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Applying for jobs: Does ALMP participation help?

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Abstract

This paper calculates the impact of Active Labour Market Programmes through the use of three new indicators measuring the application performance of the unemployed. These indicators can be measured repeatedly and therefore allow the usage of Panel Regression methods, cancelling out any unobserved individual heterogeneity. To implement the new approach, data on 30,000 applications has been collected. Using this data, a large positive effect for unemployed with a long term unemployment forecast was estimated. For unemployed without such a forecast, the effect is much smaller. The paper also shows that the new evaluation approach fulfils the requirements of a good controlling instrument: It is accurate, detailed, non-intrusive, inexpensive and therefore easy to keep up to date, easy to understand and communicate.

JEL classification #: I38, J64, J68
Key words: evaluation, treatment effect, active labour market program, job search

1. Introduction

Many national labour agencies use a large proportion of their resources for Active Labour Market Programmes (ALMPs), with the intention to make the reintegration of unemployed persons quicker and longer lasting. In 2007, the average OECD member country spent 0.56 of its GDP on ALMPs. In order to improve the quality of these expensive programs, a good controlling instrument is needed. This controlling instrument should estimate the ALMP effects in an unbiased way. It should be easy to understand and communicate and therefore being trusted. It should be detailed so that its findings can be used to identify which ALMP is successful for which group of unemployed. Ideally, the instrument would indicate why an ALMP is successful or unsuccessful, so existing programs can be adapted. It should be relatively cheap so it can be applied on a regular basis, to keep the results updated and relevant for the current labour market.

Unfortunately, such an instrument doesn't exist yet. In some ways this is not surprising, as the challenges are nontrivial: A direct comparison between participants and non-participants of a certain ALMP is not possible, as it is very likely that characteristics which influence the decision of participation (by the unemployed or case worker) also influence the outcome on the labour market. Comparing only very similar participants and non-participants as done through the intensively used matching approach has limits because it can only rely on the characteristics recorded in databases. Often, many important features and skills of the unemployed are missing in these records.

This study tries another attempt at the old research question; how can one measure the effect of an ALMP accurately? It doesn't do this by applying more sophisticated statistical tools, but instead through a different approach and different data. As part of this study, a nine months data collection period was carried out at an agency of the Swiss unemployment insurance in the city of Zurich. During this time, all applications written by the unemployed at this agency, their characteristics and outcome were documented. A sample of 30,000 applications was then coded and recorded electronically. Further data on the unemployed and the ALMP was collected through surveys among the case workers and the persons responsible for the ALMP. Through this, a very rich dataset was assembled.

Based on the idea of Falk, Lalive and Zweimüller (2005), this paper measures changes in the application process of the same person rather than comparing different individuals. It does this by measuring the probability of a job interview and the frequencies of applications and interviews per week, indicators which can be repeatedly observed. While Falk et al. applied an experimental design (by adding ALMP diplomas to randomly chosen applications, comparing the impact of the diploma on the success rate) this new approach measures the impact on a purely observational base, comparing applications before, during and after ALMPs.

The method of comparing the success of applications has been frequently used in the discrimination literature (under the name of correspondence-testing), but is new for the ALMP evaluation literature. The approach has great advantages over traditional evaluation methods: It allows cancelling out all time-invariant characteristics of an individual by using quite simple statistical tools. It permits the calculation of individual treatment effects. It is non-intrusive and since it does not need the consent of the persons involved, doesn't result in a selection bias. Because the whole spell from beginning to end can be observed, all the different effects proposed by theory can be identified. Further, it fulfils the controlling criteria mentioned above (unbiased, easy to understand and communicate and therefore trusted, detailed, inexpensive and easy to update). This makes it a very powerful controlling tool.

Using the data collected at the trial agency, the following results were calculated through panel regression estimation with fixed effects: Overall, the ALMPs had a large positive effect on the participants. Participation resulted in more interviews per week (the number is increased by 0.0308, which, at the time the average ALMP is announced, is equivalent to an 11.1 % increase), a higher probability of a job interview (plus 0.0107, which is equivalent to a 9.4 % increase) and a higher number of applications per week (plus 0.0972 or 3.9 %).

The effects are particularly large for unemployed with a long term unemployment forecast while they are quite small for unemployed with a forecast below twelve months. This difference seems to hold important information on who should be sent to participate in ALMPs: It is mainly the unemployed with low chances of a quick reintegration into the labour market who gain from the programs.

The results show further that the different subtypes of ALMPs fare very differently: On average, basic courses, the category "other courses" (a mix of IT and vocational training) and basic qualifications do well. Employment programmes and personality oriented courses on the other hand have a negative effect. Programs with negative effects don't have to be abolished altogether; but either the programs or the mix of unemployed participating have to be adapted in order to reap the benefits.

The paper is structured in the following way: In section 2, the four effects proposed by theory are illustrated and a short overview on the literature is given. The advantages of the new approach are elaborated in further details in section 3, and the data used is described in section 4. Section 5 describes the three application indicators and their development over the duration of the unemployment spell. In section 6 the ALMP effect is measured through Panel Regression analysis. The main models are presented and several sensitivity tests conducted. Section 7 looks at the distribution of the effect, to find out under what circumstances the ALMP result in a positive effect. Section 9 explains why the method is a good controlling method despite its inability to track the application process to its ultimate goal, the job, and Section 10 concludes.

2. Theory and related literature

The success of ALMPs has created great interest over the past two decades and as it is connected to the wider topic of evaluating welfare programs in general, the related literature is vast. A good overview over the literature, methods and challenges involved can be gathered from Heckman et al. 1999, Smith and Todd 2005 and a recent study by van den Berg et al. 2009.

There are four main effects proposed by the evaluation literature: the threat effect, the lock-in effect, the skill enhancement effect and the signal effect. These effects occur at different times during the unemployment spell, as illustrated by Figure 1, and have different effects on the three application indicators used in this study. The first one of these three indicators is "interviews per week". This is the indicator which policy makers are most interested in, because it captures both quality and quantity of the application process and is closely connected to the final outcome, a new job (for how close exactly, see section 9). It is a vector of the two other indicators: "interview probability" and "applications per week". Interview probability captures the chances of the application resulting in a job interview. It could be interpreted as the qualitative side of the application process. It is to a large extent determined by the employer who chooses the requirements and the number of applicants to the job opening (through his or her use of advertising). Application frequency, measured in applications per week, on the other hand can be interpreted as the search intensity, or the quantitative side. It is directly influenced by the unemployed person his or herself (and the unemployment agency, which sets a minimum requirement).

The first effect, the threat effect, starts right after the unemployed has been informed about her or his participation in an ALMP (for an overview on the threat effect, see Rosholm and Svarer 2008). This effect caught a lot of attention in research, especially after the paper of Black et al. 2003 which concluded that the threat effect is the driving forces behind the evaluated welfare program in Kentucky. It predicts that the search intensity rises after the announcement, as the unemployed is not keen on joining the ALMP. What happens to the interview probability is unclear and depends on how dry the pool of suitable jobs is. If suitable jobs are abundant, the probability should stay the same (maybe even rise because of better applications being written), if not, the probability falls as each further application is a worse job match than the one before. Because the probability of these additional applications is unlikely to be zero, one would expect the effect on interviews per week to be positive.

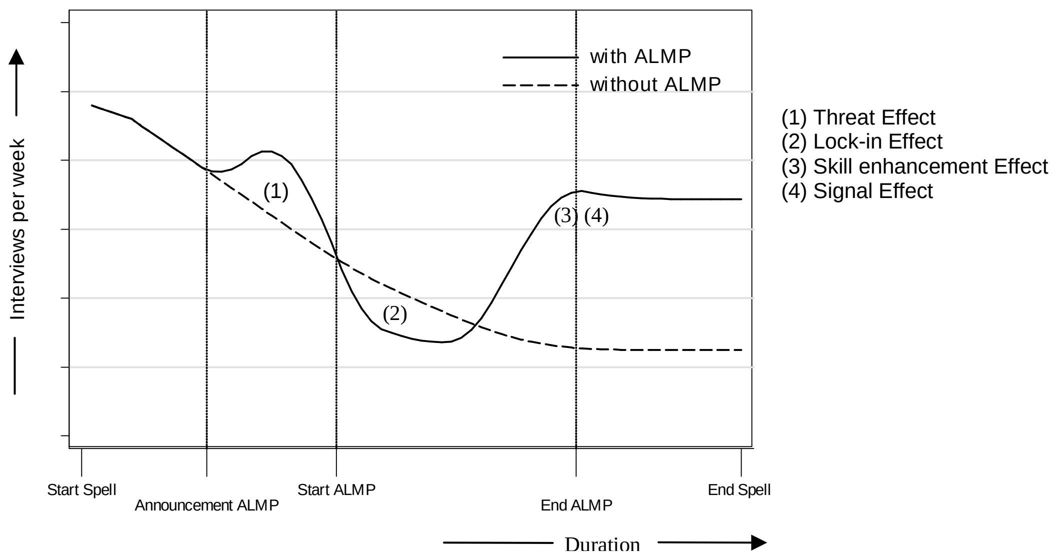


Figure 1: The four ALMP effects proposed by theory

After the ALMP has started, theory predicts the occurrence of a second effect, the lock-in-effect. This effect happens if the ALMP is demanding and doesn't leave the unemployed enough time to write as many applications as they did before the ALMP started. This will decrease the number of applications a person writes per week. Because unemployed persons are probably inclined to stop writing the applications for jobs they think they have a low chance to get, the average application probability should increase. Overall however the effect results in a lower number of invitations to job interviews. A different explanation of the lock-in effect is that an unemployed person reduces the search efforts if the program is attractive and positive treatment effects are anticipated (Carling and Richardson 2004). Finally, the lock-in effect could result if the case worker of the unemployed person reduces counselling efforts while the unemployed is participating in an ALMP (Ragni 2007). All three explanations point to lower search intensity during the ALMP.

Increasingly with the advancement of the ALMP, and especially once the ALMP has finished, the desired effects should set in, i.e. the skill enhancement and/or the signal effect. The two differ in as far the skill enhancement is an effect on the know-how of the unemployed, like better application techniques and improved language skills. The signal effect on the other hand unfolds when the unemployed is in a better position to reveal information (a signal) to a potential employer about her or his productivity (Carling and Richardson 2004). One would expect an increase of chances on the labour market through this signal, but the diploma can backfire if it actually signals a lack of knowledge (Falk, Lalive and Zweimüller 2005).

Table 1 summarizes the different effects. It also shows the overall trends in the three application indicators as predicted by theory. The overall trend for the probability of a job interview is downward: employers get more suspicious as they interpret a long duration of unemployment as a signal for low employability, low productivity or low work moral (Rosholm and Svarer 2004). As for applications per week, one would expect this indicator to rise over time as unemployed become more desperate with the end of the entitlement period nearing, opening up their search field and writing more applications. The trend for interviews per week is driven through the other two indicators, and given that the interview probability presumably falls steeply at the beginning and then flattens out, and the number of applications per week increases gradually at the beginning, but then gains momentum later in the unemployment spell, one would expect interviews per week to fall quite quickly at the beginning, flattening out and then increasing towards the end.

	Overall Trend	**Threat effect** (after announcement)	**Lock-in Effect** (during ALMP)	**Skill enhancement Effect** (after ALMP)	**Signal Effect** (after ALMP)
Interviews per week	- (steep fall at beginning, flattening and increase towards the end)	+	-	+	+ / -
Probability of a job interview	- (steep fall at beginning, later flattening)	-	+	+ (dominant indicator)	+ / - (dominant indicator)
Applications per week	+ (slow increase at beginning, later gaining momentum	+ (dominant indicator)	- (dominant indicator)	0	0

Table 1: The influence of the four effects on the application indicators, as proposed by theory

Note: “+” indicates an increase, “-“ a decrease and “0” no changes in the indicator through the effect

It is important to note at this point that these are all effects measured on a short term basis (rather than long term effects on salary, job satisfaction etc.) and on the individual level. A possible substitution effect (another worker is displaced because the unemployed finds a job, so the net gain in employment is zero) can only be measured on the macro level. There are also effects on the non-participants (threat effect through the pure existence of ALMPs) and even on employed workers (higher tax burden as ALMPs have to be paid for). There are limits to the microeconomic analysis. In terms of learning which ALMPs work and why, and to develop a controlling instrument, the micro approach seems to be the way forward however as macroeconomic analysis can estimate the effect only on a very aggregate level.

