that elapsed between the unemployment situation and the next employment. Figure A7a and table A4 present the results. I estimate that the policy reduced the unemployment duration by almost three months. Because the average nonemployment length before the reform was 15.77 weeks, the estimates represent a reduction in the nonemployment duration of 18 percent with respect to the pre-reform mean. Interestingly, I find that the reform did not affect at wages, occupation, or tenure in the first employment after displacement (see table A7).

Finally, figures A7b and A7c look at the effect of the policy reform on the probability of becoming a long term unemployed worker. As Schmieder et al. (2012) states, looking just at the initial effect of UI on nonemployment can lead to an understatement of the cost of UI extensions, if such extensions increase the incidence of nonemployment beyond the initial spell, as would be predicted by models of stigma, skill depreciation, or supply-side hysteresis. In this case, the results presented in table A5 and A6 indicate that indeed, the UI cut reduced the probability of becoming a LTU worker.

5.3 Main Results

I begin with a graphical illustration of the research design. Figure 2 plots the proportion of workers who have moved to a different province during the time they are entitled to benefit from UI against the date these workers start their unemployment spells. The illustration reveals a positive jump in mobility at the discontinuity.

Table 2 presents the results of estimating the coefficient of the parameter of interest β in equation 1 using six different specifications. The outcome variable is binary and takes the value 1 if an UI recipient has changed of province during the period the worker was entitled to receive UI, and 0 otherwise. The first column estimates β using a local linear approach with MSE-optimal bandwidth and without including controls. The RD estimate indicates that the reduction in the UI generosity increases mobility by 4 percentage points. In terms of magnitude, this represents a 25 percent increase with respect to the pre-reform mean. The results are robust to the inclusion of second (Columns 2 and 5) and third (Columns 3 and 6) order polynomials, as well as controls (Columns 4, 5, and 6). In addition, figure 3 shows that the increase in mobility due to the UI benefit cut happened from the beginning of the unemployment spell.

Notice that the measure of mobility is based on the province workers have their relation with the Social Security Administration. Therefore, the previous results could be due to an increase in the amount of people who commute, or to an increase in the quantity of workers who change their province of residence. In order to shed some light on this, I estimate equation 1 looking at whether the policy has affected the probability to migrate to non-neighbouring provinces. Table 3 suggest that the effect of the UI cut on mobility is mainly due to actual changes in the province of residence rather than to more people commuting to other provinces.[29]

5.4 Robustness

In the next paragraphs, I will test the robustness of the main results. To do so, I first estimate Equation 1 using alternative bandwidths (from fifteen days before and after the cutoff date to three months around July 15, 2012). The results are presented in Table A3, and they show that the findings in section 5.2 are not due to the bandwidth selection.

I also perform several placebo tests. First, I artificially move the cutoff date to the 15 of each month from February 2011 to November 2013. Figure A8 presents the results. The coefficients of the estimated parameter β are smaller in magnitude -with respect to the estimations in Table 2 - and statistically undistinguishable from zero. Table A8 presents a supplementary falsification test. In particular, it shows the results of estimating equation 1 using unemployed workers entitled to receive UI between 4 and 6 months.[30] The coefficients for the parameter β are smaller in magnitude than the true point estimates and they are indistinguishable from zero. Overall, these results support the idea that the findings in section 5.2 are in fact due to the reduction in the UI benefit generosity.

Yet, one additional concern about the results presented in table 2 is that they

[29]Note that the smallest province in Spain is Gipúzkoa. To cross it from east to west (minimum distance) takes an hour and a half by car. Thus, commuting distance across non-neighbouring provinces are very large.

[30]The drop in the RR happens after 180 days of unemployment. Thus, workers entitled to perceive UI during six or less than six months are not affected by the cut in the UI benefit amount.

may be driven by seasonality. In order to rule out this possibility, I supplement the RD approach with the following specification in Equation 2

$$Y_i = \alpha + \beta T_i + \gamma_1(c_i - c') + \theta X_i + \sum_{i=1}^{12} Month_i + \sum_{i=1}^{3} Year_i + \epsilon_i \tag{2}$$

The sample for this estimation contains those workers who become unemployed between 2011 and 2013. Including several years allows to control for seasonality by adding calendar month and year fix effects. The results -in figure A9- show the coefficients of the parameter β in equation 2 for different samples. The coefficient represented by a circle results from estimating equation 2 with workers who have started their unemployment spells between July 15, 2011 and July 15, 2013. The point estimate denoted with a square represents the effect of the policy on labor mobility for workers who were laid-off between October 15, 2011 and April 15, 2013. The sample used to estimate the result that appears represented with a triangle is composed by those unemployed workers who have started an unemployment spell between March 15, 2011 and November 15, 2011 or between March 15, 2012 and November 15, 2012. Next, the group is limited to those workers who start receiving UI between June 1 and August 30 in 2011 and 2012. For this case, the point estimate is represented by a rhombus. Finally, the empty circle represents the coefficient that results from estimating Equation 2 looking at workers who got displaced one month around July 15, both in years 2011 and 2012. Overall, the results show that the previous estimations are not due to the seasonality around the months of the policy.

5.5 Further results

Heterogeneity

To better understand the effect of the UI benefit cut on geographical mobility, this section looks at the heterogeneity of the effect across individuals with different observable characteristics.

I present the results in table 4.

Panel A shows the outcomes of estimating equation 1 dividing the sample by sex. The results indicate that men are the ones who respond to the policy by geographically relocating. As a matter of fact, the increase in mobility documented in section 5.2 is entirely driven by men. This is consistent with the migration literature, that shows that men are more mobile than women, as they benefit more from relocation (DaVanzo, 1976; Morrison and Lichter, 1988; Gemici, 2011).

In panel B we divide the sample in two groups depending on the age of workers at the beginning of their unemployment spell. Consistent with previous literature (see Borjas et al. (1992)), younger workers (defined as workers who are less than 36 years old) are the ones who react to the UI cut by geographically relocating.

Panel C looks at the effects of the policy on mobility across groups with different family responsibilities. Namely, Panel C divides the sample between those workers who have and who have not dependants in charge.[31] The results indicate that individuals without family responsibilities react more to the approval of the law 20/2012 in terms of relocation. A plausible explanation is that dependants remarkably increase the costs of migration (Mincer, 1978).

Another characteristic that is relevant in the migration literature is the educational attainment. The studies agree that educated individuals are more mobile than less educated workers, as they have more information and they expect greater gains from migration (Long, 1973). Results in Panel D coincide with prior findings: unemployed workers with tertiary education increase their mobility after the UI cut.

