Evaluating Active Labor Market Policies using a Spatial Regression Discontinuity Design*

Daniel Heuermann[†]
University of Regensburg

Johannes F Schmieder[§]
Boston University,
NBER, IZA

Philipp vom Berge[‡]
Institute for Employment
Research (IAB)

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Abstract

We evaluate the effectiveness of active labor market programs (ALMP) for long-term unemployed workers using a spatial regression discontinuity design and a large georeferenced data set on workers and unemployed persons in Germany. This approach allows for precise estimation of the effects of different policies, such as public employment programs, training programs, wage subsidies, or coaching, on subsequent employment prospects of job seekers. Unemployed individuals who exhaust their regular unemployment benefits (UB1) are eligible to a second tier of benefits (UB2) administered by local job centers which provide job search support in the form of ALMPs. We exploit the fact that individuals are assigned strictly geographically to these job centers to estimate the effect of these policies using a regression discontinuity design at the county borders, where policies change discontinuously while the conditions of regional labor markets vary smoothly in space. The structure of the data allows us to disentangle short- and long-term effects and, hence, to control for potential lock-in effects, as well as to shed light on dynamic employment effects over longer periods. Our preliminary results, based on outcomes over a 24 month horizon, indicate that, at least in the short term participating in ALMPs does not raise the number of days employed and if anything leads to a slight decrease.

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[†] daniel.heuermann@wiwi.uni-regensburg.de

[§] johannes@bu.edu[§]

[‡] philipp.berge@iab.de

1 Introduction

Persistently high unemployment rates after the financial crisis in 2008 have led to renewed interest in policies to support the unemployed. Extensions of unemployment benefits have played a major role as a strategy, in particular in the US and in several Southern European countries (see Schmieder and von Wachter, 2015, for a recent survey). These policies are often complemented by a paralled expansion of active labor market programs (ALMPs), which cover all public measures aimed at actively raising the re-employment chances of the unemployed.[1] Today, all OECD countries implement a differentiated set of instruments and programs. These can broadly be classified into job placement services, training programs, public employment schemes, and wage subsidies. The objective of these measures is to reduce skill mismatch, avoid skill depreciation, and lower the entry barriers into the labor market for the unemployed.

On the downside, these programs are very expensive. On average, the OECD countries spend 0.6 per cent of their GDP on ALMPs (OECD 2013). In Germany, direct spending on ALMPs for long-term unemployed persons amounts to 3.5 billion Euro annually (BIAJ, 2013). When additionally taking into account administrative costs for staff and rent, this number rises to 8 billion Euro, equalling one per cent of overall public expenditure. Given these financial dimensions, ALMPs exert substantial pressure on public households. It is, hence, of vital interest for societies and policy makers to assess whether they achieve their main objective of raising re-employment prospects of the unemployed. Given limited public budgets and the resulting need to design cost-effective sets of instruments and program, it is of particular importance to understand their relative effectiveness with regard to different target groups.

Fuelled by a rising availability of suitable data sets, the recent expansion of ALMPs has led to a surge of studies investigating their effectiveness. In their survey of the literature, Card et al. (2015) identify 154 microeconometric evaluations authored between 2007 and 2014, which add to the 97 studies originating from the time before 2007 (see Card et al., 2010). The results

[1]See Pavoni and Violante (2007) for a theoretical analysis of how such programs may interact with unemployment benefits.

from their meta-analysis show that the average impacts of ALMPs are close to zero in the short run, but rise over longer intervals and that the size of the effects varies by program and target group.

Methodologically, the key problem in any evaluation of ALMPs lies in the non-random selection of persons into treatment. This problem has been approached in the literature by numerous identification strategies, including randmized trials. However, two key challenges for the identification of treatment effects from ALMPs, that have not been properly addressed so far, arise from the potential existence of threat and spillover effects. Threat effects refer to a situation where the mere potential of being obligatorily sent to an ALMP alters the employment probability of unemployment by changing their job search intensity. Spillovers from ALMPs occur if the geographic proximity to ALMPs participants changes the level of information and/or motivation of unemployed and, as a result, their job search intensity. The uniting feature of both effects is that the impact of ALMPs may well extend to persons who are not actively taking part in any policy or program. In this case, any identification strategy that compares program participants to non-participants is likely to yield bias results.

In this paper we propose a novel identification approach based in a spatial regression discontinuity design, which is capable of controlling for threat effects and spillovers when addressing the effectiveness of ALMPs. Drawing on a large, georeferenced sample of unemployed persons in Germany, we exploit the fact that treatment intensity varies discontinuously in space due to the substantial degrees of freedom that job centers have when deciding on the set of instruments and policies they use. As a result of this autonomy, unemployed persons belonging to different job center districts have different ex-ante probabilities of participating in ALMPs. Given that no other variables chang discontinuously at job center borders, the key idea of our identification approach is difference in employment probabilities between workers close to the borders can plausibly only arise from differences in the sets of policies implemented by boch job centers. The key identifying assumption underlying this approach is that all other variables that determine employment chances behave smoothly at the border. Below, we provide evidence that this assumption is satisfied.

We employ the spatial RD approach to separately evaluate the effectiveness of training measures, wage subsidies, public employment schemes, individual counselling, and mobility support. In order to take account for potential lock-in effects and to measure medium-term effects, we provide evidence over the course of two years. Overall, our results are sobering. For all policies together, we find evidence for a significantly negative effect of program participation on employment probabilities. This negative effect rises in size over the course of 24 months after participation. At the same time, participation in ALMPs significantly raises the number of days individuals continue to receive benefit payments over the next two years.

The paper is structured as follows. The next section explains the institutional background and describes the data. In section three we derive the spatial regression discontinuity design. Section four contains preliminary results based on the spatial regression discontinuity design and section five concludes.

2 Institutional Background, Data and Sample

2.1 Institutional Background

The implementation of ALMPs in Germany is organized in a two-tier system, which follows the systematic split into a regular unemployment insurance (UI) branch, also called unemployment benefits 1 (UB1) and second tier called unemployment benefits 2 (UB2), which is a means tested form of benefits with features both of classical UI systems and welfare systems. Since a series of labor market reforms in the early 2000s ('Hartz reforms'), legal competence for the second tier rests with the so called job centers. Active and passive labor market policies in the UI branch are implemented by the local employment agencies, which are organized in larger geographic units. These cover, on average, three job center districts.

In this paper we are concerned with the effectiveness of ALPMs with respect to UB2 recipients. For this group, 408 job centers in Germany are responsible for implementing both passive and active labor market policies. Job centers were created in 2005 with the Hartz-reforms and are legally independent public corporations. They are provided with global budgets and, as a result, have substantial degrees of freedom of how to actively support UB2 recipients. While the legal instruments the job centers can use are defined in the Social Security Codes II and III, no pre-defined budget exists for the use of specific instruments. In addition, according to §16f in the Social Security Code II, job centers are legally allowed to spent part of their budget freely, i.e., on any type of support for unemployed they deem helpful. Finally, job centers have access to various federally funded program, which further increase their room for maneuvre. Job center policies are in most cases steered by the 'Traegerversammlung', which is effectively a governing board consisting of members of the Local Labor Agency and the county administration. This board defines the overall strategy and the priorities to be set within each fiscal year. Given the flexible budgets, case workers can decide freely and on a case-by-case basis which instruments to be implemented for each person, according to her personal needs.