There have been several studies on Swiss ALMPs since they’ve been introduced in the late nineties. Lalive et al. (2000), accounting for participation selectivity using a multivariate duration model, estimate that during an ALMP, participants have a lower exit rate through the lock-in effect. Once the ALMP is finished, the authors find a strong positive effect for women, but none for men. Gerfin and Lechner (2002), using the matching approach, found that wage subsidies work well, but conclude that vocational training programmes show disappointing performance. A study of Lechner and Smith (2007) concludes that the current allocation of unemployed to ALMP by case workers is inefficient and that efficiency is as low as if a random rule would be used. In a recent study, Lalive et al. (2008) used both “timing-of-events” and matching estimation. While the estimation based on “timing-of-events” showed that none of the Swiss ALMPs shortened unemployment duration, the matching results were similar to those of Gerfin and Lechner, concluding that wage subsidies show good results while training and employment programmes do not. In a macroeconomic study, Zweimüller et al. (2006) estimated that the positive effect of wage subsidies has a darker side: a very small negative effect on all non-participants actually results in a negative overall effect for the whole economy. Employment programmes on the other hand have a negative impact on the participants. Through their deterring effect however, they have a small positive impact on all non-participants, which results in an overall positive effect. For many of the ALMPs used in Switzerland therefore, the calculated results are mixed at best. They seem to work well for certain groups, but in average fare quite poorly. This weak performance doesn't seem due to an especially bad provision of ALMPs in Switzerland, but rather reflects what researchers have found all over the world.

3. The new approach and its methodological advantages

While many statistical approaches have been used over the years, they all had to come to terms with the fact that, with the existing data, very sophisticated methods had to be applied, many of those relying on strong assumptions. Heckman et al. (1999) pointed out that "the best solution to the evaluation problem lies in improving the quality of the data on which evaluations are conducted and not in the development of formal econometric methods to circumvent inadequate data." The innovation of the new approach being applied in this study is indeed not the statistical method but new indicators, possible through a unique data set especially collected for this study.

The idea of the new approach is based on the work of Falk, Lalive and Zweimüller (2005). These authors introduced a new indicator into the ALMP evaluation literature; the probability of a job interview. Falk et al. (2005) recruited ten unemployed persons and got them to write 20 applications each. While the quality of the applications was held constant, a diploma of an IT training course attended by the applicant was attached to 10 randomly chosen applications of each unemployed. The outcome of the application (did the application lead to a job interview?) was then reported back by the unemployed to the authors. The focus of the paper was on the signal effect of the IT courses: how well is a course received by potential employers? The study produced interesting results: while on average adding the diploma had a negative (not significant) effect, the individual effects spread from positive to negative. Adding the IT-diploma was clearly disadvantageous when applying for jobs which required good IT skills. The fact that someone had to attend an IT course organized by the unemployment insurance was taken as a signal for low IT knowledge.

The approach used by Falk et al. is related to the "correspondence testing" method which is commonly applied in discrimination research: Two fictional applications are sent out which differ only in the gender or nationality of the applicant, and the researcher compares the success of both applications. A good overview over correspondence testing is given by Bertrand and Mullainathan 2004 who used the approach using African-American and white American-sounding names to test for discrimination. The method has been used by Oberholzer-Gee 2008 using applications from unemployed and employed to test for an unemployment stigma. In recent papers, Carlsson and Rooth (2007) measured the effect of different ethnic backgrounds and Drydakis (2009) the effect of the gender of the applicant on the application success.

While common in the discrimination literature, the approach has not been used in the ALMP research. However, the ALMP effect can be analysed by using the probability of a job interview as indicator, measuring how employers “discriminate” between ALMP participant and non-participants. This new indicator has a tremendous advantage over other indicators used so far in studies, e.g. duration, number of months unemployed in the next year and salary in the new job, which lies within the fact that it can be measured several times over the duration of unemployment instead of only once. This makes it possible to calculate an effect not just by comparing two persons, but by comparing the same person over time. Thus unobserved heterogeneity between persons which is time-invariant can be completely eliminated.

Furthermore, the new indicator allows the calculation of individual treatment effects instead of average treatment effects over all participants or groups of participants. This enables the researcher to observe the distribution of the effects among individuals participating, and simplifies identifying groups of individuals who benefit from the ALMPs (Falk, Lalive and Zweimüller 2005). Because the new approach conducts its estimation without a control group, another issue can be avoided: Sianesi 2004 argues that, depending on the program, all unemployed persons will join an ALMP, if only the duration of the spell is long enough. If the reason that the person doesn’t participate in an ALMP is that she or he found a job before the ALMP could have been announced, this could lead to a distortion of the estimation not in favour of the ALMPs.

The idea of Falk, Lalive and Zweimüller (2005) is used for this study again, but modified in two main aspects. In addition to the indicator “probability of a job interview”, two additional indicators are used: the number of applications per week and interviews per week. A second difference is that instead of the experimental design, a purely observational design is implemented. While such an observational approach allows less control over the application process (the quality of the application cannot be held constant, for example), it has several advantages: It is not as time consuming and allows therefore collecting data on a much higher number of observations. It is non-intrusive because it doesn’t change the application process; the data represent the “normal” behaviour outside the monitoring period. The consent of the unemployed isn’t necessary to collect the data as in Switzerland; it is already standard that some data on applications is collected by the case workers. This is an advantage because no special incentives to participate in the data collection have to be created and therefore potential distortions can be avoided. In contrast to the way correspondence testing is usually used, no fictional applications have to be created; this has the advantage that applications are as real as possible. Forging applications can be difficult for researchers if applications from a whole range of educational and occupational backgrounds have to be mimicked. And because the whole unemployment spell from beginning to end can be observed, all effects proposed by theory can be identified and measured, not just the signal effect. All those characteristics make it possible to create a powerful controlling instrument which fulfils all the criteria mentioned in the introduction (unbiased, easy to understand and communicate and therefore trusted, detailed, inexpensive and easy to update).

4. Data

Data on the application process is systematically gathered in all Swiss unemployment insurance agencies, using a self-reporting sheet filled out by the unemployed person. The unemployed track all their applications over the course of a month and hand the sheet over to the case worker at the end of the month. Most of these forms are filled out by hand, and while they are archived for quality checks and lawsuits, the information isn't stored electronically. The data has not been used for research so far.

In order to make this data source accessible and by this enabling the new form of evaluation, the data on the application sheets has to be stored electronically. This has been done as a trial run in a single agency of the Swiss unemployment insurance, the Zurich-Staffelstrasse agency. Being a medium sized agency with both clients from city and rural areas and with a wide variety of occupations, this agency seemed well suited. Data on 30,000 applications was gathered between 1st of July 2007 and 31st of March 2008.

For efficiency reason, a stratified sample of the persons registered during the observational period was taken: The sample contains all unemployment spells with at least one ALMP participation (a quarter of all unemployed registered at Zurich-Staffelstrasse) and a random selection of a third of the spells in which the unemployed did not attend an ALMP. This sample led to a database containing data of 806 unemployment spells. Applications within the lay-off period and applications during the last month of unemployment were dropped, as these periods are subject to different rules by the unemployment insurance. Including them would distort the analysis. Spells which consisted solely of applications of the above mentioned kind were dropped with them.

This leaves 738 observed spells, 338 of which are treated spells (unemployed participated at some stage of the unemployment spell in one or several ALMPs), containing a total of 17,910 applications. The 400 untreated spells (unemployed didn't participate in an ALMP at any time of the spell) include 12,081 applications. The number of observations decreases steeply as the duration of the spell increases; more and more unemployed leave as they find a job. As shown in Figure 2, over the first few weeks of unemployment the majority of applications stem from unemployed who will not participate in an ALMP during their spell. As time passes on, an increasing amount of the data comes from persons with ALMP. The case number can be low when looking at the later stages of the unemployment spell (that explains some of the high fluctuation in Figure 3 to 5).

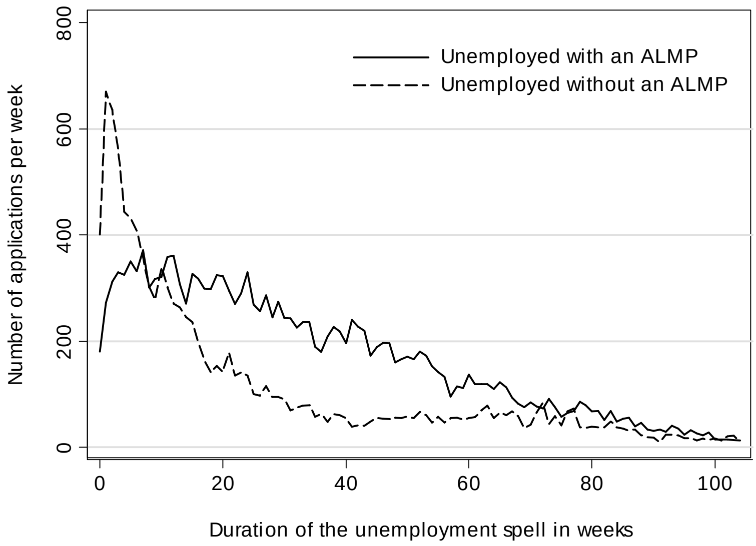


Figure 2: Number of observations recorded in the dataset, per week of the spell

Note: The graph shows the number of applications recorded in each of the weeks of the spell. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP").

Two objections to the data quality could be raised, both in connection to the self-reporting nature of the application sheets. The first possible objection could be that not all records are truthful and that some unemployed record applications they have never written. While wrongly recorded data (on purpose or by mistake) cannot be ruled out, the amount of purposeful cheating should be rather small, as case workers regularly check back with employers if the unemployed have indeed applied to the job indicated on their self-reporting sheet. Even if a small amount of cheating remains, this could only distort the calculation if more or less cheating is going on after the ALMP has started. There is nothing pointing to such an effect. The second objection could be that because of the requirement to write at least 8 to 12 applications, many unemployed don't bother writing all their applications down and instead stop once the minimum has been reached, therefore depriving the dataset of all their other applications. Again, this doesn't seem to be the case, neither according to statements by the case workers, nor showing up in the data. The applications are more or less evenly distributed over the stretch of a month, especially when looking at unemployed with ALMP (see Annex 1). If only the first 10 or so applications would be recorded, you'd expect an accumulation at the beginning of the month.

There is one more issue which has to be addressed in connection to the reporting sheet: Among other entries, the unemployed record the outcome of the application, whether they had an interview, a job offer or a rejection. The case workers at the trial agency reported that there was some confusion about the meaning of "job interview" when unemployed were carrying out personal applications (showing up at a company's door step and asking for a job). Some unemployed recorded such a personal application as an interview, others didn't. A sensitivity test in section 6 checks if the results change if applications from unemployed who reported almost all of their personal applications to be successful are left away. If not otherwise mentioned, all applications are used.

Apart from the self-reporting application sheets, data sources used include the electronically registered data of the unemployment insurance on the unemployed persons, a survey conducted among the case workers at Zurich Staffelstrasse (gathering additional data on the unemployed, e.g. a forecast regarding the unemployment duration of each person and the motivation to participate in the ALMP) and a survey among the employees responsible for the organization of ALMPs at the Office for Economy and Labour of the canton of Zurich (gathering diverse data on the ALMPs).

5. Changes in the three application indicators over time

To get an overview, the three application indicators are plotted over the duration of the unemployment spell. The duration is plotted until the 104th week, after which the entitlement time frame in Switzerland expires. Most unemployed use their benefits up beforehand, usually in the 18th month. There are several deviations from this pattern for persons who haven't paid into the unemployment insurance (shorter benefit period), elderly (longer period) and persons who participate in a work subsidy scheme (longer period).

The changes in the **number of interviews per week** over time are shown in Figure 3. The similarity between the two groups is striking: For the first 10 weeks the number of interviews per week is exactly the same. For the remainder of the spell the development seems similar for both groups, with the unemployed without an ALMP showing higher volatility and a slightly higher level. This indicator can be considered a result of both other indicators. Its downward trend however, as the next two graphs show, clearly stems from the decreasing probability of a job interview over time, while the gently raising number of applications per week does little to offset this downward trend.

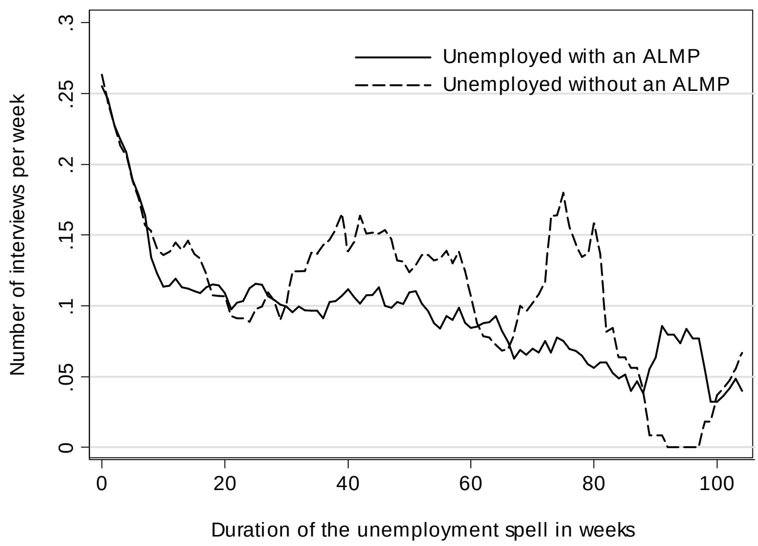


Figure 3: Frequency of interviews

Note: The graph shows the average number of interviews per week, giving equal weight to each unemployed registered in a certain week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP"). Because of low observational numbers in certain weeks, a nine week moving average is used.