Panel E in Table 4 divides the sample in three groups depending on the labor earnings of the year before they become unemployed (deflated to 2009 euro using the CPI). For the sample we analyse, workers located at the 25% bottom of the income distribution are those with earnings below €13,887.18 . The top 25% is

[31] Dependants are defined as descendants younger than 26 or with a disability grater than 33%; or ancestors older than 65 or with a disability greater than 33% who live with the person who became unemployed.

made up by those unemployed workers with pre-earnings above €19,830.44. This panel may be specially interesting as the literature shows that workers face important liquidity constraints at unemployment (Rothstein and Valletta, 2017). In this sense, unemployment benefits can help to fund moving costs to unemployed workers who are willing to look for jobs and to work in distant labor markets (Ardington et al., 2009). What Panel E shows is that just those workers who do not face liquidity constrains -they are located at the top 25% of the income distribution - react to the reduction in the benefit amount of the UI by changing of province.

Mobility across urban areas and regions

In this section, I analyze whether the previous findings are robust to additional definitions of geographical units. Namely, I look at mobility across urban areas and autonomous regions (*Comunidades Autónomas*)[32].[33]

Table 5 looks at the effect of the UI cut on mobility across urban areas. This definition is quite interesting as urban areas are a good approximation for local labor markets. Yet, a word of caution is needed. Because we can just identify municipalities with more than 40,000 inhabitants, many municipalities that belong to urban areas cannot be followed. Because of this, I loss 50 percent of the baseline sample. Still, the results presented show that the reform has increased mobility across urban areas by 6 percentage points, a 28 percent increase in relation with the pre-reform mean.

Table 6 presents the results of estimation equation 1 looking at mobility across regions. The RD estimates indicate that the reduction in the UI generosity increases mobility across states by 5 percentage points. Because geographical relocation across states before the reform was about 11 percent, the results indicate that the policy

[32] Spain consists of 17 autonomous regions (which are comparable to states in other countries). Seven out of the seventeen regions cover just one province.

[33] The definition of urban area is constructed by the Spain's Ministry of Development since 2008. In Spain, there are 85 urban areas. Despite they account for just 10% of the surface, more than 68% of the population lives in urban areas. In addition, less than 25% of the employment happens outside urban areas.

change increased mobility acrossst ates by 45 percent with respect to the pre-reform mean. It is interesting that the increase in mobility across provinces and the increase in mobility across regions due to the policy change are remarkably similar. Therefore, I analyze whether all the mobility effect is driven by mobility across states and not within states. Table 7 shows the results of estimating equation 1 using as dependent variable a categorical variable that takes the value 1 if the worker has changed of province but non of state, 0 otherwise. The results show that the increase in mobility across provinces is mainly caused by an increase in mobility across states.

6. Conclusion

Labor mobility is an efficient mechanism to reduce the labor market disparities across regions. Yet, geographical relocation in the EU -across and within countries- is quite limited. This paper studies the effect of the UI generosity on recipients' mobility decisions.

To establish a causal link, I analyze an exogenous reduction in the Spanish UI benefit amount for workers who were laid-off after July 14, 2012. The results show that the cut in the UI generosity increases unemployed workers' mobility by 4 percentage points. In terms of magnitude, this represents a 25 percent increase with respect to the pre-reform mean. Educated and young men without family responsibilities and at the top 25 percent of the sample income distribution drive the results.

This paper is closely related to Rebollo-Sanz and Rodríguez-Planas (2018), which exploits the same reform. Rebollo-Sanz and Rodríguez-Planas (2018) find that the 10 percentage points drop in the UI replacement rate reduces the expected non-employment duration by 5.7 weeks, without affecting workers' job-match quality. The results presented in this paper point towards geographical mobility as a relevant job-search mechanism to reduce the nonemployment length.

This work has important policy implications. As Chichester (2005) stated in an

OECD policy paper *Although promoting geographic mobility is not an end in itself, removing obstacles to internal migration may be an important policy issue, especially in countries where regional disparities are pronounced.* While further empirical studies are needed, the results presented in this study suggest that changing the UI design may reduce the moral hazard problems associated to UI observed in the data, increasing the incentives for job search.

In particular, the results seem to indicate that front-loading the payment of the unemployment benefits (i.e., large RR at the beginning of the unemployment spell, but decreasing steeply over the duration of the non-employment situation) could potentially increase search-effort (e.g., intensifying geographical mobility), and reduce nonemployment duration. This policy prescription was already made in Spain by the *Manifiesto de los 100 economistas*.[34] To the best of my knowdlege, Lindner and Reizer (2016) present the only empirical causal evidence on the effects of front-loading the UI. Albeit they do not look at the mechanisms, they show that front-loading unemployment benefit payments in Hungary reduced non-employment durations, increased re-employment wages, and improved the government's budget balance.

[34]The *Manifiesto de los 100* is a document signed in 2009 by one hundred leading Spanish economists that contains economic measures to reactivate the Spanish labor market.

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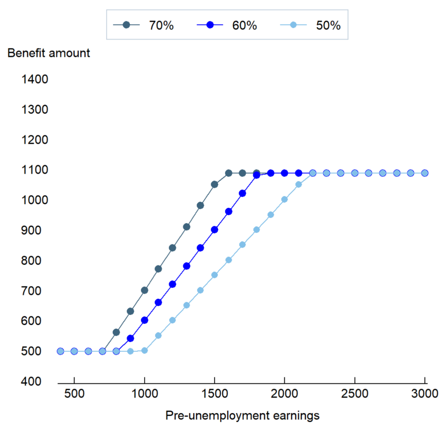
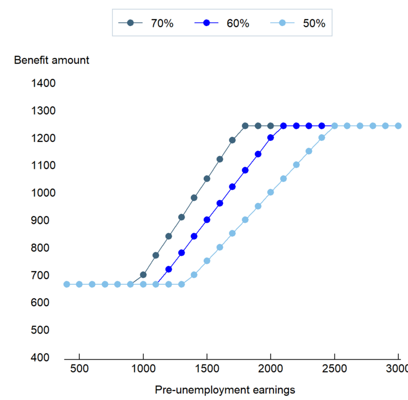
Figures & Tables