Three features of this overall setting are of key importance for our identification approach. First, the borders of the job center districts in almost all cases coincide with the borders of the 402 counties ('Kreise und kreisfreie Städte') in Germany. The counties themselves have no local authority on labor market or economic policies, but are mainly responsible for administrative issues. In addition, while in the United States access to schools is an important local amenity that leads to sorting along school district borders, in Germany education is funded and administered through the German states. There are differences across states in terms of educational quality, but there is very little variation across counties within states. Furthermore there are no local taxes that are county specific which might lead to sorting around the borders.

The second important institutional feature is that due to the degrees of freedom job centers are endowed with, the resources available for ALMP policies and the relative emphasis on different types of ALMPs vary substantially at the county borders. And finally the third feature is that, being effectively NUTS III regions with an average population of 200,000 persons, job center districts are rather small. Especially in densely populated areas their borders cut through local labor markets and commuting zones. As a result of these three features, the only variable that changes discontinuosly is the intensity of ALMPs and the particular mix of the set of instruments. In contrast, close to county borders all individual and labor market variables can be expected to evolve smoothly over space. We explain how we exploit this discontinuity in our spatial RD in more detail in Section 3.

2.2 Employment and County Level Data

The first data source we draw on are social security data provided by the German Federal Employment Agency. The data contains daily information on employment and unemployment histories on individual level. The employment data is collected from employment notifications to the social security administration, which are required by law for all jobs liable to social security contributions. These cover roughly 85 percent of employment in Germany. Self-employed and public servants are not contained in the data. The data on unemployment are taken from the German unemployment insurance system. It contains information on benefit receipt, registeration as unemployed, and participation in ALMPs. The full data set covers daily information on employment status, wages, benefit receipt, participation in ALMPs, as well as numerous covariates on individual level including precise information on home and employer addresses. From these data, we have generated summary statistics to gain first insights into the relative importance of different types of instruments and policies. Table 1 contains numbers of participants in the five most frequent types of measurs. During the period between 2006 to 2008, 38 per cent of all participants in ALMPs were taking part in measures of public employment, while 31 per cent have undergone training measures. The third row in the table shows that 16 per cent of participants were supported under the free funding opportunity contained in §16f (SGB II). Finally, 11 per cent of participants were placed into public employment schemes, while with close to two per cent, wage subsidies play only a minor role.

We complement these information taken from individual level data by aggregate measures on ALMP activities for each job center. The first data source we use encompasses annual information on the activities of each job center, which is provided by the statistical branch of the Federal Employment Agency on its website. Important in the present context, this data contains information on the absolute and relative numbers of individuals receiving ALG II, as well as on ALMP expenditure by job center from 2005 on. In addition to this data, we have obtained the annual budgets provided to each job center. These budgets are listed in a reply of the German government to an inquiry from the leftist party 'Die Linke', which is publicly available in the collection of electronic documents in the online library of the German parliament (Bundesregierung 2011). In Table 2, we have merged this budgetary information for the years 2005 to 2008 with information on unemployment by job center region. The upper part of the table contains the budget available for each unemployed person for integration measures ('Eingliederungstitel') like training measures, public employment schemes, and wage subsidies. The lower part of the table shows the annual sums spent for administrative costs ('Verwaltungskosten'), which mainly cover staff costs and rent.

The table yields two notable facts. First, it shows that the job centers differ pronouncedly with respect to the budgets available for each unemployed. In 2005, the smallest amount available for each unemployed was 221 Euro (Job Center Munich Land), while the largest amount was 2,823 Euro (Job Center Landau). Secondly, with a rise from 583 to 1,055 Euro, the sum of integration funds per unemployed has more than doubled over the period of four years. During the same period, administrative funds have risen from 6,7 to 8,5 billion Euros. The more procounced growth of integration budgets in contrast to administrative budgets provides further evidence for the notion that job centers have been able to diversify their policies over time.

2.3 Sample of UB2 Recipients

From the individual data set we take all individuals that have received benefits from UB2 for at least one day between 2005 and 2013. Given the German UI system, an UB2 entrant may either come from receiving UB1, after she has exhausted her benefits, or directly from employment, e.g., if she did not qualify for UB1 due to a very short employment spell. An individual may also enter UB2 after any other spell of non-participation in the labor market (e.g. education, staying at home, living abroad, etc).

For this sample we have obtained the exact home addresses as of June 30th for each year, either as they are recorded in the employment data or in the unemployment data. Using GIS software we have geocoded all addresses and translated them into exact latitude and longitude coordinates. Using these geographic coordinates, we have determined the closest county border for each all individuals and have computed the shortest distance to this border in kilometers. In addition, we have generated concentric circles around each person and calculated the average attributes of all benefit recipients within these circles. Important for us, beyond demographic characteristics, these attributes encompass information on average participation of each person's individual reference group in measure of ALMP.

3 Methods

3.1 Distance-to-Border Regression Discontinuity Design

We are interested in estimating the effect of active labor market programs on individual employment outcomes. For every individual i, let c indicate the county of residence and n the closest neighboring county. We denote a border between the two counties as b, and a subscript b indicates the closest county border for that observation. Let the T_{ic} indicate a treatment such as average expenditure on active labor market programs, or expected days spend in active labor market programs. To the extent that job centers treat all employees in their respective county identically, this would only vary on the county level, however if job center policies vary over space there may well be intra county variation. Consider the following model how ALMP treatment may affect employment outcomes:

$$y_{ic} = \beta T_{ic} + X_{ic}\pi + \varepsilon_{ic} \tag{1}$$

Since T_{ic} is likely correlated with the state of the labor market in county c, as well as with other county characteristics, estimating this equation using OLS likely leads to significant omitted variable bias.

To overcome the omitted variable bias we employ a spatial regression discontinuity design, where we use the discontinuity at the boundary as an instrument for the treatment variable. Let $dist_{ib}$ be the distance from the closest border. For each possible treatment variable, we multiply this distance with -1 if individual i is in a county that has a lower value of the treatment T_{ic} then the county on the other side of the border, so that:

$$Dist_{ib} = \begin{cases} -dist_{ib} & if\, T_{ic} < T_{in} \\ dist_{ib} & if\, T_{ic} \geq T_{in} \end{cases}$$

We then estimate the following equation:

$$y_{ic} = \alpha + \delta D(Dist_{ib} \geq 0) + f(Dist_{ib}) + \theta_b + \varepsilon_{ic} \tag{2}$$

Since we have many borders and thus individuals with $Dist_{ib} \geq 0$ may be far away from individuals with $Dist_{ib} < 0$, we also include border fixed effects θ_b so that the identification comes only from individuals living close to either side of a border. The coefficient δ captures how the outcome variable varies at the borders. Estimating equation (2) using the treatment variables T_{ic} as an outcome as well as employment outcomes, yields a Wald estimator of the treatment effects in equation (1), by dividing the reduced form by the first stage coefficient.

3.2 Spatial Fixed Effects Estimator

The distance to border design yields consistent estimates of the causal effect of ALMP, as long as individuals are smoothly distributed throughout space, so that at each point close to a border we get a similar number of individuals just on the other side of the border. This may be violated in practice, since border usually run in between towns and villages, not through towns, so that many individuals who live close to the border may not have a direct counterpart on the other side of the border who is actually nearby. We get around this by using the Spatial Fixed Effects Estimator used by Magruder (2012), which in turn is based on Conley and Udry (2010) and Goldstein and Udry (2008).