Looking at the development of the second indicator, **probability of a job interview** (Figure 4), one notices that both groups start off with similar chances: one in ten applications are successful. The similarity of that starting level, and in fact the whole development over time, is again surprising. One would expect quite stark differences between the two groups: Case workers send the persons with bad chances to an ALMP, and let the others search without training.

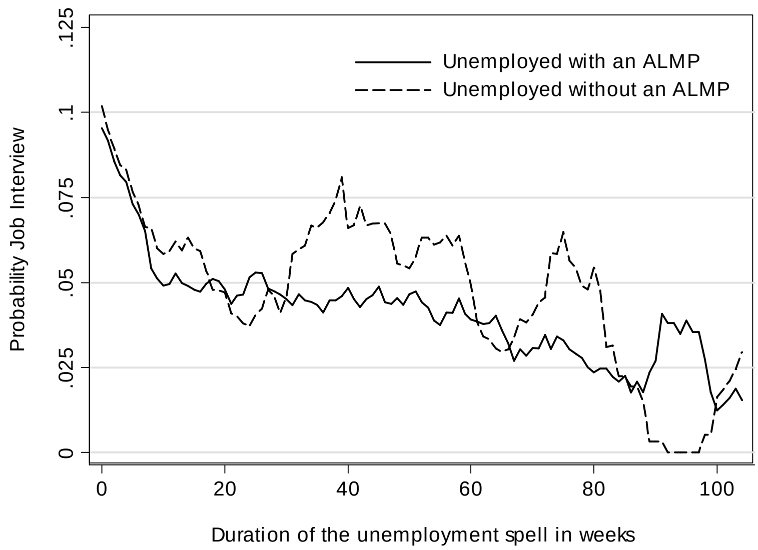


Figure 4: Probability of a job interview

Note: The graph shows the average probability of a job interview, giving equal weight to each unemployed registered in a certain week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP"). Because of low observational numbers in certain weeks, a nine week moving average is used.

Chances drop for both groups quickly over time. This is what theory predicts: Employers get more wary as time progresses, taking the long unemployment duration as a signal for low employability. Unemployed themselves might broaden their search field which could entail a fall in the proportion of successful hits. Just as important though are the changes in the group composition: the successful unemployed leave early and the remaining ones have a lower average chance.

For unemployed with ALMP there seems to be a stabilization of the interview probability after the first six month of unemployment, before the indicator drops again after the twelfth month to almost zero over the remaining duration of the entitlement frame. The development is very similar for the unemployed without ALMP, but because of the lower number of observations, the indicator is more volatile.

The **number of applications per week** represents the quantitative side of applications (Figure 5). Again, both the treated and control group start off in a very similar way, with the member of the treated group starting just above the control group. The number of applications per week gently drops till the 6^{th} month and then picks up again. Apart from a remarkable increase at the very end of the entitlement period, the indicator is relatively stable.

According to theory, one would probably expect more of an upward trend over time, especially as the end of the entitlement period comes nearer. The application number seems to take the minimum requirement of the unemployment insurance (8 to 12 applications a month) as orientation. Case workers of the regional placement centre don't seem to pressure the unemployed into writing more applications as time passes by.

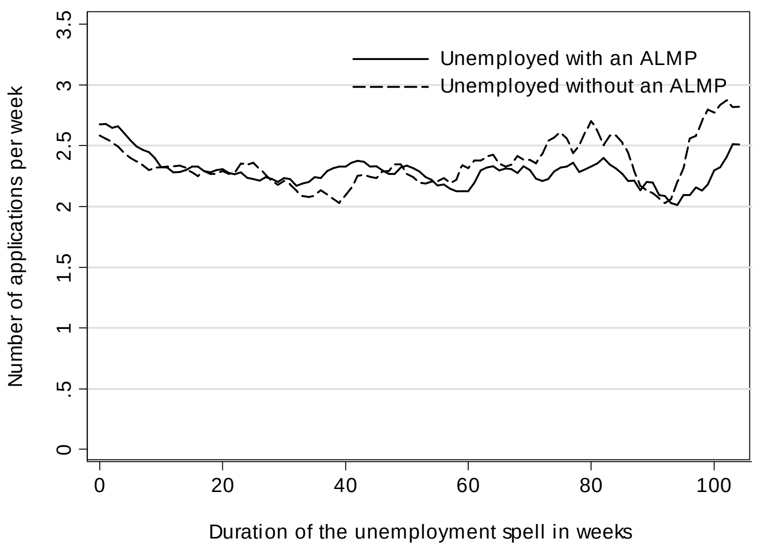


Figure 5: Search intensity

Note: The graph shows the average number of applications per week, giving equal weight to each unemployed registered in a certain week. The duration is plotted until the 104^{th} week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP"). Because of low observational numbers in certain weeks, a nine week moving average is used.

Summarizing, one can conclude that the differences between the two groups in all three indicators are very small. This is surprising as one would think behaviour and chances on the labour market as captured by the three indicators would be a main influence on the decision of ALMP participation. The closeness of the level and the development of the three indicators over the entire duration indicates that either a) the two groups are in fact very similar (i.e. that participation is random, at least in terms of labour market chances as captured by three indicators) and that the ALMPs have no influence at all, or b) that the ALMP participants actually do fare worse over time but that this is offset by the ALMPs.

6. Measuring the effect through Panel Regression

Unlike most studies on ALMP, which compare different persons with each other, the rich panel data at hand allows to compare applications of the same person over time. This eliminates a tremendous amount of unobserved heterogeneity. Because heterogeneity can be controlled for, widely understood statistical instruments like the regression method can be used, and there is no need to rely on strong assumptions.

Frame of Analysis

Whatever the estimation strategy or sample used, there are always three sets of regressions conducted in the following, one each for the three application indicators. For job interview probability the observational unit is the individual application and the dependent variable measures if the application resulted in a job interview (taking on the value 1 if successful, and 0 if unsuccessful). For the other two indicators, weekly number of interviews and applications, the panel is transformed so that the observational unit is one week of the unemployment spell. The unit shows the number of interviews or applications in that particular week.

The effect of the ALMP is captured by the regression coefficient of a dummy variable which indicates if the application was sent off before (0) or after the ALMP announcement (1). The announcement is chosen as the focal point as it divides the spell into a period before the application behaviour of the unemployed was influenced by a participation, and a period where it is influenced, therefore capturing all possible effects of the ALMP.

To calculate the coefficient of the effect dummy accurately, control variables are added to the model. The first set of control variables is a set of 13 duration dummies which indicate in which months the application was sent off (the dummies are: 1^{st} month, 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months). For the number of applications per week, this is simply the month in the unemployment spell that particular week is part of. For interview probability and the number of interviews per week, the month in which the applications are sent off is relevant, and not the month in which the interviews occur; the dataset does not contain information about the date of the job interview (the indicator “interviews per week” is therefore the number of interviews achieved by the applications sent off in a certain week). These dummies capture the influence of time in a very flexible way. It is a very important set of control variables, as two of three application indicators fall steeply over time. Without the duration dummies, the results are heavily distorted. As applications after announcement are later in the spell than applications before announcement, the estimation wouldn't correctly distinguish between the effect and the influence of time.

An additional variable is added which indicates how many weeks before or after the ALMP announcement the application was sent off. If the application was sent off before the announcement, the value is negative. The variable thereby controls for any correlation between the ALMP effect and duration relative to the announcement (a cumulative effect for example). This model belongs to the family of event study models, which study the impact of an event on a variable of interest, often the stock price of a company (for a recent overview of this methodology, see Khotari and Warner 2006). It is common to document graphically the development of the indicators of interest around the "event", thereby identifying the short term effect. This is done in Figure 6. Because of high fluctuations, moving averages are used. These moving averages are calculated separately for the weeks before and the weeks after the announcement. The value for the week of the announcement is calculated with both the data from before and after the announcement. The graph shows that there is a positive gap between the two values, for both probability of a job interview and interviews per week (i.e. the value is higher when using the moving average based on data after the event). This simple descriptive analysis indicates that ALMPs have a positive effect. The number of applications in the week of the event on the other hand is a bit smaller when calculated as a moving average of the weeks after the announcement, indicating a negative effect of the ALMP on the search intensity.

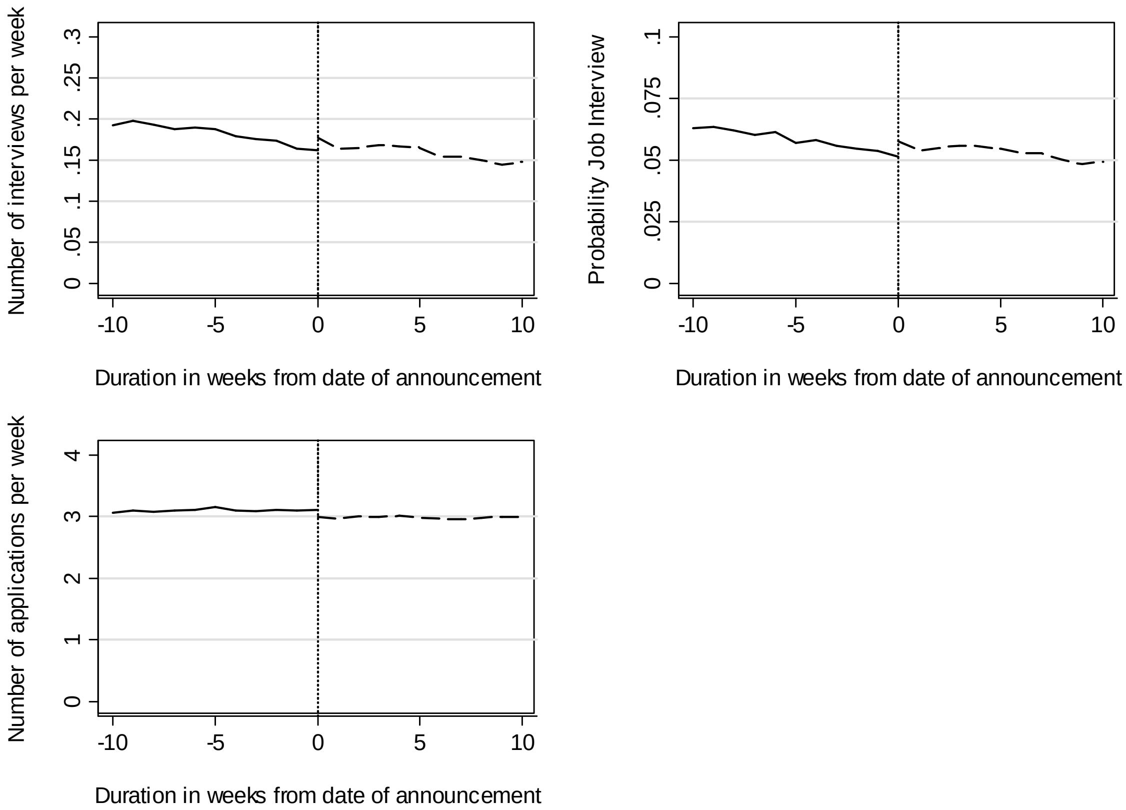


Figure 6: Development of the application indicators before and after the ALMP announcement

Note: The graph shows the average development in the three indicators ten weeks before to ten weeks after the ALMP announcement (the announcement is marked with a vertical line). Because of low observational numbers and high volatility in the indicators, a nine week moving average is used. The moving average is applied separately to the weeks before and the weeks after the announcement. The value for the week of the announcement (week 0) is calculated once through a moving average with data before the announcement and once with data after the announcement. Data from 203 unemployed was used (the effect can only be calculated for ALMP participants with at least one observed application before and one application after the announcement).

One more variable is added to the model, the unemployment rate in the occupation of the unemployed person who writes the application. This variable is measured on a monthly interval (e.g. for an application in September the unemployment rate of the occupation in September is used), and is calculated as the deviation from the median value. This variable is an important control variable as the state of the labour market might have both a large influence on the success of the application and on the performance of the ALMP. To prevent any bias, the control variable is added to the model. Finally, fixed effects are included, and thereby all time invariant differences between the unemployed are controlled for.