Figure 1: UI Benefit Amount

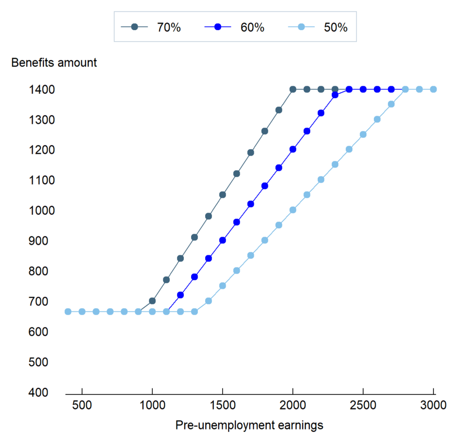
(a) No Dependants



(b) One Dependant



(c) More than One Dependant



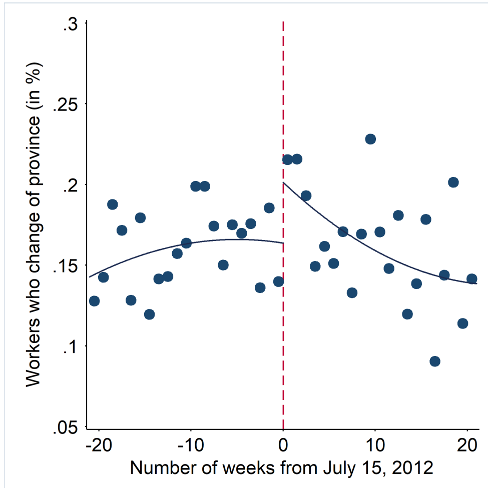
Note: I calculate the unemployment benefit amount for displaced workers with different family circumstances. The "70%-line" corresponds to the benefit amount unemployed workers receive in the first 180 days of unemployment. The "60%-line" ("50%-line") corresponds to the UI benefit amount in the remainder of the unemployment spell for workers who become unemployed before July 15, 2012 (from July 15, 2012 onwards). From 2010 to 2016, the IPREM index was fix. This implies that the maximum and minimum UI benefit were constant during this period. Specifically, the UI benefit amount for displaced workers could not be below €497.01 for people with no dependants or below €664.75 for workers with dependants in charge. In addition, the benefit amount could not exceed €1,087.20 if the displaced worker had no dependants, nor €1,242.52 or €1,397.84 for unemployed individuals with one and more than one dependants respectively.

Table 1: Summary Statistics

	All (1)	Pre-reform (2)	Post-reform (3)	Difference ((3)-(2))
Main Outcome Variables				
Change of Province	0.163	0.1631	0.166	0.004
	[0.370]	[0.368]	[0.371]	(0.004)
Covariates				
Panel A: Worker characteristics				
Male	0.599	0.612	0.584	-0.029***
	[0.490]	[0.487]	[0.493]	(0.006)
Age(years)	36.47	36.28	37.71	0.427***
	[6.769]	[6.769]	[6.750]	(0.081)
Dependents	0.591	0.588	0.595	0.006
	[0.844]	[0.839]	[0.841]	(0.007)
Below secondary education	0.564	0.583	0.541	-0.04***
	[0.496]	[0.493]	[0.498]	(0.006)
Secondary education	0.291	0.285	0.298	0.01**
	[0.454]	[0.451]	[0.457]	(0.005)
Tertiary education	0.145	0.131	0.162	0.03***
	[0.351]	[0.338]	[0.367]	(0.004)
Experience(years)	12.896	12.627	13.474	0.847***
	[6.622]	[6.634]	[6.560]	(0.074)
Earnings (in log)	9.683	9.689	9.671	-0.018***
	[0.367]	[0.374]	[0.351]	(0.004)
Panel B: Last employment characteristics				
High skill occupation	0.122	0.115	0.137	0.022***
	[0.328]	[0.319]	[0.344]	(0.004)
Medium-high skill occupation	0.214	0.206	0.231	0.025***
	[0.410]	[0.405]	[0.422]	(0.005)
Medium-low skill occupation	0.448	0.459	0.421	-0.038***
	[0.497]	[0.498]	[0.494]	(0.006)
Low skill occupation	0.216	0.219	0.210	-0.08*
	[0.412]	[0.413]	[0.408]	(0.005)
Private firm	0.932	0.934	0.929	-0.004*
	[0.251]	[0.248]	[0.257]	(0.003)
Open-ended contract	0.673	0.656	0.708	0.05***
	[0.469]	[0.475]	[0.455]	(0.005)
Panel C: Local labor markets				
Unemployment rate	22.81	21.50	25.64	4.133***
	[6.453]	[6.003]	[6.483]	(0.069)
Panel D: UI characteristics				
UI duration	20.30	20.15	20.64	0.496***
	[5.193]	[5.212]	[5.134]	(0.058)
Observations (N)	27,698	15,319	12,379	27,698

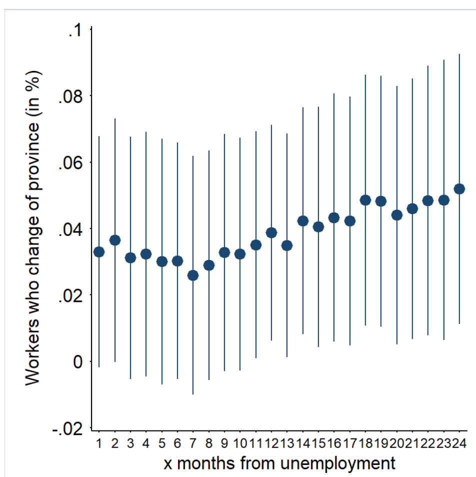
Note: Columns 1-3 report means and standard deviations in brackets. Column 4 reports differences of groups means between columns 3 and 2 with standard errors in parenthesis. ***,**,and * denote significance at the 1,5 and 10 percent levels.

Figure 2: Graphical illustration of the RD design



Note: The figure plots the proportion of workers who have moved to a different province during the time they are entitled to receive UI (y-axis) against the week workers start receiving UI (x-axis). The vertical line represents the week of the policy implementation. The lines represent the fitted values based on a fourth order polynomial without covariates. The IMSE-optimal number of quantile-spaced bins is 24 bins below the cutoff and 30 above it. The average bin length is around 3 weeks below the cutoff and two and a half above it.

Figure 3: Mobility Decision



Note: The figure the cumulative probability of moving during the unemployment spell. For example, the point represented in $x = 8$ results from estimating the local linear model in equation 1 using as dependent variable a categorical variable that takes the value 1 if the person has changed of province during the first 8 months since the start of the unemployment spell, 0 otherwise.