Consider the data generating process:

$$y_{ic} = \beta T_{ic} + \varepsilon_{ic} \tag{3}$$

The problem is that $E[\varepsilon_{ic}|T_{ic}] \neq 0$, since treatment is correlated with many other factors that vary through space. However, suppose that we can write:

$$\varepsilon_i = f(lat_i, lon_i) + u_i$$

where $E[u_i|lat, lon] = 0$ and $f(.)$ is a continuous function in space (that is of longitude lon and latitude lat). Let $\mathcal{R}(i)$ be the set of all individuals within a radius of r of individual i. Consider all individuals i' in a radius r. By continuity of $f()$ we get that:

$$\lim_{r\to 0} \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} f(lat_{i'}, lon_{i'}) = f(lat_i, lon_i)$$

Therefore we get that:

$$\begin{aligned}
\lim_{r\to 0} \left\{ y_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} y_{i'} \right\} &= \lim_{r\to 0} \left\{ \beta \left[T_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} T_{i'c'} \right] + \varepsilon_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} \varepsilon_{i'} \right\} \\
&= \beta \lim_{r\to 0} \left\{ \left[T_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} T_{i'c'} \right] \right\} + \lim_{r\to 0} \left\{ u_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} u_{i'} \right\}
\end{aligned}$$

Let $\tilde{T}_i = \lim_{r\to 0} \left\{ \left[T_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} T_{i'c'} \right] \right\}$ and $\tilde{y}_i = \lim_{r\to 0} \left\{ y_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} y_{i'} \right\}$and we get that the estimator:

$$\hat{\beta} = \frac{Cov(\tilde{y}_i, \tilde{T})}{Var(\tilde{T})}$$

is a consistent estimator for β, since $\lim_{r\to 0} \left\{ u_{ic} - \frac{1}{n_{\mathcal{R}(i)}} \sum_{i' \in \mathcal{R}(i)} u_{i'} \right\} = 0$. This suggests a straightforward estimator, we simply transform the treatment and outcome variables of interest, by subtracting for each person the average of treatment / outcome variable in a radius r from the treatment / outcome of that person. Once we have the transformed varialbes $\tilde{T}_i$ and $\tilde{y}_i$, we simply regress the transformed outcome variable on the transformed treatment variable to obtain an unbiased estimate of β.

The intuition behind this transformation is straightforward, since factors ε_{ic} influencing the outcome apart from the treatment variable vary smoothly through space, subtracting the average of individuals in a small neighborhood will difference out the influence of these factors, but also differences in the treatment. Only for individuals at the border where T_i varies discontinuously is not all the variation differenced out and thus the observations close to the cutoff provide the identification.

While we think the spatial FE estimator is preferred to the border distance RD, the latter has been used in the past and is very intuitive. We will present results for both estimators below.

3.3 Dynamic Regression Discontinuity Design

The previous literature has suggested that the time horizon is important for evaluating the effects of ALMPs, since in the short run lock-in effects can dominate any positive employment effects. To develop a deeper picture of the dynamic effects, we estimate how the treatments and outcomes of UB2 recipients vary at the county border using a dynamic regression discontinuity design:

$$y_{ict} = \alpha_t + \delta_t D(Dist_{ib} \geq 0) + f_t(Dist_{ib}) + \varepsilon_{ict} \, for \, t = -12, ..., 24 \tag{4}$$

where the subscript t indexes the month since entry into UB2. We estimate this equation separately for each month relative to the entry into UB2. The estimates for α_t trace out how the dependent variable changes over the months before and after entry into UB2 for individuals just next to the border on the side with less ALMPs, while the estimate of δ_t provide an estimate of how much the profile shifts, relative to individuals on the other side.

4 Results

In this section we present results based on a preliminary dataset of a 25 percent sample of the IEB covers the years up until 2009. We will focus on individuals who entered UB2 during

2006 and 2007, which allows us to follow them up to 2 years after entry into UB2. This is an important caveat, since the literature has found that active labor market programs often lead to a lock-in effect initially where individuals stay unemployed longer, since they are in a program and therefore not actively looking for a job. The positive effects may then take some time to materialize. We are have now obtained a 100 percent version of the IEB data covering the time period until 2013, which will allow us to follow UB entrants from 2006 to 2009 for at least 4 years or even longer (for the earlier entrants) and will make it possible to analyze lock-in vs. long-term effects in detail. We are currently working on cleaning this data and geocoding the addresses for all years.

Another caveat is that in our current data we only have geocoded locations for 2008. We currently extrapolate these locations to the earlier years. This will undoubtedly introduce measurement error. In principle since we are looking at UB2 entrants from years prior to 2008, this could also lead to more systematic biases since the location in 2008 itself is endogeneous. It seems somewhat unlikely to us that individuals would move (especially while unemployed) in response to ALMP policies. When we restricted the data to individuals that did not move between counties from 2006 to 2008 (county of residence is available in all years), this did not change our results. In any case, in our new dataset we will have addresses for all years, allowing us to sidestep this issue.

We next explore the validity of the border discontinuity design, show the variation of ALMP around the borders, and then present estimates based on the Distance-to-Border RD design and the Spatial FE Design.

4.1 Validity of RD

Using our preliminary data, we first calculated for each county and each year the average time UB2 recipient who entered in that year spend in an ALMP. We then calculated for each individual who entered UB2 during 2006 and 2007 the distance to the closest county border. If ALMP in the county where the UB2 recipient lived is smaller than in the next closest county, we multiplied this distance with minus one. We restrict the data to individuals who live within

10 kilometers of an inner-German county border, that is we drop individuals where the closest border borders a neighboring country. Furthermore we drop all borders between counties where the two neighboring counties are not in the same state in order to avoid confounding effects stemming from differences in state level policies (in practice this restriction makes no difference).

Figure 2 shows the density of observations around the county borders. Each dot consists of all individuals living in a one kilometer bin of distance to the border. A first noteworthy feature is that the density increases towards the border from both sides. This is due to a simple geometric feature: For example consider a county that is a perfect circle with a 10 km radius. The area of a band that is between 0 and 1 km from the border is given as: $A_2 = \pi(10km)^2 - \pi(9km)^2 = 59.7km^2$, which is more than twice as large as for example a band that is between 5 and 4 km: $A_2 = \pi(5km)^2 - \pi(4km)^2 = 28.3km^2$. Furthermore counties that are small enough can not have anyone living for example 10 km from the closest border. A second noteworthy feature is that the density increases up to the last kilometer from the border and then dips for the last bin. This is because in practice most county borders do not run through cities or towns, but in between them. While they are often very close, this means that fewer people live right next to a border than for example 1 kilometer away from it. And finally a third feature of this plot is that it is asymmetric, with somewhat more mass to the right, especially in the 2 to 5 km distance range. The reason for this excess mass appears to be that several large cities in Germany, such as Munich or Hamburg, are also their own counties. Since these cities often have higher spending on ALMPs per unemployed, they tend to end up on the right of the cutoff in these graphs and due to their large populations create the hump on the right. While the shape looks unusual for an RD density plot, there is no obvious discontinuity in the density at the cutoff.