Note that the sets of control variables overall are parsimonious, only adding variables which would distort the calculations of the effect. The data is rich enough to add many other variables to the model, which would explain the outcome (for example the characteristics of the application). However, by adding more variables they are effectively held constant when estimating the effect. If the unemployed writes different types of applications after the ALMP, this should not be hold constant as it is part of the effect.

The estimation is done through Ordinary Least Square (OLS), and heteroskedasticity robust standard errors are reported. If not mentioned differently, data from all ALMP participants are used (there is no exclusion of outliers). All applications except the ones from the lay-off period and the last month are included. As described in the data section, these applications have to be dropped as both the lay-off period and the last month are subject to different rules by the unemployment insurance which would potentially distort the analysis.

Results

Table 2 shows the average effect of the ALMPs used at the Zurich-Staffelstrasse agency. The effect is large: An increase of 0.0308 in the number of interviews per week is the equivalent of 7.3 % when measured against the value of the constant, 0.4214. The constant can be interpreted as the number of interviews in the first month of unemployment. At the time the average ALMP is announced (104 days after the unemployment spell has started (median)) that baseline interview frequency has decreased to 0.2774 (measured as the sum of the constant and the coefficient for the dummy of the fourth month of unemployment). The relative effect is then the equivalent to a rise of 11.1 %.

The interview probability is increased by 0.0107, which is the equivalent of 7.0 % measured in the first month of unemployment, and 9.4 % after 104 days. The effect on applications per week is relatively small: The unemployed write 0.0972 applications per week more after the announcement. That is an increase of 3.6 % in the first month, or 3.9 % measured after 104 days. Both effects, the effect on interview probability and the one on search intensity, feed into the effect of the first indicator, interviews per week. However, changes in the number of interviews per week stem mainly from changes in the interview probability, while the search intensity increases just a little through the ALMP and has only a small influence on the increase in interviews per week.

Only the coefficient for the effect on interview probability is statistically significant (on the 10 %-level), despite the large size of the effect on interviews per week. The standard errors are large, indicating that there is considerable heterogeneity hidden behind the average effects. This heterogeneity will be further investigated below.

The control sets behave as assumed: The coefficients of the duration dummies are highly negative and increasing over time, at least when regressing on interviews per week and interview probability. This shows that these indicators are falling over the duration of the spell. The variable “application date relative to announcement” has a negative influence. This indicates that there might be a small interaction between the effect and the duration i.e. that the effect is decreasing over time. However, the coefficient is not significant and the effect relatively small. The unemployment rate in the profession of the unemployed person has a large negative influence on both interviews per week and the interview probability, but a small positive effect on the search intensity.

Dependent variable:	Interviews per week	Interview Probability	Applications per week
Mean	0.1355	0.0493	2.7478
Std. Dev.	0.4752	0.2165	1.6552
Overall ALMP Effect	0.0308	0.0107+	0.0972
(Dummy is 1 after ALMP announcement)	(0.0215)	(0.0061)	(0.0732)
Duration (omitted dummy: Month 1)			
Month 2	-0.1394**	-0.0344**	-0.1900
	(0.0394)	(0.0094)	(0.1273)
Month 3	-0.1596**	-0.0465**	-0.2278+
	(0.0426)	(0.0110)	(0.1350)
Month 4	-0.1440**	-0.0391**	-0.2239
	(0.0502)	(0.0134)	(0.1530)
Months 5 to 6	-0.1443*	-0.0420**	-0.2205
	(0.0560)	(0.0152)	(0.1783)
Months 7 to 8	-0.1674*	-0.0454*	-0.1811
	(0.0700)	(0.0194)	(0.2214)
Months 9 to 10	-0.1780*	-0.0516*	-0.0699
	(0.0838)	(0.0242)	(0.2687)
Months 11 to 12	-0.1691+	-0.0416	-0.1933
	(0.0974)	(0.0285)	(0.3166)
Months 13 to 15	-0.1903	-0.0506	-0.0773
	(0.1161)	(0.0338)	(0.3752)
Months 16 to 18	-0.2072	-0.0611	0.0045
	(0.1356)	(0.0400)	(0.4618)
Months 19 to 21	-0.2182	-0.0606	-0.0170
	(0.1557)	(0.0465)	(0.5393)
Months 22 to 24	-0.1699	-0.0370	-0.0751
	(0.1808)	(0.0541)	(0.6130)
Month 25 and more	-0.2820	-0.0722	0.1109
	(0.2040)	(0.0641)	(0.7272)
Application date relative to announcement (in weeks)	-0.0007	-0.0005	-0.0044
	(0.0020)	(0.0006)	(0.0066)
Unemployment rate in occupation	-0.0135**	-0.0056**	0.0103
(in percentage point deviation from the median rate)	(0.0052)	(0.0017)	(0.0174)
Fixed effects	yes	yes	yes
Constant	0.4214**	0.1532**	2.7351**
	(0.0879)	(0.0270)	(0.2695)
Sample			
All unemployed / only ALMP participants	ALMP	ALMP	ALMP
Number of applications or weeks	6518	17910	6518
Number of unemployed	338	338	338
Estimation			
OLS (with robust standard errors)	yes	yes	yes
R-squared	0.1178	0.1454	0.1864
F-value	4.8861	3.8608	3.2209

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
All applications except the ones from the lay-off period and the last month of unemployment are used.

Table 2: The ALMP effect on the three indicators

Although not all overall effects are statistically significant when measured as the average over all participants, there are some groups which gain heavily from the ALMP. The most important of these groups in terms of size and the gain through the ALMP is the group of the unemployed with a long term unemployment (LTU, i.e. a duration of more than 12 months) forecast. The forecast is an individual duration prediction recorded by the case worker at the start of the unemployment spell. Among ALMP participants, both groups of unemployed with a LTU forecast and unemployed ones are roughly of the same size. Annex 2 shows the characteristics of groups split according to the duration forecast. In average, the unemployed with a LTU forecast are older and worked more often in the hospitality industry and public administration. This group has an above average proportion of unemployed with no further education. In terms of ALMP, they participate more often in employment programmes and personality oriented courses, less often in Basic courses and language courses.

Because the two groups differ largely regarding the ALMP effect, the results are shown again in Table 3, this time with the sample split into two: One regression is conducted for the group with a forecast of more than 12 months (LTU); the other regression only uses data from the group with a forecast of less than 12 months (Non-LTU). The results show that the effect is very strong for unemployed with an LTU forecast while quite weak for the other group, no matter what indicator is examined. The group with a LTU forecast experiences an increase of 0.0386 interviews per week. Measured against their baseline number in month one (as measured by the constant), this effect is equivalent to 19.4 %. After 104 days, the effect is equivalent to an even larger increase of 27.6 %. Interview probability increases by 0.0132 (an increase of 23.5 % in the first month and 32.3 % after 104 days), once the ALMP has been announced. And the third indicator, applications per week, increases by 0.2071 (8.2 % in the first month, 8.7 % after 104 days). The effect of ALMP on the application indicators of participants with an LTU forecast is positive, very large and statistically significant.

Dependent variable:	**Interviews per week**		**Interview Probability**		**Applications per week**	
Subsample: Forecast =	**LTU**	**Non-LTU**	**LTU**	**Non-LTU**	**LTU**	**Non-LTU**
Mean	0.1033	0.1782	0.0382	0.0648	2.7034	2.7482
Std. Dev.	0.4073	0.5479	0.1917	0.2463	1.5657	1.6716
Overall ALMP Effect	0.0386+	0.0150	0.0132+	0.0043	0.2071*	0.0280
(Dummy is 1 after ALMP announcement)	(0.0216)	(0.0371)	(0.0069)	(0.0102)	(0.1012)	(0.1083)
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes	yes
Application date relative to announcement	yes	yes	yes	yes	yes	yes
Unemployment rate in occupation	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Constant	0.1991*	0.6253**	0.0562+	0.2425**	2.5145**	3.0000**
	(0.0901)	(0.1513)	(0.0289)	(0.0438)	(0.3662)	(0.4404)
Sample						
All unemployed / only ALMP participants	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP
Number of applications or weeks	3496	2851	9451	7835	3496	2851
Number of unemployed	166	162	166	162	166	162
Estimation						
OLS (with robust standard errors)	yes	yes	yes	yes	yes	yes
R-squared	0.2748	0.1825	0.1864	0.1178	0.2244	0.1806
F-value	2.3576	3.1401	3.2209	4.8861	1.0121	0.7125

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Table 3: The ALMP effect for unemployed with (without) a Long Term Unemployment forecast

Unemployed with a forecast of less than 12 months on the other hand only show an increase of 0.0150 interviews per week (which is equivalent to 2.4 % after the first month, 3.0 % after

104 days), an increase in the interview probability of 0.0043 (1.8 %, 2.1 %) and an increase of 0.0280 applications per week (0.9 %, 1.0 %). The ALMP have also a positive effect on this group. Compared with the group with a LTU forecast, the effect pales though.

The next table (Table 4) shows the decomposition of the overall effect into its partial effects. The simple dummy measuring the overall effect is substituted by three dummies which switch to 1 when the application is written after the announcement and before the start of the ALMP (threat effect), or between start and end of the ALMP (lock-in effect) or after the ALMP has finished (skill enhancement and signal effect). Because they both happen at the same time, their combined impact is measured. The coefficients compare the effect relative to the situation before announcement.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Mean	0.1355	0.1033	0.1782	0.0493	0.0382	0.0648	2.7478	2.7034	2.7482
Std. Dev.	0.4752	0.4073	0.5479	0.2165	0.1917	0.2463	1.6552	1.5657	1.6716
Partial Effects									
1. Threat Effect	0.0339	0.0159	0.0252	0.0097	0.0006	0.0071	0.1075	0.2495*	-0.0085
(Dummy is 1 between announcement and start ALMP)	(0.0274)	(0.0264)	(0.0435)	(0.0073)	(0.0080)	(0.0116)	(0.0855)	(0.1244)	(0.1217)
2. Lock-in Effect	0.0279	0.0508*	-0.0020	0.0118+	0.0203*	-0.0006	0.0865	0.1842+	0.0735
(Dummy is 1 between start and end ALMP)	(0.0233)	(0.0248)	(0.0430)	(0.0068)	(0.0079)	(0.0119)	(0.0839)	(0.1100)	(0.1288)
3. Skill enhancement and 4. signal effect	0.0269	0.0710*	-0.0168	0.0126	0.0308**	-0.0060	0.0678	0.1778	0.0300
(Dummy is 1 after the ALMP ended)	(0.0302)	(0.0331)	(0.0542)	(0.0088)	(0.0101)	(0.0154)	(0.1054)	(0.1406)	(0.1630)
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Application date relative to announcement	yes	yes	yes	yes	yes	yes	yes	yes	yes
Unemployment rate in occupation	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.4213**	0.2038*	0.6344**	0.1531**	0.0579*	0.2456**	2.7368**	2.5078**	3.0038**
	(0.0880)	(0.0903)	(0.1542)	(0.0270)	(0.0288)	(0.0442)	(0.2696)	(0.3669)	(0.4427)
Sample									
All unemployed vs. ALMP unemployed	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP
Number of applications	6518	3496	2851	17910	9451	7835	6518	3496	2851
Number of unemployed	338	166	162	338	166	162	338	166	162
Estimation									
OLS (with robust standard errors)	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.2172	0.2754	0.1827	0.1454	0.1872	0.1179	0.2233	0.2245	0.1807
F-value	2.1041	2.1213	2.7494	3.4545	3.0716	4.2914	0.6704	0.9337	0.6584

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.
Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Table 4: The ALMP effect split into its partial effects

All partial effects result in sizeable changes on at least one indicator, but not all of them in the direction proposed by theory. Regarding the threat effect, there is indeed evidence of changes showing up on the indicator “applications per week” once the ALMP has been announced. The effect only exists for the group with a LTU forecast where it is strong (+ 9.9 % more applications per week, when measured against the constant). The group without a LTU forecast shows no sign of the threat effect.

The lock-in effect doesn't seem to exist at all. The unemployed don't seem to decrease their search intensity once the ALMP has started; on the contrary. The LTU group increases search efforts by 7.3 %. At the same time, the LTU group experiences a steep increase in the interview probability which overall results in a similarly steep increase on interviews per week. The group without a LTU forecast doesn't show any changes worth mentioning. The lack of a lock-in effect during the ALMP is not so much surprising from a practical point of view as many of the ALMPs include application training. If the lock-in effect exists at all, it is overlaid by the skill enhancement effect which might start even before the ALMP has finished.