Table 2: Effect of the reform on geographical mobility

Outcome	Mobility across provinces					
Bandwidth	Optimal bandwidth					
Days around the reform	111.743	175.936	212.955	109.358	171.550	209.504
Reform (T_i)	0.04**	0.05**	0.06**	0.04**	0.05**	0.06**
	[0.019]	[0.022]	[0.026]	[0.020]	[0.023]	[0.028]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	6,037	9,817	11,942	5,893	9,543	11,653

Note: The outcome variable is a dummy that takes the value 1 if workers have changed of province during their UI entitlement length, 0 otherwise. All results are calculated using the MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 1 estimates β from the local linear model specified in Equation 1. Columns 2 and 3 include higher order polynomials, and Columns 4 to 7 also include controls (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required, and dummies for 14 sectors. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous increase in mobility at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Effect of the reform on mobility across non-neighbouring provinces

Outcome	Mobility across non-neighbouring provinces					
Bandwidth	Optimal bandwidth					
Days around the reform	97.458	132.683	189.316	88.189	132.692	193.867
Reform (T_i)	0.03**	0.05***	0.05***	0.04**	0.05***	0.06***
	[0.014]	[0.016]	[0.018]	[0.015]	[0.017]	[0.019]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	5,225	7,090	10,470	4,677	6,995	10,551

Note: The outcome variable is a dummy that takes the value 1 if workers have changed to a non-neighbouring province during their UI entitlement length, 0 otherwise. All results are calculated using the MSE-optimal bandwidth suggested byCalonico et al. (2014). Column 1 estimates β from the local linear model specified in Equation 1. Columns 2 and 3 include higher order polynomials, and Columns 4 to 7 include also controls (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required, and dummies for 14 sectors. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous increase in mobility at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of the reform on geographical mobility by group

Outcome	Mobility across provinces					
Panel A: According to gender						
Only Men	0.06**	0.08**	0.10**	0.06**	0.07**	0.10**
	[0.028]	[0.034]	[0.041]	[0.028]	[0.034]	[0.041]
Only Female	0.00	0.01	0.01	-0.00	0.01	0.02
	[0.029]	[0.034]	[0.038]	[0.029]	[0.033]	[0.039]
Panel B: According to age						
≤ 35	0.06*	0.15***	0.17***	0.09**	0.17***	0.18***
	[0.034]	[0.048]	[0.051]	[0.040]	[0.050]	[0.052]
> 35	0.00	-0.03	-0.05	-0.01	-0.03	-0.05
	[0.023]	[0.032]	[0.038]	[0.024]	[0.032]	[0.037]
Panel C: According to family responsibilities						
With dependents	0.02	0.03	0.01	0.02	0.02	0.01
	[0.024]	[0.029]	[0.036]	[0.022]	[0.029]	[0.036]
Without dependents	0.08***	0.11***	0.11***	0.08**	0.11***	0.13***
	[0.032]	[0.036]	[0.039]	[0.034]	[0.039]	[0.041]
Panel D: According to education						
Below secondary	0.04*	0.04	0.03	0.03	0.03	0.04
	[0.020]	[0.029]	[0.037]	[0.021]	[0.028]	[0.039]
Secondary education	0.02	0.04	0.03	0.01	0.04	0.03
	[0.039]	[0.047]	[0.047]	[0.040]	[0.046]	[0.047]
Tertiary education	0.06	0.08	0.10	0.06	0.09*	0.12**
	[0.045]	[0.06]	[0.070]	[0.043]	[0.048]	[0.061]
Panel E: According to earnings						
25% bottom income dist.	0.01	0.05	0.08*	0.01	0.04	0.07
	[0.030]	[0.041]	[0.050]	[0.031]	[0.041]	[0.048]
25-75% income dist.	0.04	0.05	0.05	0.04	0.04	0.05
	[0.026]	[0.031]	[0.035]	[0.026]	[0.031]	[0.034]
25% top income distr.	0.08*	0.10*	0.14**	0.09*	0.12**	0.16**
	[0.045]	[0.052]	[0.067]	[0.045]	[0.055]	[0.066]
Panel F: According to province of last employment (PLE)						
PLE is the province of birth	0.02	0.02	0.02	0.02	0.02	0.02
	[0.018]	[0.023]	[0.028]	[0.018]	[0.021]	[0.026]
PLE is not the province of birth	0.03	0.05	0.05	0.04	0.06	0.07
	[0.030]	[0.039]	[0.048]	[0.032]	[0.040]	[0.047]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
N	26,883	26,883	26,883	26,883	26,883	26,883

Note: The table reports the coefficient of the parameter β based on estimating equation 1 separetely for each of the different groups. The bandwidth is calculated using MSE-optimal bandwidth, suggested by Cattaneo et al. (2018b). Standard errors (in brackets) are clustered at the day of entry at unemployment. In column (1) we estimate a local-linear regression. We add covariates in column (2). Column 3 shows that the results are robust to change the functional form (inclusion of second order polynomials). *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of the reform on geographical mobility across urban areas

Outcome	Mobility across urban areas					
Bandwidth	Optimal bandwidth					
Days around the reform	98.883	150.408	197.115	102.650	147.630	196.745
Reform (T_i)	0.06**	0.08**	0.09**	0.06**	0.08**	0.10**
	[0.030]	[0.035]	[0.039]	[0.030]	[0.035]	[0.040]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubi
Covariates				✓	✓	✓
Eff. N	2,670	4,156	5,666	2,699	4,025	5,585

Note: The outcome variable is a dummy that takes the value 1 if workers have changed of urban area during their UI entitlement length, 0 otherwise. All results are calculated using the MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 1 estimates β from the local linear model specified in Equation 1. Columns 2 and 3 include higher order polynomials, and Columns 4 to 7 include also controls (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required, and dummies for 14 sectors. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous increase in mobility across urban areas due to the policy change.