An important test for the plausibility of the identification assumptions in the RD design is that predetermined characteristics evolve smoothly at the cutoff. Figure 3 shows how average characteristics of UB2 entrants in our sample evolve around the border. Panel (a) shows the average years of schooling of the UB2 recipients. Interestingly education declines towards the border, which likely reflects that the fact that the borders tend to be in more rural areas, while individuals living further away from the county border are more likely to live in cities. The shape is reversed for experience, which seems to be driven by the age of the UB2 entrants (not shown), where individuals further away (who are likely more urban) are younger. The share of women among the entrants is essentially flat throughout space (notice the scale) and individuals close to the border have spend somewhat more time in regular UI benefits prior to entering UB2, also likely due to their higher experience and therefore longer eligibility for benefits. Importantly all characteristics evolve very smoothly around the cutoff and do not suggest that there is any sorting at the cutoffs but instead that individuals on both sides are quite comparable to each other.

4.2 Estimates based on Distance-to-Border RD Design

We now turn to estimates of the effect of ALMPs using the Distance-to-Border RD Design outlined in section 3. As a first step we document that ALMP does indeed increase significantly at county borders. Figure 4 (a) shows the average number a new entrant into UB2 spends in ALMP over the subsequent 2 year period. As can be seen, to the left of the border, UB2 entrants spend about 46 days in various active labor market programs. Right at the border there is a sharp jump to around 62 days, suggesting that individuals who live just on the other side of the border spend on average around 18 days (or close to 50 percent) more in ALMPs than individuals who are entering UB2 in counties with more restrictive ALMP policies than their neighbors. Figure 4 (b) shows the number of days individuals receive UB1 benefits over the next 2 years. Since UB2 recipients are typically not eligible for UB1 benefits when they enter UB2 and not very likely to requalify for UB1 over the relatively short period of 2 years, it is not surprising that the level of UB1 receipt in this figure is low and that there is no discontinuity at the border.[2] By contrast, panel (c) shows the number of days spend in UB2 over the next 2 years. Quite strikingly time spend in UB2 increases discontinuosly at the border by almost 10 days, suggesting that more intense ALMP policies by jobcenters

[2]Individuals who had very low earnings prior to becoming unemployed may be eligible for UB1, but since their UB1 benefits are so low they may also qualify for UB2 benefits.

keep UB2 recipients longer in UB2. This is consistent with panel (d), which shows that the number of days individuals are employed decreases by around 9-10 days over the next two years. While this could reflect the lock-in effect that individuals who are put into ALMP are by definition not working and thus kept back from the labor market, these results suggest that at least over a 2 year horizon higher intensity of ALMPs do not improve labor market outcomes, despite their relatively large costs. This could of course be different over longer time periods and could mask substantial heterogeneity in effectiveness of different individual ALMP policies, something which we address below.

4.3 Estimates based on Spatial FE Design

The Distance-to-Border RD Design is intuitive and allows for a straightforward graphical representation, however it relies crucially on the assumption that the density of UB2 entrants is continuous through space and in particular around the county borders. We know however that except for some larger cities, county borders typically do not cut directly through towns and cities, but instead may pass close to them. To see that this could be problematic for the RD design, consider a single border with a city on each side of the border. Both cities may be exactly one kilometer from the border, but they may be at different points along the border and in practice not very close to each other. The Distance-to-Border RD would put both cities at the one kilometer distance from the border and use them for comparison, even though the actual distance may be quite large and they man not actually be in the same labor market or easy to commute between.

The spatial FE estimator on the other hand does not suffer from this shortcoming. Given a radius r for the spatial FE transformation, each individual is only compared to other individuals who are at most r kilometers away from them. By choosing a smaller and smaller r we are getting arbitrarily close to the ideal of only comparing individuals who live right next to each other but on different sides of a county border.

We therefore apply the spatial FE transformation to our data for different radii, 10km, 5km and 2km, and present both graphical evidence as well as regression estimates. For the graphical evidence, we show the average values of the transformed variables in bins of distance to the closest border as before. This highlights how the transformation works and shows how only observations close to the border contribute to identification. Figure 5 shows the average days spent in ALMP by distance to border after the spatial FE transformation with a 10km radius. Given the 10km radius, the outer most points should be close to zero, except for measurement error. This suggests that with a 10km radius specification these points do not contribute to identification in the spatial FE regressions. As we approach the border from the left, the average days spent in ALMP of individuals falls relative to the average of all individuals in a 10km radius. This is because the average increasingly contains individuals on the other side of the border where they spend more time in ALMP. At the border the difference is almost 10 days. On the other side we see a reverse pattern, although not quite symmetric. Just on the right of the border average days in ALMP are about 5 days more than in a 10 km radius. In fact this asymmetry suggests a violation of the smooth density assumption that would be required for the Distance-to-Border RD design, but that does not constitute a problem for the spatial FE design. Ineristingly we still see a jump of around 15 days at the border. The other 3 panels show similar, patterns consistent with Figure 4 before. No jump and almost no variation for UB1 receipt and about a 8 day jump for time spend in UB2 and employment.

Table 3 shows spatial FE estimates, that is estimates of the equation

$$\tilde{y}_{ic} = \beta \tilde{T}_{ic} + \varepsilon_{ic} \tag{5}$$

where $\tilde{y}_{ic}$ is an outcome variable with the spatial FE transformation defined in section 3.2 and $\tilde{T}_{ic}$ is the transformed treatment variable. As a treatment variable we use the average time a UB2 recipient in a given county spends in ALMP. Since days spent in ALMP may vary throughout the county, we first show in column 1 the effect of Average days in ALMP in a county on the actual change in ALMP at the county border spent in ALMP. The top panel shows the estimates for a 2 km radius, the middle panel for a 5 km radius and the bottom one for a 10 km radius. The coefficient in the top Panel of 0.81 implies that at the border individuals who are in a county that sends on average UB2 recipients for one additional day into ALMP spend 0.81 days extra in ALMP. The coefficient is relatively precisely estimated, though note that we cannot reject a coefficient of 1. For larger radii the precision increases and the coefficient is very close to 1.

Column (2) of Table 3 shows the effect of being in a county with an additional day of ALMP intensity on days receiving UB2. The result confirms the previous graphical evidence, that additional time in ALMP increases time spent in UB 2. In particular one additional day spent in ALMP increases time in UB 2 by about 0.4 to 0.5 days. Similarly column (3) shows that days spent in employment decline for each day in ALMP by about 0.4 to 0.5 days, with relatively precisely estimated point estimates. The coefficients on UB1 are in magnitude close to zero and except for the 10 km radius not statistically significant.

A particularly attractive feature of the border discontinuity design is that, unlike in most other RD designs, there are a very large number of discontinuities, namely at each between county border. Since the mix of different ALMPs varies across job centers, each border not only constitutes a slightly different experiment since the mix of ALMPs changes differently at each one. This allows us to separately identify the effects of different ALMPs, which would not be possible with a single experiment or a single border. For that purpose we estimate the following equation:

$$\tilde{y}_{ic} = \beta_1 \tilde{T}_{ic}^{EducProg} + \beta_2 \tilde{T}_{ic}^{EmpProg} + \beta_3 \tilde{T}_{ic}^{OtherALMP} + \beta_4 \tilde{T}_{ic}^{PSA} + \varepsilon_{ic} \tag{6}$$

where we allow for differential effects of 4 major groups of ALMP policies.