Once the ALMP has finished, the positive effect is very large for the group with a LTU forecast. The leading indicator is interview probability, but there is also an increase in search intensity, compared with the situation before the announcement. For interviews per week and interview probability, the measured effect is at its strongest here, indicating the strong sustainability of the positive ALMP effect for this group.

The non-LTU group on the other hand shows negative effects for probability and interviews per week after the ALMP has finished. These effects are relatively small and don't differ significantly from zero. The negative effects could therefore be purely random. If a negative effect would remain in a larger sample, its most likely explanation would be that it stems from a negative signal sent out to potential employers.

Sensitivity analysis
A possible criticism questioning the validity of the results could be that the results are distorted because the composition of the observed group of unemployed changes over time. This criticism will be addressed in test 1. Further, while there are good reasons why the main estimation (Table 2 and 3) has been conducted with the specification chosen (those reasons will be stated below), it is interesting to see how robust the estimates are when the estimation strategy is changed. In order to test this, the main model is changed in six aspects. Test 2 observes how the estimates change when the panel structure is changed. The other tests incorporate changes regarding the duration variables (test 3), the observations used (dropping outliers in test 4 and personal applications with an unusual high success rate in test 5) and check the non-anticipation assumption (test 6).

A potential issue regarding the balance of the sample (test 1) is that the panel might become less balanced as unemployed with low chances remain in the pool and unemployed with above average chances leave because they find a job. If the ALMP has a better effect on unemployed with low chances (as shown in Table 3), the calculated average effect might overestimate the true effect of the ALMP. Figure 7 shows that the chances of the remaining pool of unemployed don't deteriorate as much as one might expect. For each person, the average of the three indicators before the announcement is calculated (pre-announcement value). At the moment of the announcement, the sample is complete; the average pre-announcement values over the whole sample of ALMP participants are an interview probability of 0.0632, 0.1857 interviews per week and 2.9264 applications per week. Each week after the announcement, the sample looses members. The sample average of the pre-announcement values falls because of the changes in the group composition; members with high pre-announcement values leave the group. As a benchmark, a second line in the graph represents what would happen if no members would have left the group (i.e. the attrition is corrected): the line is horizontal as the average value would stay constant. Figure 7 shows that there is some deviation of the uncorrected sample mean of pre-announcement values from that constant, but the difference is relatively small. With other words, the estimation of the ALMP effect should not be biased by an imbalance in the sample.

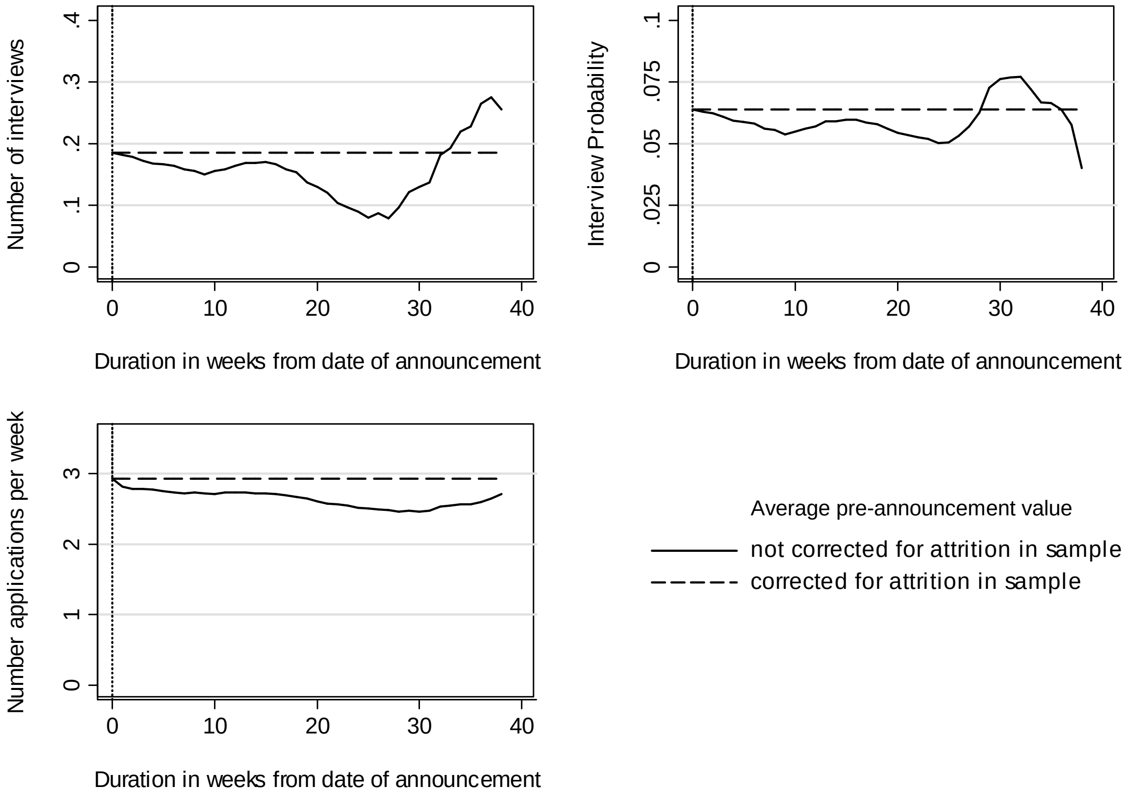


Figure 7: Assessment of sample attrition (development of pre-announcement values in sample)

Note: The duration is plotted until the 38th week after the announcement (the maximum for any person in the sample). A total number of 322 ALMP participants are observed (only ALMP participants with at least one observed application before the announcement can be assessed). Because of low observational numbers in certain weeks, a nine week moving average is used.

In terms of the balance between unemployed with a LTU forecast and unemployed without such a forecast, a similar conclusion can be made. As time progresses, an increasing number of applications might stem from unemployed with a LTU forecast. Again, changes in the balance of the sample over time might have an impact on the results: the calculated effect might be larger for unemployed with a LTU forecast because there are more applications after the announcement. The graph in Annex 3 shows how many applications stem from unemployed with a LTU forecast and how many applications from unemployed without such a forecast, and plots the development of these numbers over the duration of the unemployment spell. The balance does not change as quickly as one might have anticipated – the sample only changes its balance slowly. Finally, as part of this first test, the main model is recalculated (Annex 4). Instead of one dummy switching to 1 once the ALMP has been announced, this model entails three dummies: One switches to 1 between 0 and 10 weeks after the ALMP announcement and is zero before and after this period. The second dummy switches to 1 between 11 and 20 weeks after the ALMP announcement and the third dummy in week 21 and later. The results show clearly that the large difference between the effect on unemployed with LTU forecast and on unemployed without such a forecast is not just due to the fact that unemployed with LTU forecast tend to remain longer in the sample. The results show that in all three assessed periods after the announcement, the LTU forecast unemployed fare better than the Non-LTU ones.

Test 2 (Annex 5) shows what happens when all unemployed are added to the estimation, even the ones who haven't participated in an ALMP. The effects of the ALMP are smaller. The reason for this is that the model now assumes that the effect of duration is exactly the same for the ALMP-participants as for the rest of the unemployed. That is not necessarily true: Indeed, when using separate duration dummies for the treated and control groups, the coefficients of the separate duration dummies are quite different (not shown in the table). Using different duration sets for both groups, the size of the effect coefficients increase. There is no gain in adding the control group members to the regression, as they don't add any information on the size of the effect.

The third column shows the results when dropping the fixed effects and pooling all the applications. The same duration dummies are used for both groups here, but a new dummy variable is introduced, which switches to one if the unemployed writing the application is an ALMP participants at some stage of his or her spell (in the following referred to as the treated-dummy). The coefficient of this dummy is interesting, as it shows that there is large negative selection into the programs: The participants have a lower performance than non-participants in terms of interviews per week and interview probability, as shown by the negative coefficient of the treated-dummy. In the regression on the number of applications per week, the treated-dummy has a positive coefficient, indicating that ALMP participants write more applications than non-participants all other variables in the model kept constant.

In a last step of this test, many characteristics are added to the regression, which level out the differences in the application indicators between participants and non-participants which can be explained by these characteristics. The added variables are gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The separate duration dummies are kept in the regression. Indeed, through this the treated dummy is now almost zero for interview probability. It is even positive for applications per week and interviews per week, although the coefficient for the latter is small and not statistically significant. Together with the different sets of duration dummies, these variables seem to explain the differences in performance in the 3 application indicators rather well.

What happens to the coefficient of the effect dummy? The effects get stronger when moving from the regression with fixed effects to pooled regressions (apart from the regression on applications per week). Once the set of characteristics of the unemployed are added, the coefficient get smaller again, in fact to about the size they have in the standard specification, using fixed effects and only the data from ALMP participants (again, apart from applications per week). This shows that the core results are robust in terms of the estimation of the counterfactual development of the three application indicators, even when comparing applications of persons who participated in an ALMP with applications of unemployed who didn't participate.

The results of test 3 are shown in Annex 6. The standard model contains 13 dummies. This seems to be the best way to model the effect of time in a flexible way, allowing for non-linear influences. The results in Annex 6 show that if no time variables were used at all, the ALMP effects are smaller, in some regressions even negative. This downward shift of the effect coefficients is to be expected; as the effect dummy now partly includes the negative effect of time on the indicators (it does that since the applications after the announcement are by definition later in the spell than the applications before the announcement). The model is then tested by adding a more simple set of time dummies (only 5 instead of 13), and by adding two continuous variables (duration in weeks, duration in weeks squared). The effects tend to be weaker for the whole sample and even negative for the group without a LTU forecast. The effect for the group with LTU forecast on the other hand is quite robust. The test shows considerable robustness for the main finding; that ALMP should be used mainly for unemployed with low chances on the labour market.

Test 4 (Annex 7) looks at the influence of outliers. Outliers were not excluded in the main estimation as there was no reason to suspect that the ALMP effect would be different for them. To conduct test 3, the main results are recalculated, this time without unemployed who show at any stage of their unemployment spell more than 15 applications a week or 5 interviews per week. Unemployed with an overall interview probability above 0.75 are not covered. If the unemployment spell is longer than 2 years, it is cut off after this point. Overall, 314 applications are dropped (1.8 % of the observations), 19 of them from unemployed with a LTU forecast. Accordingly, the results for the participants with a LTU forecast changes very little (the effect becomes a bit stronger). For the group without the LTU forecast on the other hand, the effect gets weaker on two of the indicators. Again, the main conclusion, that ALMP should be mainly used for unemployed with a LTU forecast, remains valid.

Test 5 (Annex 8) recalculates the estimates, this time dropping all applications of unemployed who reported a success rate of 0.9 and higher for their personal applications. Such a high success rate is extremely unlikely and shows that the unemployed person has probably understood the term “interview” differently from the research team (as described in section 4). Through this, 130 applications of 7 unemployed are dropped. Leaving these applications away, the effect becomes larger for interview probability and interview per week when looking at the overall results and the results for group without a LTU forecast. The effect on interview per week almost doubles in size for unemployed without a LTU forecast. However, the effect remains considerably larger for unemployed with a LTU forecast.

The next test, test 6 (Annex 9), checks if the participants anticipated the ALMP. If that were the case, the threat effect would start to exert pressure well before the course was announced. In order to check for that a new dummy variable is introduced into the model. This dummy variable switches from 0 to 1 if the application was written during the month just before the announcement. If the participants don't anticipate the participation, the coefficient should be zero or close to it. The results show that the coefficients of this ‘placebo’ dummy are insignificant (even on the 10 %-level) in all nine estimations. Some of the coefficients are relatively large, but this could be either due to anticipation of the ALMP or due to random fluctuations. By introducing a dummy for the month before the announcement, the effect dummy now measures the difference between applications written until a month before the announcement and applications written after the announcement. The performance of the applications until a month before the announcement is slightly weaker than the average application before the announcement (as indicated by the positive placebo coefficients). Therefore, the estimated effect of the ALMP becomes larger in the placebo estimation. The average effect over all participants is now significant for the indicators interviews per week as well. The differences between the group with a LTU forecast and the group without one remain large.

Concluding over the six tests conducted, the results show that the coefficients are robust. The coefficients are particularly stable for the group of the LTU-unemployed. The coefficients for the non-LTU group vary and even change signs, but generally stay small. The main result, that the effect is much larger for the LTU group, holds throughout all changes.

7. Who gains?

The regressions in the last section show the average effect over all participants, the effect over the unemployed with a LTU forecast and the effect over unemployed without such a forecast. Because of its panel structure, the data set allows venturing beyond these average results by calculating individual treatment effects for each participant. This is useful because it gives further insights into which groups gain most from ALMP.