Table 6: Effect of the reform on geographical mobility across states

Outcome	Mobility across states					
Bandwidth	Optimal bandwidth					
Days around the reform	87.067	138.702	192.647	80.463	138.467	195.550
Reform (T_i)	0.04***	0.06***	0.06***	0.05***	0.06***	0.06***
	[0.014]	[0.019]	[0.020]	[0.018]	[0.020]	[0.021]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	4,686	7,466	10,572	4,309	7,366	10,597

Note: The outcome variable is binary and takes the value 1 if workers have changed of state during their UI entitlement length, 0 otherwise. First column estimates β from the local linear model specified in equation 1. In the first column, as well as in columns 2 and 3, the bandwidth is calculated using MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 2 adds covariates to the previous specification (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Column 3 includes a quadratic control function on the running variable. Finally, the last 6 columns look at alternative and bandwidths in order to assess the robustness of the analysis. Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous increase in mobility across states at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of the reform on geographical mobility across provinces within states

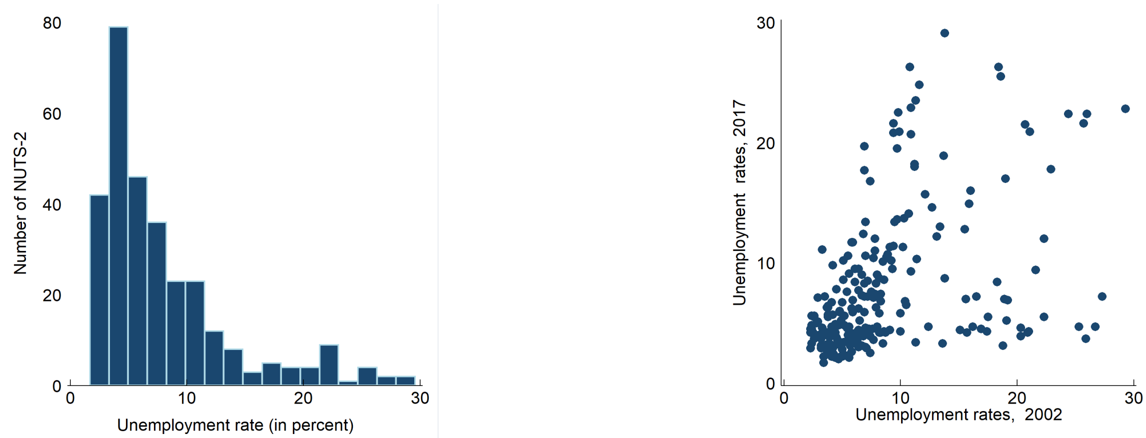
Outcome	Mobility across provinces within states					
Bandwidth	Optimal bandwidth					
Days around the reform	226.022	181.534	275.992	167.043	177.564	262.089
Reform (T_i)	0.01*	0.01	0.00	0.01	0.00	0.00
	[0.009]	[0.013]	[0.014]	[0.009]	[0.013]	[0.014]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	12,560	10,102	15,320	9,111	9,793	14,497

Note: The outcome variable is binary and takes the value 1 if workers have changed of state during their UI entitlement length, 0 otherwise. First column estimates β from the local linear model specified in equation 1. In the first column, as well as in columns 2 and 3, the bandwidth is calculated using MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 2 adds covariates to the previous specification (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Column 3 includes a quadratic control function on the running variable. Finally, the last 6 columns look at alternative and bandwidths in order to assess the robustness of the analysis. Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous increase in mobility across states at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Figure A2: Local Unemployment Rates in the EU-28

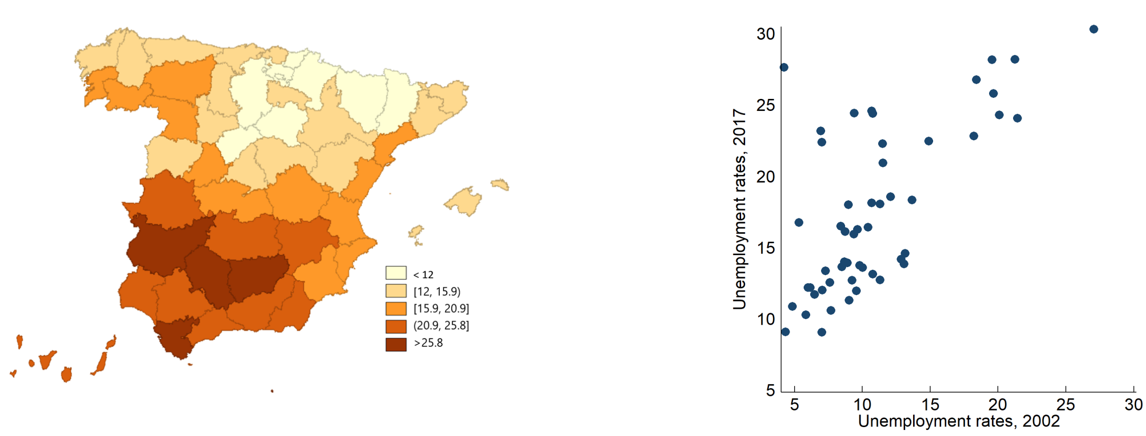
(a) Unemployment Distribution, 2017 (b) Unemployment Persistence



Note: Figure A2a shows the distribution of the unemployment rates in the 273 EU NUTS-2 regions (territorial units with an average of 1.8 million inhabitants). The histogram points towards tremendous regional disparities in unemployment. Namely, unemployment rates in 2017 ranged from less than 3 percent in Praha (Czech Republic) or Trier (Germany), to more than 25 percent in Dytiki Makedonia (Greece), or Andalucía (Spain). Apart from such an uneven distribution across space, local unemployment rates exhibit strong persistence over time. Figure A2b plots local unemployment rates in 2002 against the rates in 2017. The figure depicts that local unemployment rates in 2017 were significantly correlated with those of 15 years before. *Source: Eurostat.*

Figure A3: Local Unemployment Rates in Spain

(a) Unemployment Distribution, 2017 (b) Unemployment Persistence



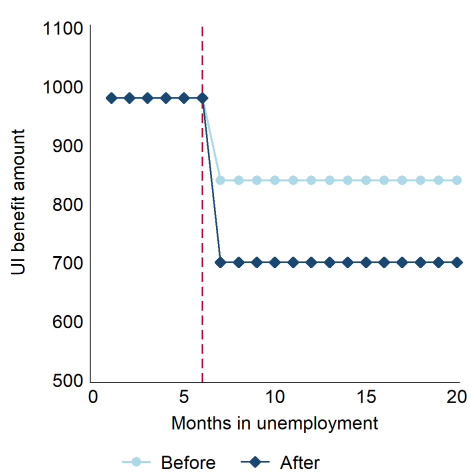
Note: Figure A3a shows the unemployment rate by province or NUTS-3 regions (this represents territorial units with an average population of about 0.9 million inhabitants) in Spain in 2017. The map shows large disparities in unemployment, with some provinces in the south having an unemployment rate twice as large as some provinces in the north. In addition, figure A3b shows that local unemployment rates in 2017 were highly correlated (0.68) with those in 2002. *Source: Spanish National Institute of Statistics (INE).*

Table A1: UI Duration

Accumulated employment days within the last 6 years	UI duration (days)
Less than 360	0
360 - 539	120
540 - 719	180
720 - 899	240
900 - 1,079	300
1,080 - 1,259	360
1,260 - 1,439	420
1,440 - 1,619	480
1,620 - 1,799	540
1,800 - 1,979	600
1,980 - 2,159	660
2,160 or more days	720