Table 3 shows estimates of equation (6). It is clear that with a 2km radius we lack precision. With a 5km radius, we find that education, employment and other ALMPs increase time in UB2, while quite strikingly time assigned to PSAs, privat job search agencies, appears to reduce time in UB2 almost one for one, though with a relatively large standard error. Interestingly, and warranting caution, this positive effect of PSA on UB2 recipiency does not seem to translate to more employment and goes away when going to the 10 km radius. The most robust result on employment appears to be that the other ALMP programs have a negative effect on employment in all three specifications. The closest to a positive employment effect seems to be associated with the actual employment programs. Given the nature of these programs, where the unemployed are directly placed into specifically created jobs, a positive effect would be unsurprising and infact expected. In fact a coefficient of less than 1 would still suggest that the employment program is crowding out regular, i.e. unsubsidized, forms of employment. These specifications are a bit too imprecise to draw strong conclusions, but we are hopeful that these will be more informative once we estimate these with our much larger and more comprehensive dataset that should provide quite a bit of extra precision.

4.4 Dynamic Estimates

We now turn to estimates of the dynamics of ALMP assignment and subsequent labor market outcomes. For this purpose we estimate equation (4) for each month from 12 months before UB2 entry to 24 months afterwards and plot the resulting estimate for the individuals to the left and to the right of the county border. Figure 6 shows these dynamic results for some of the main outcomes. Panel (a) shows days spent in ALMP. Since many UB2 entrants received UB1 before (and exhausted UB1), many were also in ALMP prior to UB2 entry. However the levels were essentially identical giving us further confidence in the border RD design since it shows that there are no differences in terms of UB1 policies that could confound our results. After UB2 entry the gap opens up and individuals in the high intensity ALMP counties spend about 50 percent more time in ALMPs than in the low intensity counties just on the other side of the border. Interestingly the difference appears immediately and remains pretty constant from around 6 months onwards and it does not appear that it is concentrated at a particular time of the UB2 spell. Panel (b) shows a similar figure for education programs again.

In Panel (c) we look at days employed as an outcome variable. Prior to entering UB2, individuals spent about 20 days per month in employment (or more plausibly about 2/3 of individuals were employed), which drops in the months before entering UB2. Again reassuringly the pre-trends and levels are almost identical and furthermore over the first 7-8 months there is no difference after entering UB2. Interestingly there thus does not appear to be a lock-in effect early on. After about 8 months there is a small gap with the group on the low ALMP intensity side of the border returning quicker to work with about 0.5 additional days per month in employment. This difference remains constant throughout the 24 months window. While this is still consistent with lock-in effects, since ALMP levels are also higher throughout the entire 24 months period, there is no sign of a reversal towards the end that would point towards positive long-run effects of the policies.

Panel (d) of Figure 6 shows that the negative employment effects of ALMP also translate into lower earnings of around 10 to 15 Euro per month from month 10 onwards, with no sign of a reversal towards the end.

5 Conclusion

Active labor market programs are a major policy tool with many governments and UI agencies putting high hopes in these programs to help job seekers find back into work faster. The spatial regression discontinuity design proposed in this paper provides a powerful method to identify the causal effects of such ALMP programs on labor market outcomes.

While the results presented here are preliminary and investigate only short to medium run impacts, they appear somewhat sobering at this stage. At least over a 2 year horizon, individuals who are assigned to jobcenters that invest significantly higher resources into a variety of ALMP policies do not appear to benefit from these programs but rather spend more time on unemployment benefits 2, spend less time in employment and have lower monthly earnings.

In currently ongoing work we are expanding our sample (from a 25 percent sample to the 100 percent) and time frame (adding 4 more years, allowing for a longer time horizon). Furthermore we will have better measures for ALMP participation as well as local expenditures on ALMP.

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Table 1: Share of ALMPs by Type

	2006	2007	2008	All Years
Training	31.1	29.9	32.1	31.1
Flexible Funding	16.1	20.4	18.1	18.2
External Placement Service	11.4	8.2	13.9	11.1
Public Employment	37.7	39.5	34.1	37.7
Wage Subsidy	1.9	1.9	1.8	1.9

Table 2: Descriptive Statistics of Job Center Budgets

Year	Mean	SD	Max	Min
Integration funds per unemployed by jobcenter				
2005	1,061	583	221	2,823
2006	1,586	751	417	4,700
2007	1,852	852	722	4,919
2008	2,388	1,055	594	6,884
Administrative funds by job center (in Million Euro)				
2005	6,715	116,999	206,781	814
2006	7,688	13,472	239,716	1,076
2007	8,032	13,644	233,596	1,080
2008	8,549	16,359	267,963	1,099

Table 3: RD Estimates of the Effect of ALMP - Employment Outcomes - Treatment Mean ALMP - Controlling for Spatial FE

	(1) Days in ALMP over next 2 years	(2) Days receiving UB 2 over next 2 years	(3) Days employed over next 2 years	(4) Days receiving UB 1 over next 2 years
Spatial FE Radius 2 km				
Average days in ALMP	0.81	0.51	-0.42	0.044
	[0.084]**	[0.20]*	[0.21]*	[0.068]
Observations	101840	101840	101840	101840
Mean of Dep. Var.	56.8	525.7	310.8	37.8
Spatial FE Radius 5 km				
Average days in ALMP	0.97	0.45	-0.43	0.017
	[0.038]**	[0.092]**	[0.095]**	[0.031]
Observations	274700	274700	274700	274700
Mean of Dep. Var.	56.8	525.9	310.3	38.0
Spatial FE Radius 10 km				
Average days in ALMP	1.03	0.39	-0.47	0.048
	[0.022]**	[0.055]**	[0.057]**	[0.018]**
Observations	366185	366185	366185	366185
Mean of Dep. Var.	55.9	523.5	312.8	38.3