Technically, the individual effects are calculated using the residuals after estimating the main models (Table 2). The residuals capture everything which cannot be explained through the average treatment effects, the duration dummies, the application date relative to announcement, the unemployment rate in the occupation and the fixed effect. Latter makes sure that any time-invariant personal characteristics are not part of the residual. The only systematic component in the residuals should therefore be the personal treatment effect, measured as the deviation from the average effect. It is captured by calculating the difference between the mean of all the residuals before the announcement and the mean of all the residuals after the announcement. In order to calculate the absolute individual treatment effect, the difference is simply added to the average ALMP effect. Note that the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement. Altogether, the individual effects can be calculated for 203 unemployed.

Figure 8 shows the average ALMP effect on the three application indicators. It illustrates that there are many winners, but also some losers among the participants.

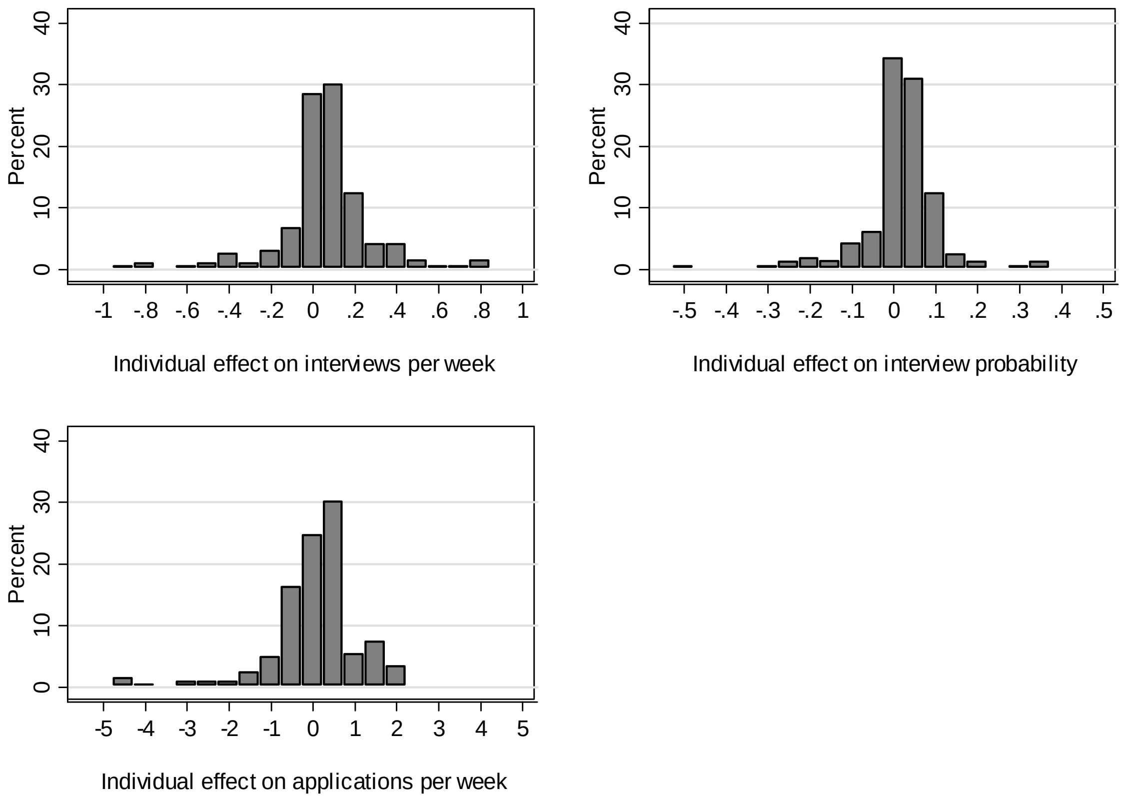


Figure 8: Distribution of the individual effects
Note: The graph shows the distribution of the ALMP effect on the three indicators (as calculated from the estimation in Table 2). Data from 203 unemployed was used (the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement). Extreme outliers are not shown in the graphs (interview probability: four persons below 0.5 and one above 0.5; applications per week: one below -5 and two above 5; interviews per week: seven below -1 and three above 1).

Regressions can now be run, explaining the individual effects through different independent variables to see under what circumstances the ALMP effect is increased or diminished. The first set of independent variables used is a set of ALMP type dummies (Table 5). In order not to overstretch the number of observations, each category of ALMP entails at least 16 unemployed persons. This is admittedly a very low number still, so the results are only preliminary. The categories used are “basic course” (which focuses on situation analysis, general information about unemployment and application training), “personality oriented course” (assessing and developing soft skills), “basic qualification course” (alphabetization and very basic German), “language course” (German courses), “other courses” (IT courses and vocational training for different industries) and “employment programmes” (workplaces for the unemployed with a training component). The observational number is indicated in parentheses in Table 5).

The different ALMP types have very different effects. The results show that the omitted category, basic course, has strong positive effects on all three indicators (its coefficient are shown by the constant). Interviews per week rises by 0.0791 (the overall ALMP effect for the assessed group of the 203 unemployed is 0.0281), interview probability by 0.0277 (overall

0.0114) and applications per week by 0.1242 (0.0940). Against the strong performance of this ALMP type which is also the most commonly used one, all other types fare worse, at least in terms of interview probability and interviews per week (the ALMP type coefficients show the relative performance compared to the omitted category, the basic course).

Apart from the basic course, basic qualifications courses and “other course” also do well. The effect of the language courses is around zero as can be seen by adding the coefficients of the constant and the coefficient of the language course. Employment programmes and personality oriented courses do even worse, resulting in a negative effect on the application performance of its participants.[1] It might surprise that the effect of these two ALMP types is not just zero but negative (many previous evaluations actually identify negative impacts of programs, see Sianesi 2008). This negative effect can stem from a decrease in motivation through the announcement (as part of the threat effect), a lower number of applications while on an ALMP (lock-in effect) and/or a bad signal sent to potential employers when adding the course diploma to the application (see Falk et al. 2005). The observational number is too low in order to measure the partial effects on a program type base.

Dependent variable: Individual ALMP effect on	**Interviews per week**	**Interview Probability**	**Applications per week**
Mean	0.0281	0.0114	0.0940
Std. Dev.	0.5520	0.1532	1.3052
ALMP Type (omitted: Basic course (90 participants))			
Personality oriented course (30 participants)	-0.1363	-0.0569	0.0311
	(0.1152)	(0.0393)	(0.2389)
Basic qualifications course (16 participants)	-0.0346	-0.0040	-0.0397
	(0.0722)	(0.0154)	(0.2298)
Language course (17 participants)	-0.0815	-0.0216	-0.3994
	(0.1179)	(0.0286)	(0.3735)
Other course (18 participants)	-0.0699	-0.0021	0.0442
	(0.1584)	(0.0471)	(0.2865)
Employment programme (32 participants)	-0.0959	-0.0355	-0.0135
	(0.1050)	(0.0338)	(0.2192)
Constant	0.0791	0.0277+	0.1242
	(0.0702)	(0.0151)	(0.1795)
Sample			
All unemployed vs. ALMP unemployed	ALMP	ALMP	ALMP
Number of unemployed	203	203	203
Estimation			
OLS (with robust standard errors)	yes	yes	yes
R-squared	0.0088	0.0193	0.0076
F-value	0.4576	0.7455	0.3126

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Data from 203 unemployed used (the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement).

Table 5: The effect of different types of ALMP

Note that all coefficients but one (the effect of the basic course on interview probability) are insignificant, despite their large size. This means that not all participants have the same gain

[1] Interestingly, those two ALMP types are also the longest ones. This raises the questions if the lock-in effect is responsible for the weak performance. This doesn’t seem to be the case, as the search intensity as measured by the number of applications per week is not reduced during these two types. Rather, it is the interview probability which is decreased during and after the ALMP.

from the ALMP types and there is a lot of variation in these individual effects, even when split up according to the ALMP type. Since the observational number is quite small, one would probably obtain significant differences with a larger sample.

In order to find out under what circumstances the ALMP work best, characteristics can be added to the regression. The dataset is very rich and allows for a multitude of factors to be tested (both characteristics of the unemployed person and the ALMP). However, the influence of many of those factors is not large enough to be significant on basis of the small observational set.

Table 6 shows how different characteristics of the unemployed person influence the ALMP effect. In the first block entered are three age group dummies. The results show that ALMP work best for the unemployed below the age of 30 (the omitted category). The coefficients are not statistically significant however, despite the considerable size of the coefficients. The next variables entered indicate the highest education the unemployed has attained. The results show that the higher the education of the unemployed, the better the results. The worst results show unemployed with no further education at all and unemployed with an apprenticeship, the best result unemployed with a university degree. This is surprising, because there is a broad choice of ALMP for unskilled persons.

Foreigners and women experience a larger effect on the number of interviews per week than Swiss and men: Foreigners gain more than Swiss because the ALMP results in a larger change in the search intensity, while women have a higher increase on interview probability than men. If the unemployed searches for a job in the same occupation as previously held (overall 73 % of all ALMP participants), he or she shows a much better ALMP effect. A search for a job in the same occupation increases the ALMP effect on interviews per week by 0.1484, the effect on interview probability by 0.0666 (significant on the 10 %-level) and the effect on applications per week by 0.1389 compared to searching a job in another occupation. This sheds a critical light on retraining and participants learning new skills because they cannot or do not want to go back to their old occupation. One could argue that this is merely an indication for motivation, but this effect is measured separately through the next variable. Motivation to participate in the ALMP has a strong positive effect, but the difference between motivated and unmotivated unemployed is not statistically significant. After controlling for motivation, the coefficient for the dummy which indicates if the person has been sanctioned once or several times during the unemployment spell is almost zero.

As a last characteristic, the forecast of the case worker on duration is added to the regression. Three groups are used here, and the gains for persons with a longer duration forecast seem to hold even if comparing persons with 0 to 5 months forecasts with the ones of 7 to 11. Comparing the two extreme ends, unemployed with 0 to 5 months forecasts and those with a LTU forecast, the following differences are statistically significant: The ALMP effect on interviews per week is 0.2069 higher. This is an enormous difference, considering the average effect is 0.0281.

Dependent variable: Individual ALMP effect on:	Interviews per week	Interview Probability	Applications per week
Mean	0.0281	0.0114	0.0940
Std. Dev.	0.5520	0.1532	1.3052
Age (omitted: below 30)			
Age 30 - 39	-0.0144	-0.0169	0.2621
	(0.0857)	(0.0254)	(0.3988)
Age 40 to 49	-0.1660	-0.0457	0.0391
	(0.1183)	(0.0310)	(0.3229)
Age 50 and older	-0.1164	-0.0544	0.0575
	(0.0985)	(0.0340)	(0.3089)
Education (omitted: no further education)			
Apprenticeship	-0.0171	0.0080	-0.0030
	(0.1483)	(0.0337)	(0.2184)
Gymnasium	0.1566	0.0425	0.1491
	(0.1096)	(0.0347)	(0.3116)
Technical college	0.2393*	0.0677+	0.4153
	(0.1036)	(0.0346)	(0.3600)
University	0.2644*	0.0459+	0.6861
	(0.1208)	(0.0275)	(0.9044)
Education not known	0.1171	0.0237	0.1596
	(0.1242)	(0.0388)	(0.4079)
Of foreign origin	0.0444	-0.0118	0.2508
	(0.1146)	(0.0281)	(0.2537)
Woman	0.0474	0.0237	-0.2798
	(0.0800)	(0.0207)	(0.2115)
Former industry (12 dummies)	yes	yes	yes
Participant is searching for a job in the same profession than previously held	0.1484 (0.1147)	0.0666+ (0.0385)	0.1389 (0.2460)
Not motivated to participate in ALMP	-0.0846	-0.0225	-0.2271
	(0.0805)	(0.0204)	(0.4329)
Sanctioned at least once during spell	-0.0003	-0.0102	-0.1267
	(0.0920)	(0.0264)	(0.2612)
Unemployment duration forecast (omitted: Forecast 12 months and more & forecast unknown)			
Forecast 0 to 5 months	-0.2069+	-0.0590	-0.3772
	(0.1171)	(0.0367)	(0.2708)
Forecast 6 to 11 months	-0.1585	-0.0384	-0.1540
	(0.0997)	(0.0298)	(0.1972)
Constant	-0.0872	0.0042	-0.1843
	(0.2077)	(0.0583)	(0.5449)
Sample			
All unemployed vs. ALMP unemployed	ALMP	ALMP	ALMP
Number of unemployed	203	203	203
Estimation			
OLS (with robust standard errors)	yes	yes	yes
R-squared	0.1185	0.1278	0.0873
F-value	1.2388	1.3751	0.7564

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Data from 203 unemployed used (the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement).