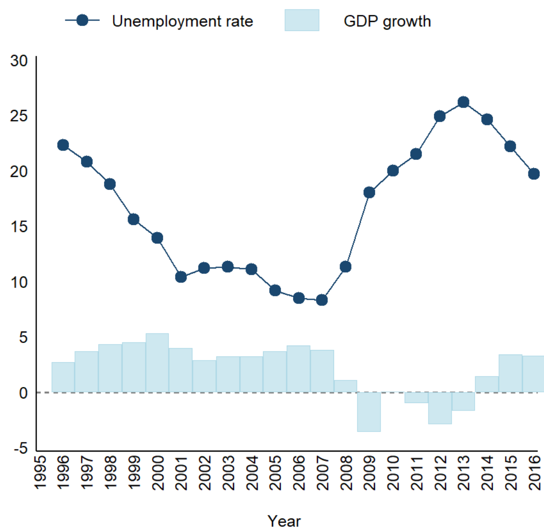
Note: Just employees who have worked under a Social Security regime that covers against the situation of unemployment during at least 360 days in the six years previous to the displacement are entitled to receive UI. For workers with this minimum amount of contributions, the minimum length of UI is 120 days. For each additional 180 days contributed the UI duration increases around 60 days, up to a maximum of 720 days. *Source: Servicio Estatal de Empleo, SEPE*

Figure A4: Effect of the RR Drop on the UI Benefit Amount



Consider two identical individuals with an average gross wage in the 180 days prior displacement of €1,400, no family responsibilities, and who are entitled to 20 months of UI (average person in the sample). The only difference between these two workers is that one of them (worker A) got displaced on July 13, 2012, whereas the other one (worker B) started the unemployment spell on July 16, 2012. Figure A4 represents how the policy affects to these representative workers in the sample. During the first 6 months of unemployment, both receive €980. However, after the 6 month, worker A receives €840 in terms of unemployment benefits per month, while worker B monthly UI benefit amounts €700. Conditioning on exhausting their UI entitlement, worker B would receive €2,000 less of UI than worker A.

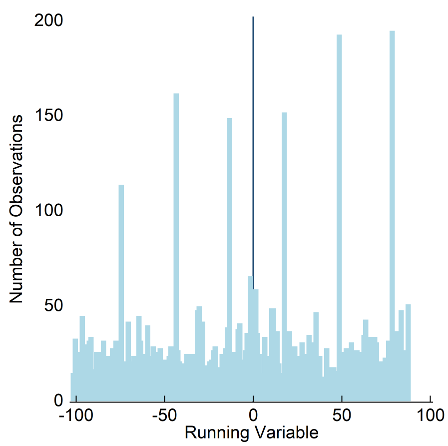
Figure A5: Unemployment Rate and GDP Growth over Time in Spain



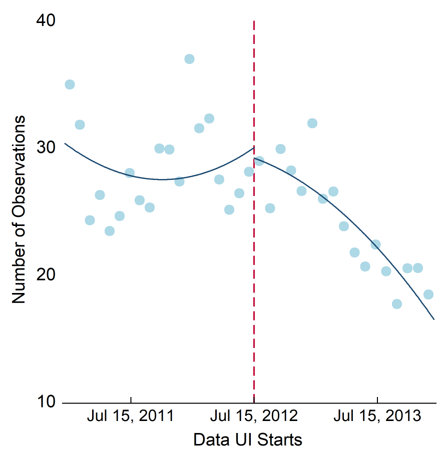
Source: Spanish National Institute of Statistics (INE)

Figure A6: Distribution of UI Inflows

(a) Histogram



(b) RD Plot



Note: Figure A6a shows the graphical representation of running the density test for the running variable proposed by Cattaneo et al. (2018b). Formally, the value of the statistic is positive (0.1615), bus statistically undistinguishable from 0 (p-value of 0.8717). Figure A6a also indicates that the distribution of UI entries is not random, as there are important peaks at the beginning of each month (the average number of workers who start UI per day is 26 (see figure A6b), while the average amount of workers who start receiving UI on the first day of the month is 154). Figure A6b plots the average number of workers on the y-axis and the day they start receiving UI on the x-axis. The MV-optimal number of evenly distributed bins is 19 below the cutoff and 17 above it. The average bin length is around 30 days in both sides. Both figures suggest that there is no bunching around the cutoff of July 15, 2012. A6b also points towards a decrease in the number of new UI recipients over time, reflecting the recovery of the Spanish economy after the second term of 2013.

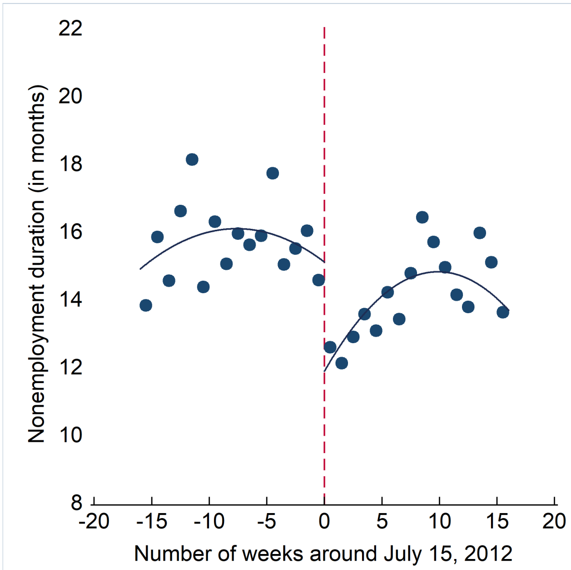
Table A2: Balanced test on Covariates

	RD estimate	Standard errors	Eff. N
Panel A: Worker Characteristics			
Male	-0.02	0.022	6,184
Age (in years)	-0.13	0.233	6,140
Less than secondary education	0.00	0.022	8,436
Secondary education	-0.01	0.028	5,609
Tertiary education	-0.00	0.015	5,339
Dependents	0.11	0.072	5,158
Experience (in years)	-0.09	0.154	6,695
Earnings in the year prior the displacement (in logs)	0.01	0.023	5,339
Panel B: Last Employment Characteristics			
High occupation	-0.01	0.019	5,669
High-Medium occupation	-0.00	0.023	5,262
High-Low occupation	0.02	0.027	4,809
Low occupation	-0.01	0.019	6,284
Private firm	-0.00	0.009	3,908
Open-ended contract	0.00	0.020	5,921
Agricultural sector	0.00	0.005	4,583
Manufacturing	-0.02	0.018	6,515
Utilities	0.00	0.004	5,921
Construction	0.02	0.025	5,960
Trade	0.02	0.021	4,360
Transport and storage	0.01	0.013	5,230
Accommodation and food services	-0.02	0.013	3,908
Information and communication	-0.02	0.014	6,465
Finance, insurance, and real state activities	-0.00	0.004	6,643
Professional, scientific, and technical activities	0.00	0.012	6,140
Administrative and support activities	-0.01	0.014	6,284
Education, human health, and social work	0.02	0.016	3,547
Other services	-0.01	0.010	8,008
Public administration sector	0.01	0.011	3,677
Panel C: Local labor market			
Unemployment rate	-0.15	0.543	4,677
Panel D: UI characteristics			
Maximum UI entitlement (months)	-0.24	0.231	5,339