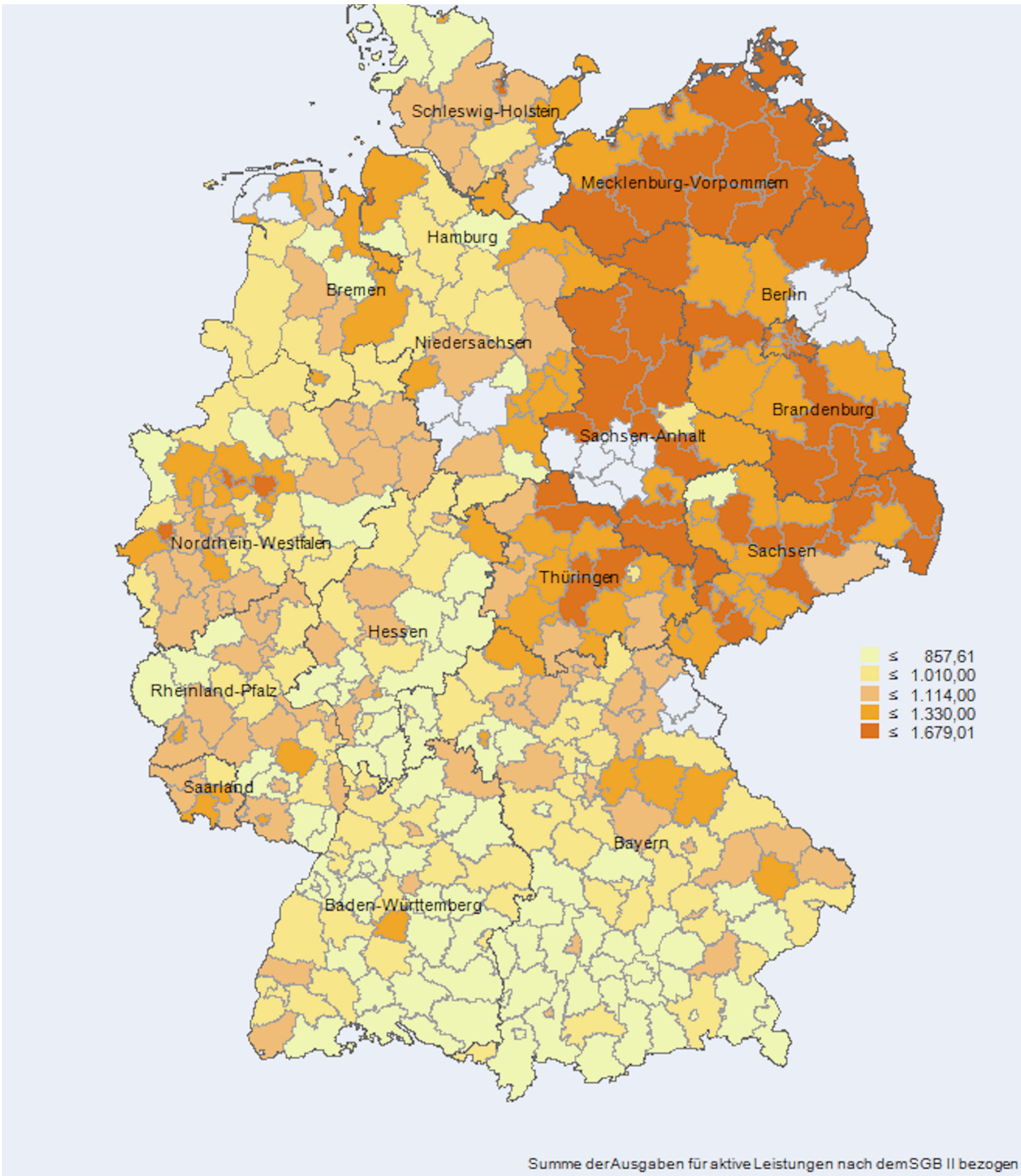
Notes: Coefficients from RD regressions. Local linear regressions (different slopes) on each side of cutoff. Standard errors clustered on day level (* P<.05, ** P<.01)).

Table 4: RD Estimates of the Effect of ALMP - Employment Outcomes - Treatment Mean ALMP - Controlling for Spatial FE

	(1) Days in ALMP over next 2 years	(2) Days receiving UB 2 over next 2 years	(3) Days employed over next 2 years	(4) Days receiving UB 1 over next 2 years
Spatial FE Radius 2 km				
Days in education program	0.93	1.81	-0.70	-0.053
	[0.34]**	[0.83]*	[0.87]	[0.28]
Days in employment program	0.76	0.15	1.17	-0.13
	[0.26]**	[0.64]	[0.66]	[0.22]
Days in other ALMP program	0.70	0.63	-1.03	0.16
	[0.16]**	[0.40]	[0.41]*	[0.13]
Days in PSA	1.07	-0.90	-0.52	0.022
	[0.41]**	[0.98]	[1.02]	[0.33]
Observations	101840	101840	101840	101840
Mean of Dep. Var.	56.8	525.7	310.8	37.8
Spatial FE Radius 5 km				
Days in education program	1.05	0.79	-0.41	0.20
	[0.16]**	[0.39]*	[0.41]	[0.13]
Days in employment program	1.08	0.77	0.10	-0.16
	[0.12]**	[0.30]*	[0.31]	[0.10]
Days in other ALMP program	0.93	0.50	-0.65	0.057
	[0.076]**	[0.18]**	[0.19]**	[0.062]
Days in PSA	0.75	-1.03	-0.48	-0.049
	[0.19]**	[0.45]*	[0.47]	[0.15]
Observations	274700	274700	274700	274700
Mean of Dep. Var.	56.8	525.9	310.3	38.0
Spatial FE Radius 10 km				
Days in education program	1.06	0.97	-0.81	0.15
	[0.099]**	[0.24]**	[0.25]**	[0.081]
Days in employment program	1.13	0.33	-0.21	0.032
	[0.075]**	[0.19]	[0.19]	[0.062]
Days in other ALMP program	0.97	0.35	-0.52	0.013
	[0.046]**	[0.11]**	[0.12]**	[0.038]
Days in PSA	1.00	-0.22	-0.24	0.083
	[0.11]**	[0.26]	[0.27]	[0.087]
Observations	366185	366185	366185	366185
Mean of Dep. Var.	55.9	523.5	312.8	38.3

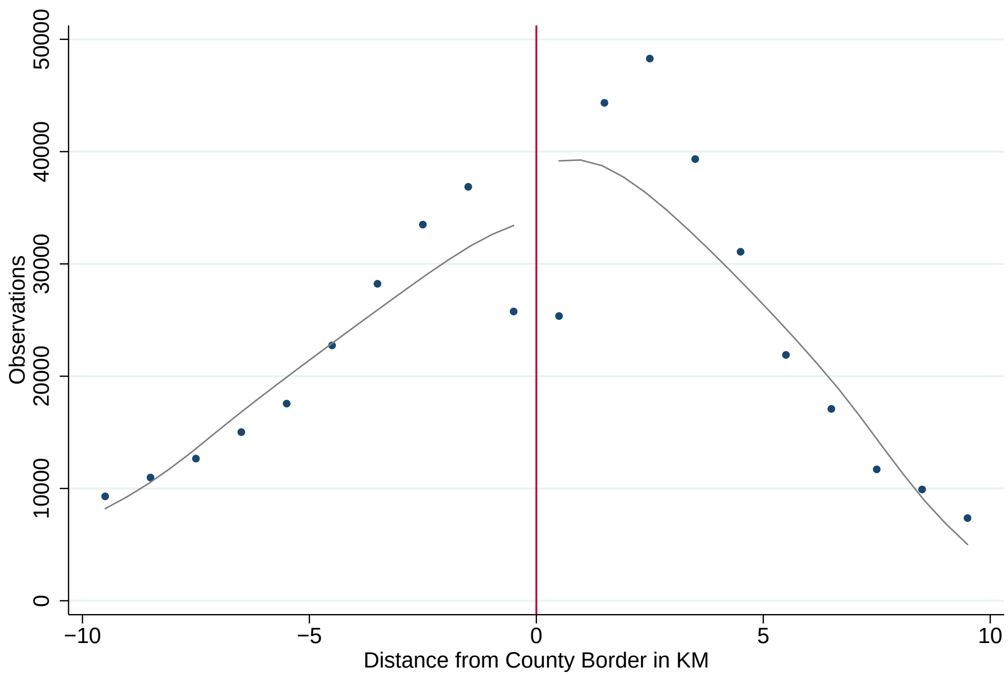
Notes: Coefficients from RD regressions. Local linear regressions (different slopes) on each side of cutoff. Standard errors clustered on day level (* P<.05, ** P<.01)).