Table 6: The influence of different characteristics on the ALMP effect

One has to keep in mind that Table 5 shows the effect the way the ALMP types are currently used on the unemployed of the Zurich-Staffelstrasse agency. These estimates do not just tell a story about the ALMP itself, but also about its participants and how well they are adapted to the course itinerary. To improve performance of the ALMP types, one can adapt the ALMP to the existing participants, or select the participants differently for an existing ALMP, or one can do both.

8. Getting a job

A possible criticism to the new approach could be the fact that job interviews only provide a stepping stone on the way to find a new job and end unemployment. While this is true by definition, a job interview takes a job seeker a far way, as the data shows. The following numbers are based on the data of all unemployed who left unemployment with a job and who started the spell after 1st of July 2007 and ended it before 31st of March 2008. Only for this group the entire application history from start till end of the unemployment spell is known. This group only entails 76 unemployed; because of the low number of observations, the following results cannot be further assessed for subgroups (e.g. ALMP participants vs. non-participants, unemployed with LTU forecast vs. Non-LTU forecast etc.).

The average person who left unemployment with the opportunity to start a new job wrote 36 applications (median value). Please note that this is a group with above average chances, because they found a job during the nine months of unemployment monitored. The probability of getting the job when writing an application is therefore 5.2 %. Within that process, the biggest hurdle is getting a job interview. In average, it took the unemployed 7.1 applications for each job interview (median), resulting in a probability of 14.1 %. It then took them in average 2 interviews (median) to actually get a job. The chances of a job, given an interview, are 50.0 %.

	Median	**Mean**
Probability job interview given an application	0.1409	0.2038
Probability job offer given a job interview	0.5000	0.5372
Probability job offer given an application	0.0520	0.1065
Number of unemployed	76	76
Number of applications	2,053	2,053

Notes: The table only captures unemployed who i) left unemployment with a job and ii) started unemployment on 1 July 2007 or later and finished their spell on 30 March 2008 or earlier. Thereby, all applications of a person could be recorded in the database. Because of these selection criteria, the reduced sample is not representative for the overall sample.

Table 7: Probability of getting a job (reduced sample)

The relative impact of the ALMPs on the overall probability of a job remains exactly as measured by the different regressions in this study, as long the ALMP doesn’t change the probability of a job interview. This is unlikely of course, as most acquired know-how would work both when writing the application and in the job interview environment (e.g. language skills, self assurance, showing newly acquired job skills). It is therefore plausible that the ALMP effect on the probability of a job interview is are going have an effect on the probability of the job, given an interview, as well.

It is difficult to envisage a characteristic which has a positive impact on getting to an interview, but then a negative one on getting the job (or the other way round). The calculated effects on the probability of a job interview can therefore be taken as a lower boundary of the overall effect on getting a job.

9. Conclusion

While many previous studies applied methods which had to rely on strong assumptions in order to calculate accurate and unbiased estimates of the ALMP effect, the new approach used in this study doesn’t. This is possible through the use of new indicators and data, which allows measuring the outcome several times before, during, and after the ALMP. This allows excluding time-invariant characteristics and to solve the selection bias.

The new instrument can be relatively easily applied to measure the effect of ALMPs by labour market institutions, as it combines several good controlling characteristics: It is a detailed, accurate and unbiased instrument utilizing relatively simple statistical tools. It can be easily understood by the persons responsible for the controlling process and communicated to involved partners. This makes it a trustworthy controlling instrument. It is inexpensive; the biggest cost involved is that the case worker has to update the application sheets (that is not just a cost though as it shows to the unemployed that these sheets are taken seriously). It can be easily updated on a regular base. This is an important characteristic as the ALMP might have different effects depending on the condition of the labour market (McVicar and Podivinsky 2008).

The method was applied as a trial run in one agency in Switzerland, the Zurich-Staffelstrasse agency. 30,000 applications were collected, along with much information on the unemployed and the ALMP used. Through this, a very rich dataset could be assembled. Estimates based on this data show that on average, the ALMPs have a strong positive effect on the chances of a job interview, the weekly number of applications and the weekly number of interviews when applied to unemployed with a long term unemployment forecast. Applied to unemployed without such a forecast, the ALMP show relatively little impact. There are stark differences between the ALMP types as well. While most types do well, personality oriented courses and employment programmes have a negative impact on the application performance of the unemployed. These are preliminary results of course since they stem from the unemployed of a single agency.

In order to gain more insight into the ALMPs and to start using the proposed method as a controlling tool, more data now needs to be collected. It is worth the effort: ALMPs are an expensive tool in financial terms. If they don't work, they are costly in human terms too, because both the participants and the case worker hope that these programs will shorten unemployment. It is time to start controlling this instrument thoroughly and on the basis of quantitative data, and thereby improve its quality and reputation.

Bibliography

Bertrand, M. and S. Mullainathan (2004), Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination, *American Economic Review*, 94(4), 991 - 1013.

Black, D. A., Smith, J. A., Berger, M. C. and B. J. Noel (2003), Is the Threat of Reemployment Services More Effective than the Services Themselves? Evidence from Random Assignment in the UI System, *American Economic Review* 93, 1313 - 1327.

Carling, K., and K. Richardson (2004), The Relative Efficiency of Labor Market Programs: Swedish Experience from the 1990s, *Labour Economics* 11, 335 - 354.

Carlsson, M., Rooth, D.-O., 2007. Evidence of Ethnic Discrimination in the Swedish Labor Market Using Experimental Data. *Labor Economics* 14, 716 - 729.

Drydakis, N. (2009), Sexual orientation discrimination in the labour market, *Labour Economics* 16, 364 – 372.

Falk, A., Lalive, R. and J. Zweimüller (2005), The Success of Job Applications: A New Approach to Program Evaluation, *Labour Economics* 12(6), 739 - 748.

Gerfin, M. and M. Lechner (2002), A Microeconometric Evaluation of the Active Labour Market Policy in Switzerland, *Economic Journal* 112(482), 854 - 893.

Heckman, J. J., LaLonde, R. J. and J. A. Smith (1999), The Economics and Econometrics of Active Labor Market Programs, *Handbook of Labor Economics*, Vol. III, ed. by O. Ashenfelter and D. Card, Elsevier.

Khotari, S. P. and J. B. Warner (2006), Econometrics of Event Studies, in Eckbo, B. E. (ed.), *Handbook of Corporate Finance: Empirical Corporate Finance, Volume A*, Handbooks in Finance Series, Elsevier/North-Holland, Ch. 1

Lalive, R., van Ours, J. C. and J. Zweimüller (2008), The impact of Active Labor Market Programs on the Duration of Unemployment in Switzerland, *Economic Journal* 118(525), 235 - 257.

Lalive, R., van Ours, J. C. and J. Zweimüller (2000), The Impact of Active Labor Market Policies and Benefit Entitlement Rules on the Duration of Unemployment, IZA Discussion Paper No. 149.

Lalive, R., Zehnder, T. and J. Zweimüller (2006), Makroökonomische Evaluation der aktiven Arbeitsmarktpolitik der Schweiz, Swiss State Secretariat for Economic Affairs (SECO).

Lechner, M. and J. Smith (2007), What is the Value Added by Caseworkers? *Labour Economics* 14(2), 135 - 151.

McVicar, D. and J. M. Podivinsky (2008), Does the Impact of Active Labor Market Programs Depend on the State of the Labour Market? The Case of the UK New Deal for Young People. Discussion Paper.

Oberholzer-Gee, F. (2008), Nonemployment Stigma as Rational Herding: A Field Experiment, *Journal of Economic Behavior and Organization* 65(1), 30 - 40.

OECD (2009): Public expenditure and participant stocks on LMP. OECD Stat Extracts. Data extracted August 2009.

Ragni, T. (2007), Die Wirksamkeit der öffentlichen Arbeitsvermittlung in der Schweiz, Direktion für Wirtschaftspolitik Diskussionspapier, Swiss State Secretariat for Economic Affairs (SECO).

Rosholm, M. and M. Svarer (2008), The Threat Effect of Active Labour Market Programs, *Scandinavian Journal of Economics* 110(2), 385 - 401.

Rosholm, M. and M. Svarer (2004): Estimating the Threat Effect of Active Labour Market Programmes, IZA Discussion Papers 1300, Institute for the Study of Labor (IZA).

Sianesi, B. (2008), Differential Effects of Active Labour Market Programs for the Unemployed, *Labour Economics* 15, 370 - 399.

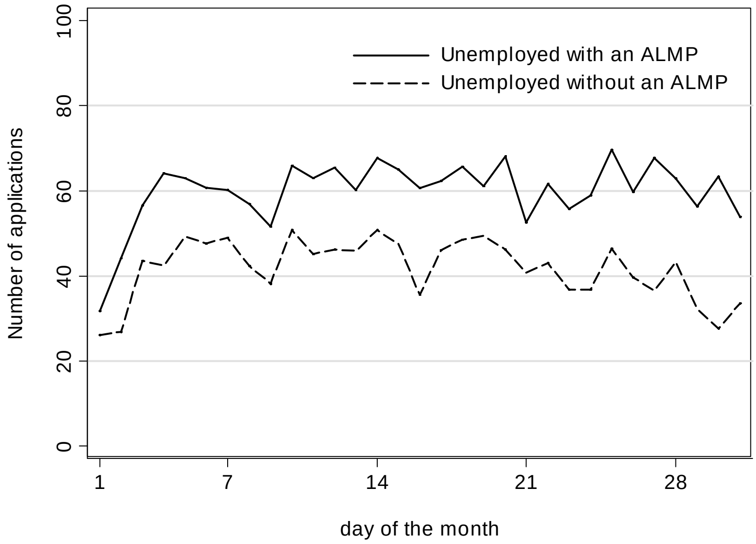
Sianesi, B. (2004), An Evaluation of the Swedish system of Active Labour Market Programmes in the 1990s, *Review of Economics and Statistics* 86(1), 133 - 155.

Smith and Todd (2005): Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators?, *Journal of Econometrics* 125, 305 - 353.

Van den Berg, G. J., Bergemann, A. H.,, M. Caliendo (2009): The Effect of Active Labor Market Programs on Not-Yet Treated Unemployed Individuals, *Journal of the European Economic Association* 7(2-3), 606 - 616.

Annex

Annex 1: Applications recorded in a typical month at the Zurich-Staffelstrasse agency



Note: Averages over the nine month of data collection are shown. Day 30 and day 31 were reweighed because their lower number of appearance. December was not taken into account.

Annex 2: Characteristics of ALMP participants

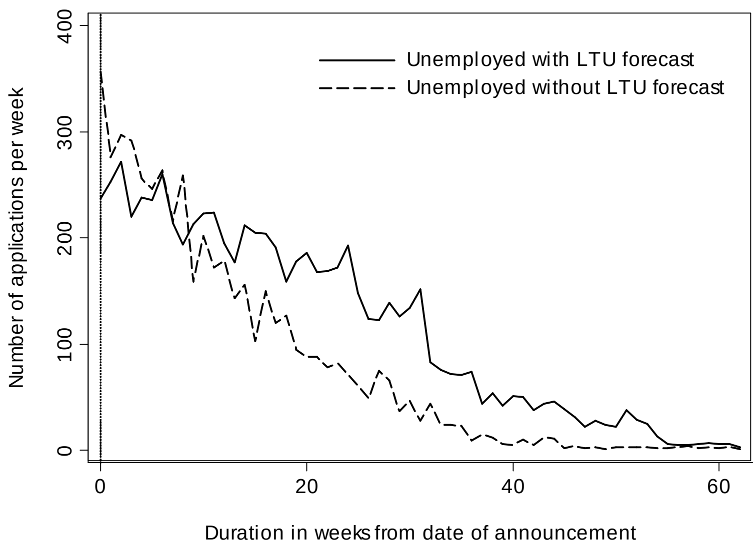
Unemployment duration forecast:	**0-6 months**	**7-12 months**	**13 and more months**	**no forecast**
Age	35.20	39.58	42.54	44.70
Women	0.57	0.44	0.48	0.20
Swiss	0.50	0.49	0.48	0.60
Industry				
No answer, first sector or “private household	0.35	0.18	0.14	0.00
Industry	0.11	0.06	0.08	0.30
Building and Constructing	0.07	0.21	0.14	0.00
Trade and Commerce	0.19	0.18	0.22	0.10
Hospitality industry	0.02	0.05	0.06	0.10
Transport and Communication	0.04	0.03	0.03	0.10
Financial services	0.13	0.09	0.12	0.30
Business services (incl. IT)	0.04	0.02	0.02	0.00
Public administration	0.02	0.03	0.04	0.10
Health and social services	0.02	0.07	0.07	0.00
Other services	0.02	0.09	0.07	0.00

Annex 2: Characteristics of ALMP participants (continued)

Unemployment duration forecast:	0-6 months	7-12 months	13 and more months	no forecast
Highest attained educational				
no further education	0.35	0.40	0.50	0.40
Apprenticeship	0.22	0.19	0.19	0.30
Gymnasium	0.02	0.06	0.05	0.10
Technical college	0.15	0.16	0.07	0.00
University	0.15	0.07	0.08	0.20
Education not known	0.11	0.11	0.10	0.00
ALMP				
Basic course	0.63	0.54	0.31	0.30
Personality oriented course	0.06	0.11	0.16	0.30
Basic qualifications course	0.06	0.06	0.07	0.00
Language course	0.11	0.08	0.05	0.10
Other course	0.06	0.07	0.08	0.00
Employment programme	0.09	0.13	0.33	0.30
N	54	108	166	10

Note: Only unemployed with an ALMP at some stage of their spell are covered. Apart from age, baseline probability, ALMP treatment effect and the number of observations, all numbers are proportions

Annex 3: Sensitivity test 1 - development of the number of applications after the announcement



Note: The graph shows the total number of applications per week sent out by any of the 338 ALMP participants. The duration is plotted until the 62nd week after the ALMP announcement (this is the maximum duration for any person in the sample).