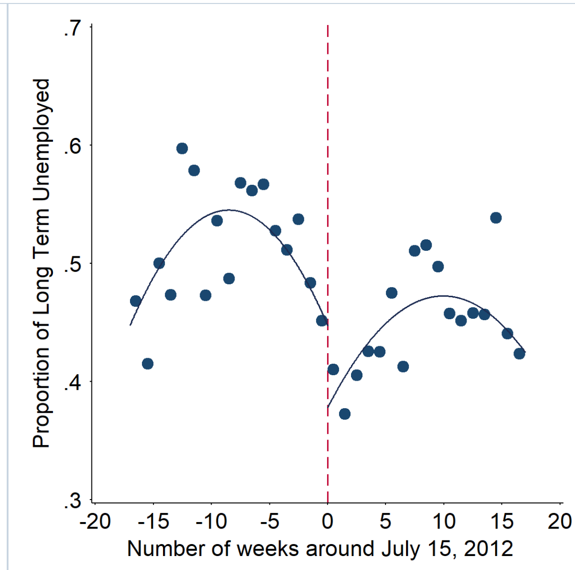
Note: The table shows the RD results of estimating equation 1 using as outcome variables the control variables of the original model. The bandwidth for each regression is estimated separately using CER-optimal bandwidth (see Cattaneo et al. (2018a)). All regression include covariates. Standard errors are clustered by day of starting the UI. Panel A focuses on workers' characteristics, and Panel B on those of the workers' last employment; Panel C looks at the unemployment rate on the province of last employment for each individual during the term they become unemployed; and panel D at the UI duration each sampled worker is entitled to receive. None of the coefficients is statistically distinguishable from 0. This test supports the validity of the RD design. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A7: Effect of the Reform on Labor Market Outcomes

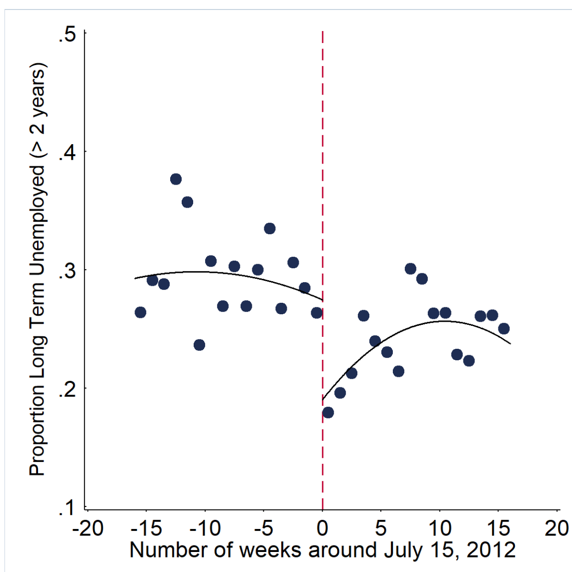
(a) Nonemployment Duration



(b) Long Term Unemployment (> 1 year)



(c) Long Term Unemployment (> 2 years)



Note:

Table A3: Alternative bandwidths

Outcome	Mobility across provinces					
Days around the reform	15	30	45	60	75	90
Reform (T_i)	0.11***	0.08**	0.07**	0.06**	0.05**	0.05**
	[0.040]	[0.033]	[0.029]	[0.025]	[0.023]	[0.021]
Control Function	Linear	Linear	Linear	Linear	Linear	Linear
Covariates	No	No	No	No	No	No
Eff. N	911	1,651	2,447	3,151	3,822	4,800

Note: The outcome variable is a dummy that takes the value 1 if workers have changed of province during their UI entitlement length, 0 otherwise. This table reports the coefficient β based on estimating Equation 1 using smaller bandwiths than the optimal bandwidth suggested by Calonico et al. (2014). In particular, I estimate Equation 1 using from 15 days before and after the reform (Column 1) to 90 days around the policy change (Column 6). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results suggest that the findings presented in section 5.2 are not due to the bandwidth choice. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect of the reform on nonunemployment duration

Outcome	Nonemployment duration					
Bandwidth	Optimal bandwidth					
Days around the reform	120.718	160.484	215.481	112.172	159.477	204.800
Reform (T_i)	-2.93***	-3.31***	-3.42***	-3.01***	-3.41***	-3.43***
	[0.771]	[0.992]	[1.146]	[0.769]	[0.946]	[1.105]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	6,073	8,233	11,395	5,662	8,074	10,807

Note: The outcome variable is the number of months from the beginning of the unemployment spell until the next employment spell. All results are calculated using the MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 1 estimates β from the local linear model specified in Equation 1. Columns 2 and 3 include higher order polynomials, and Columns 4 to 7 also include controls (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required, and dummies for 14 sectors. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous decrease in the nonemployment length at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Effect of the reform on the LTU

Outcome	Long Term Unemployment (> 1 year)					
Bandwidth	Optimal bandwidth					
Days around the reform	133.069	183.247	186.797	127.082	187.912	169.631
Reform (T_i)	-0.09***	-0.09***	-0.07	-0.09***	-0.09***	-0.04
	[0.028]	[0.034]	[0.045]	[0.027]	[0.031]	[0.040]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	7,138	10,191	10,350	6,694	10,275	9,177

Note: The outcome variable a cathegorical variable that takes the value 1 if the worker spend more than 1 year out of employment, 0 otherwise. All results are calculated using the MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 1 estimates β from the local linear model specified in Equation 1. Columns 2 and 3 include higher order polynomials, and Columns 4 to 7 also include controls (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required, and dummies for 14 sectors. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous decrease in the nonemployment length at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Effect of the reform on the SLTU