Figure 1: Spending on ALMP per Recipient of Unemployment Benefits 2 (UB2) in 2009



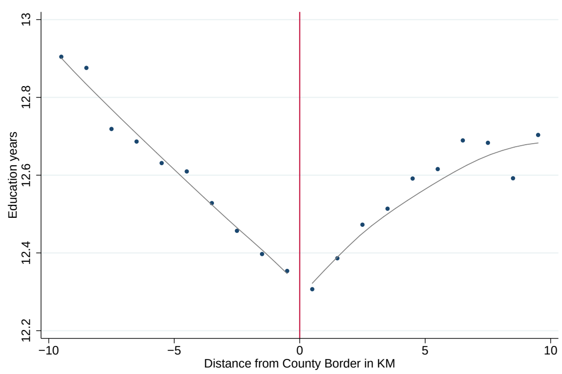
Notes: The maps shows the average spending on ALMP per UB2 recipient in 2009 on the county level. Spending is measured in Euro. Source: Statistics of the German Federal Employment Agency.

Figure 2: Density Around County Borders

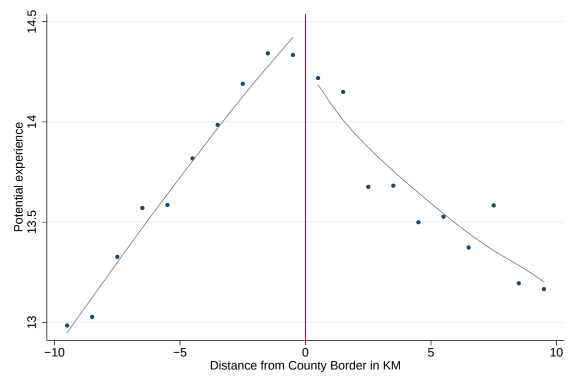


Notes: Each bin contains the number of individuals within a 1 kilometer bandwidth of distance from the nearest county border. For each individual the distance is measured as the distance to the nearest county border. If the adjacent border has a higher average intensity of ALMP, the distance is multiplied with -1, so that the observations to the left correspond to individuals who are on the side with a lower propensity to send the long term unemployed into active labor market programs.

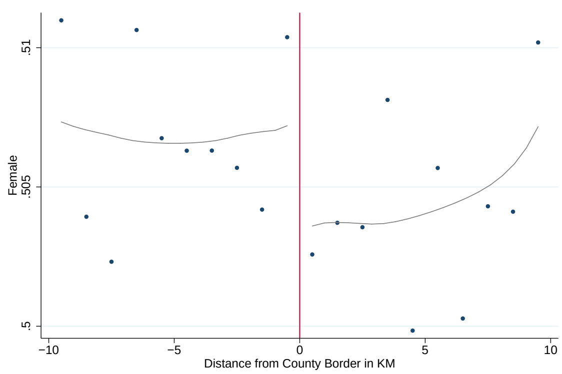
Figure 3: Smoothness of Observable Characteristics Around County Borders



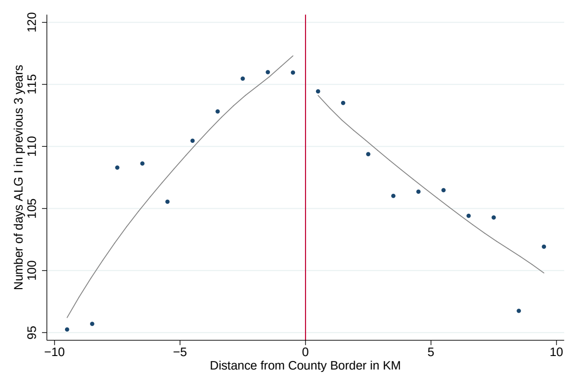
(a) Average years of schooling



(b) Average years of experience



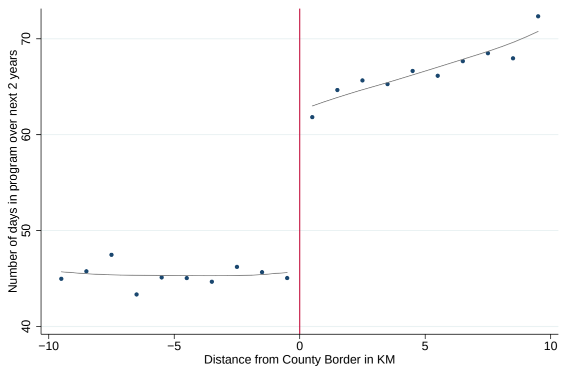
(c) Share female



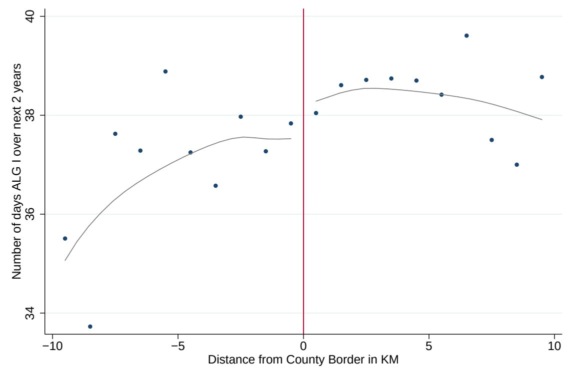
(d) Average days receiving UI benefits in previous 3 years

Notes: Each bin contains all individuals within a 1 kilometer bandwidth of distance from the nearest county border. Panel (a) shows the average years of schooling in each bin. Panel (b) the years of experience observed in the data. Panel (c) the share of individuals who are female, and Panel (d) the number of days individuals have received regular unemployment benefits (UB1) in the 3 years prior to entering unemployment benefits 2 (UB2). For each individual the distance is measured as the distance to the nearest county border. If the adjacent border has a higher average intensity of ALMP, the distance is multiplied with -1, so that the observations to the left correspond to individuals who are on the side with a lower propensity to send the long term unemployed into active labor market programs.

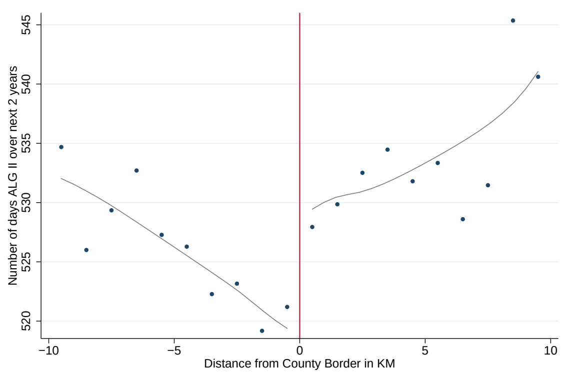
Figure 4: Variation of Days spent in ALMP and Labor Market Outcomes around Borders



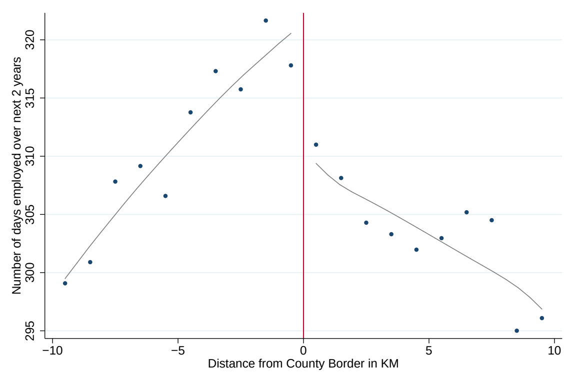
(a) Days spent in ALMP



(b) Days in UB1 over next 2 years



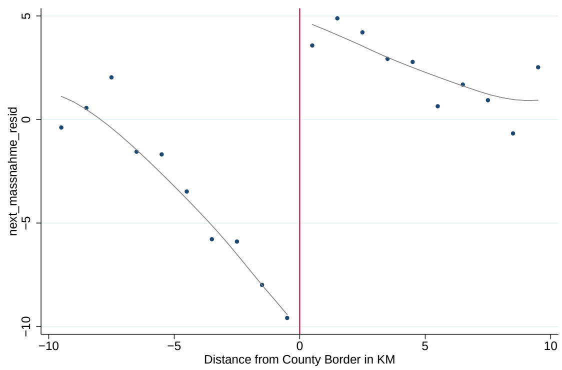
(c) Days receiving UB2 over next 2 years



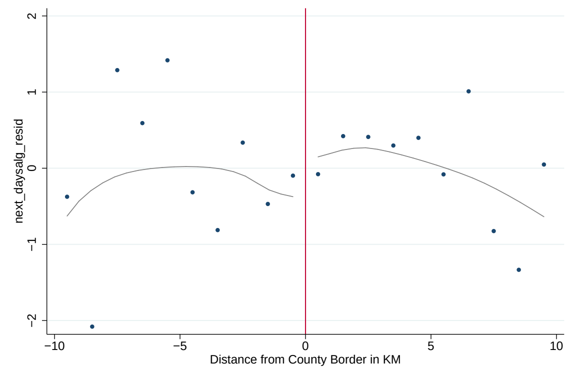
(d) Days employed over next 2 years

Notes: Each bin contains all individuals within a 1 kilometer bandwidth of distance from the nearest county border. For each individual the distance is measured as the distance to the nearest county border. If the adjacent border has a higher average intensity of ALMP, the distance is multiplied with -1, so that the observations to the left correspond to individuals who are on the side with a lower propensity to send the long term unemployed into active labor market programs.

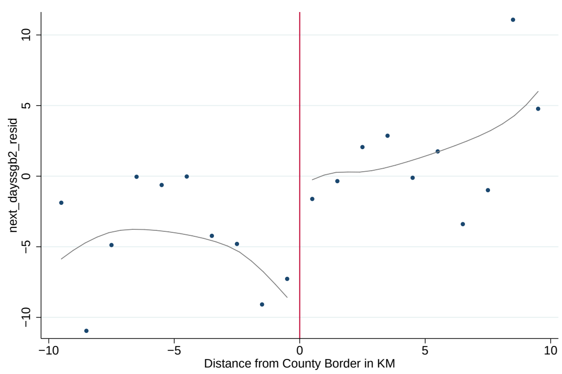
Figure 5: Variation of Days spent in ALMP and Labor Market Outcomes around Borders using Spatial FE Design



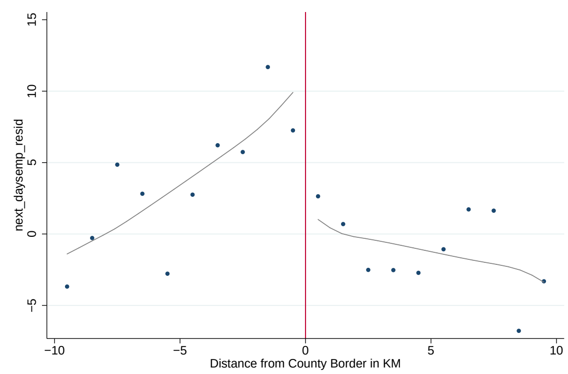
(a) Average days spent in ALMP



(b) Days in UB1 over next 2 years



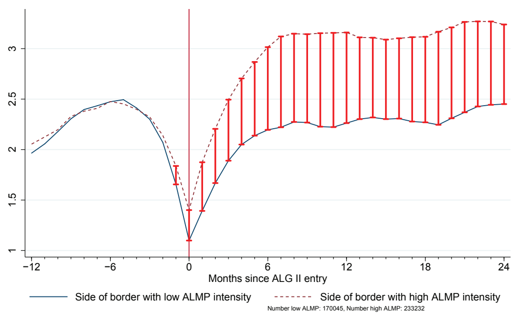
(c) Days receiving UB2 over next 2 years



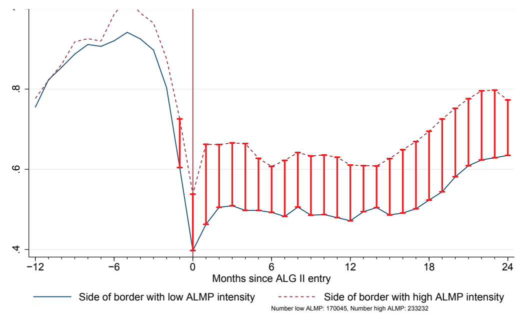
(d) Days employed over next 2 years

Notes: Each bin contains all individuals within a 1 kilometer bandwidth of distance from the nearest county border. For each individual the outcome variable is equal to the observed value for that individual minus the average value of that variable of all individuals within a 10 km radius of that individual. For each individual the distance is measured as the distance to the nearest county border. If the adjacent border has a higher average intensity of ALMP, the distance is multiplied with -1, so that the observations to the left correspond to individuals who are on the side with a lower propensity to send the long term unemployed into active labor market programs.

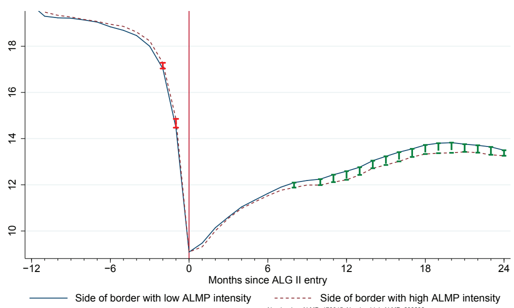
Figure 6: Dynamic Estimates of the Effects of ALMP Intensity on Labor Market Outcomes - Border Distance RD Estimates



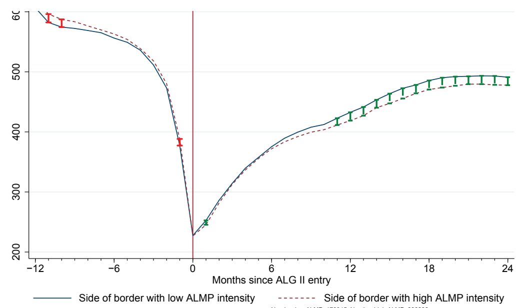
(a) Days spent in any ALMP



(b) Days spent in Education ALMP



(c) Days employed



(d) Monthly Earnings

Notes: The figures present estimates from a distributed lag model of how days spent in ALMP, employment and monthly earnings vary at the borders between high and low ALMP counties. Vertical bars indicate statistical significance.