Outcome	Long Term Unemployment (> 2 year)					
Bandwidth	Optimal bandwidth					
Days around the reform	146.053	156.380	200.840	144.991	149.111	192.271
Reform (T_i)	-0.07***	-0.09***	-0.10***	-0.07***	-0.09***	-0.10***
	[0.021]	[0.028]	[0.033]	[0.019]	[0.026]	[0.030]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	8,029	8,496	11,228	7,820	8,050	10,444

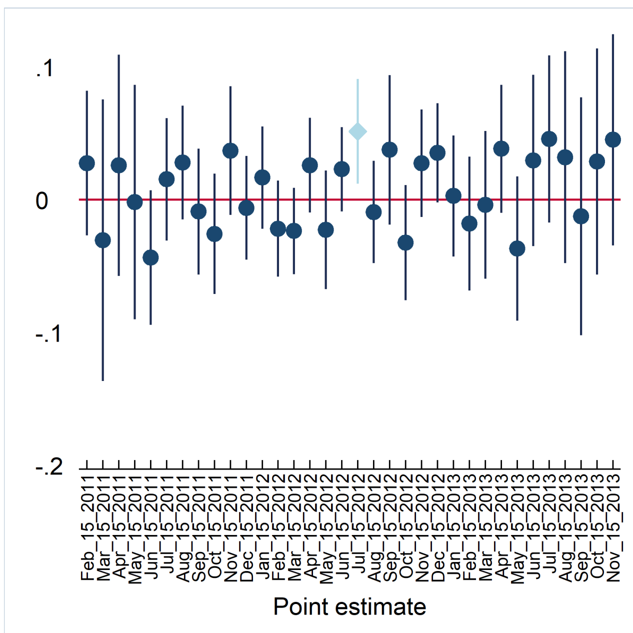
Note: The outcome variable a cathegorical variable that takes the value 1 if the worker spend more than 2 years out of employment, 0 otherwise. All results are calculated using the MSE-optimal bandwidth suggested by Calonico et al. (2014). Column 1 estimates β from the local linear model specified in Equation 1. Columns 2 and 3 include higher order polynomials, and Columns 4 to 7 also include controls (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, as well as level of skills that it required, and dummies for 14 sectors. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The results indicate a discontinuous decrease in the nonemployment length at the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Effect of the reform on Subsequent Labour Market Outcomes

Outcome	Wages		Duration		Occupation	
Bandwidth	Optimal bandwidth					
Days around the reform	187.47	187.47	138.78	125.91	209.177	126.294
Reform (T_i)	115.98	115.98	-42.27	-41.21	-0.03	-0.00
	[80.10]	[80.10]	[30.08]	[31.72]	[0.017]	[0.019]
Control Function	Linear	Linear	Linear	Linear	Linear	Linear
Covariates		✓		✓		✓
Eff. N	10,541	10,541	7,053	6,256	9,680	5,480

Note: This table looks at how the policy affected the subsequent labor market of workers in terms of wages (column 1 and 2; duration of the next employment (columns 3 and 4; and occupation (columns 5 and 6). All results are calculated using the MSE-optimal bandwidth suggested by Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1

Figure A8: Placebo test: artificial reform dates



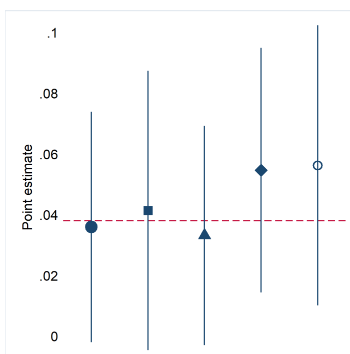
Note: The Figure shows the RD coefficients for the parameter β based on estimating the local linear model specified Equation 1 as if the reform had happened the 15 of each one of the months from July 2011 to July 2013 (the true reform date is highlighted in darker blue). The outcome variable is a dummy that takes the value 1 if workers have changed of province during their UI entitlement length, 0 otherwise. The bandwidth is calculated using MSE-optimal bandwidth suggested by Calonico et al. (2014), and the standard errors are clustered to the date when the worker starts receiving UI. There are two specifications out of 25 in with the parameter for the coefficient β is statistically significant at a 90 percent level (October 15, 2011 and December 15, 2012). However, these results are not robust to the inclusion of higher order polynomials or covariates.

Table A8: Placebo test: non-treated group

Outcome	Mobility across provinces					
Bandwidth	Optimal bandwidth					
Days around the reform	167.666	223.572	201.155	125.690	228.416	195.371
Reform (T_i)	0.01	0.00	0.0 0	0.00	-0.01	-0.01
	[0.032]	[0.040]	[0.054]	[0.035]	[0.039]	[0.055]
Control Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Covariates				✓	✓	✓
Eff. N	2,129	2,836	2,633	1,610	2,912	2,502
N	6,271	6,271	6,271	6,271	6,271	6,271

Note: The table reports the coefficient β based on estimating Equation 1 for a group of workers who were not entitled to receive more than 6 months of UI benefits. The outcome variable is a dummy that takes the value 1 if workers have changed of province during their UI entitlement length, 0 otherwise. First column estimates β from the local linear model specified in equation 1 using MSE-optimal bandwidth suggested by Calonico et al. (2014). Columns 2 and 3 add second and third order polynomials respectively. Columns 4 to 6 incorporate covariates to the previous specifications (when included, covariates are sex, age, age squared, level of education, experience, number of dependents, earnings in the year prior the displacement (in log), type of firm (public or private) and type of contract (open-ended or fix) in the last employment, 13 dummies for the sector of last employment, as well as level of skills that it required. Unemployment rate in the last province of employment, and UI duration entitlement are also incorporated). Robust standard errors (in brackets) are clustered at the day of entry in the UI. The coefficients are smaller in magnitude than the ones presented in Table 2 and statistically insignificant. *** p<0.01, ** p<0.05, * p<0.1

Figure A9: Effects of the reform on mobility, DiD



Note: The Figure shows the coefficients of the parameter β from estimating Equation 2. The point estimate represented by a circle results from estimate the aforementioned equation using workers who become displaced at any point between July 15, 2011 and July 15, 2013. The coefficient represented by a square looks at the effects of the reform on the mobility decisions of workers who become unemployed 9 months before and after the policy implementation. The other three representations are particularly interesting. They use two, one and a half, and one months before and after July 15, for the years 2011 and 2012. All estimations include covariates and the standard errors are clustered at the date workers start receiving UI. The results support the evidence presented in table 2.