Annex 4: Sensitivity test 1 - model including "time since announcement" interaction terms

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Mean	0.1355	0.1033	0.1782	0.0493	0.0382	0.0648	2.7478	2.7034	2.7482
Std. Dev.	0.4752	0.4073	0.5479	0.2165	0.1917	0.2463	1.6552	1.5657	1.6716
Effects split according to time since announcement									
1. Effect between week 0 and 10 after announcement (Dummy is 1 from week 0 to week 10)	0.0067 (0.0058)	0.0223** (0.0069)	-0.0110 (0.0098)	0.0476 (0.0726)	0.0750 (0.0947)	0.0622 (0.1094)	0.0189 (0.0204)	0.0559** (0.0212)	-0.0224 (0.0357)
2. Effect between week 11 and 20 after announcement (Dummy is 1 from week 11 to week 20)	0.0005 (0.0081)	0.0290** (0.0098)	-0.0282* (0.0144)	0.0680 (0.1038)	0.1147 (0.1302)	0.0707 (0.1677)	-0.0065 (0.0272)	0.0719* (0.0302)	-0.0907+ (0.0492)
1. Effect after week 20 (Dummy is 1 from week 20 to end of spell)	-0.0148 (0.0113)	0.0221 (0.0138)	-0.0526* (0.0212)	0.1268 (0.1368)	0.2649 (0.1688)	-0.0068 (0.2325)	-0.0319 (0.0372)	0.0737+ (0.0416)	-0.1517* (0.0703)
Control variables (duration; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	17910	9451	7835	6518	3496	2851	6518	3496	2851
Number of unemployed	338	166	162	338	166	162	338	166	162
Estimation (OLS with robust standard errors)									
R-squared	0.1457	0.1873	0.1183	0.2231	0.2240	0.1808	0.2175	0.2755	0.1834
F-value	4.1454	3.4978	4.8996	0.5850	0.8926	0.7119	2.2975	2.3413	3.2033

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Annex 5: Sensitivity test 2 – on selectivity

Annex 5a) All unemployed

Dependent variable:	Interviews per week				Interview Probability				Applications per week			
Overall Effect ALMP	0.0282	0.0334	0.0397*	0.0266	0.0087	0.0113+	0.0147**	0.0092*	0.0949	0.1100	0.0534	0.0342
(Dummy is 1 after ALMP announcement)	(0.0219)	(0.0215)	(0.0171)	(0.0171)	(0.0058)	(0.0061)	(0.0047)	(0.0047)	(0.0722)	(0.0732)	(0.0565)	(0.0570)
Duration												
Specification 1: 13 dummies (same for treated and control)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: 13 dummies (different for treated and control)	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Panel or pooled estimation												
Fixed effects	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Pooled, specification 1 (treatment dummy)	no	no	yes	no	no	no	yes	no	no	no	yes	no
Pooled, specification 1 (treatment dummy and characteristics)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Treatment dummy (ALMP at some stage of the spell)			-0.0094	0.0112			-0.0106	-0.0019			0.1984+	0.2173*
			(0.0312)	(0.0310)			(0.0078)	(0.0078)			(0.1032)	(0.1033)
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (all unemployed incl. unemployed without ALMP)												
Number of applications	10805	10805	10805	10805	29991	29991	29991	29991	10805	10805	10805	10805
Number of unemployed	738	738	738	738	738	738	738	738	738	738	738	738
Estimation (OLS with robust standard errors)												
R-squared	0.2684	0.2687	0.0161	0.0421	0.1659	0.1663	0.0086	0.0246	0.2433	0.2440	0.0090	0.0195
F-value	3.2042	1.9958	6.7740	9.4412	4.4365	3.1683	9.9932	15.1264	0.8662	0.8245	3.7452	4.2857

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The pooled specification 1 lacks the individual fixed effects from the standard model but contains an extra dummy describing if the unemployed participates in an ALMP at any time during his or her spell (treated dummy). The pooled specification 2 is like specification 1, but contains further variables: gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 5b) All unemployed with a LTU forecast

Dependent variable:	**Interviews per week**				**Interview Probability**				**Applications per week**			
Overall Effect ALMP	0.0374+	0.0435*	0.0496*	0.0544*	0.0125+	0.0151*	0.0179**	0.0183**	0.2033*	0.2106*	0.1203	0.1255
(Dummy is 1 after ALMP announcement)	(0.0216)	(0.0216)	(0.0218)	(0.0218)	(0.0067)	(0.0069)	(0.0061)	(0.0061)	(0.0967)	(0.1009)	(0.0783)	(0.0794)
Duration												
Specification 1: 13 dummies (same for treated and control)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: 13 dummies (different for treated and control)	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Panel or pooled estimation												
Fixed effects	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Pooled, specification 1 (treatment dummy)	no	no	yes	no	no	no	yes	no	no	no	yes	no
Pooled, specification 1 (treatment dummy and characteristics)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Treatment dummy (ALMP at some stage of the spell)			0.0448	0.0534			0.0091	0.0138			0.2593	0.2159
			(0.0522)	(0.0512)			(0.0134)	(0.0133)			(0.1876)	(0.1866)
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (all unemployed incl. unemployed without ALMP)												
Number of applications	5497	5497	5497	5497	14938	14938	14938	14938	5497	5497	5497	5497
Number of unemployed	294	294	294	294	294	294	294	294	294	294	294	294
Estimation (OLS with robust standard errors)												
R-squared	0.2728	0.2751	0.0121	0.0629	0.1982	0.1998	0.0085	0.0434	0.2380	0.2403	0.0128	0.0380
F-value	1.4806	1.5549	2.5685	7.3164	2.3966	2.3529	4.9068	13.5115	0.5799	0.9089	2.7294	4.3053

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The pooled specification 1 lacks the individual fixed effects from the standard model but contains an extra dummy describing if the unemployed participates in an ALMP at any time during his or her spell (treated dummy). The pooled specification 2 is like specification 1, but contains further variables: gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 5c) All unemployed without a LTU forecast

Dependent variable:	**Interviews per week**				**Interview Probability**				**Applications per week**			
Overall Effect ALMP	0.0109	0.0166	0.0373	0.0113	0.0004	0.0038	0.0152*	0.0052	0.0446	0.0531	-0.0339	-0.0609
(Dummy is 1 after ALMP announcement)	(0.0381)	(0.0372)	(0.0273)	(0.0277)	(0.0097)	(0.0103)	(0.0074)	(0.0075)	(0.1089)	(0.1090)	(0.0830)	(0.0846)
Duration												
Specification 1: 13 dummies (same for treated and control)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: 13 dummies (different for treated and control)	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Panel or pooled estimation												
Fixed effects	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Pooled, specification 1 (treatment dummy)	no	no	yes	no	no	no	yes	no	no	no	yes	no
Pooled, specification 1 (treatment dummy and characteristics)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Treatment dummy (ALMP at some stage of the spell)			0.0022	0.0293			-0.0048	0.0028			0.0991	0.1442
			(0.0432)	(0.0435)			(0.0108)	(0.0109)			(0.1315)	(0.1328)
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (all unemployed incl. unemployed without ALMP)												
Number of applications	4935	4935	4935	4935	13923	13923	13923	13923	4935	4935	4935	4935
Number of unemployed	411	411	411	411	411	411	411	411	411	411	411	411
Estimation (OLS with robust standard errors)												
R-squared	0.2620	0.2619	0.0193	0.0396	0.1432	0.1437	0.0098	0.0221	0.2257	0.2268	0.0098	0.0239
F-value	3.6299	2.1427	3.8630	4.1065	4.9027	3.2091	5.5097	6.3848	0.8542	0.7017	1.9471	2.4457

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The pooled specification 1 lacks the individual fixed effects from the standard model but contains an extra dummy describing if the unemployed participates in an ALMP at any time during his or her spell (treated dummy). The pooled specification 2 is like specification 1, but contains further variables: gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 6: Sensitivity test 3 – changing the duration modelling

Annex 6a) All ALMP participants

Dependent variable:	Interviews per week				Interview Probability				Applications per week			
Overall Effect ALMP	0.0308	-0.0014	0.0117	0.0127	0.0107+	0.0011	0.0067	0.0062	0.0972	0.0305	0.0640	0.0330
(Dummy is 1 after ALMP announcement)	(0.0215)	(0.0221)	(0.0219)	(0.0224)	(0.0061)	(0.0056)	(0.0060)	(0.0058)	(0.0732)	(0.0730)	(0.0731)	(0.0741)
Duration												
Specification 1: 13 Dummies (standard)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: No time dummies	no	yes	no	no	no	yes	no	no	no	yes	no	no
Specification 3: 5 dummies	no	no	yes	no	no	no	yes	no	no	no	yes	no
Specification 4: 2 variables (duration, duration squared)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)												
Number of applications	6518	6518	6518	6518	17910	17910	17910	17910	6518	6518	6518	6518
Number of unemployed	338	338	338	338	338	338	338	338	338	338	338	338
Estimation (OLS with robust standard errors)												
R-squared	0.2172	0.2132	0.2139	0.2141	0.1454	0.1437	0.1441	0.1441	0.2232	0.2219	0.2224	0.2219
F-value	2.3693	5.6057	3.1096	4.4200	3.8608	9.8710	5.2518	9.9042	0.7262	0.4424	0.7333	0.2746

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Specification 1 contains the following 13 duration dummies: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Specification 3 contains the following 5 duration dummies: 1-2 months (omitted), 3-4, 5-6, 7-12, 13 and more months. Specification 4 contains two continuous variables: duration in weeks and duration in weeks squared. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 6b) All ALMP participants with a LTU forecast

Dependent variable:	**Interviews per week**				**Interview Probability**				**Applications per week**			
Overall Effect ALMP	0.0386+	0.0305	0.0400+	0.0427+	0.0132+	0.0109+	0.0152*	0.0160*	0.2071*	0.1936*	0.1716+	0.1707+
(Dummy is 1 after ALMP announcement)	(0.0216)	(0.0222)	(0.0217)	(0.0226)	(0.0069)	(0.0066)	(0.0069)	(0.0068)	(0.1012)	(0.0962)	(0.0993)	(0.0997)
Duration												
Specification 1: 13 Dummies (standard)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: No time dummies	no	yes	no	no	no	yes	no	no	no	yes	no	no
Specification 3: 5 dummies	no	no	yes	no	no	no	yes	no	no	no	yes	no
Specification 4: 2 variables (duration, duration squared)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)												
Number of applications	3496	3496	3496	3496	9451	9451	9451	9451	3496	3496	3496	3496
Number of unemployed	166	166	166	166	166	166	166	166	166	166	166	166
Estimation (OLS with robust standard errors)												
R-squared	0.2748	0.2688	0.2714	0.2696	0.1864	0.1830	0.1851	0.1836	0.2244	0.2220	0.2230	0.2222
F-value	2.3576	1.5168	2.4851	1.4901	3.2209	2.9052	4.6508	3.7047	1.0121	1.5490	1.3668	1.0695

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Specification 1 contains the following 13 duration dummies: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Specification 3 contains the following 5 duration dummies: 1-2 months (omitted), 3-4, 5-6, 7-12, 13 and more months. Specification 4 contains two continuous variables: duration in weeks and duration in weeks squared. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 6c) All ALMP participants without a LTU forecast

Dependent variable:	**Interviews per week**				**Interview Probability**				**Applications per week**			
Overall Effect ALMP	0.0150	-0.0371	-0.0150	-0.0201	0.0043	-0.0118	-0.0025	-0.0061	0.0280	-0.0516	-0.0238	-0.0050
(Dummy is 1 after ALMP announcement)	(0.0371)	(0.0384)	(0.0378)	(0.0387)	(0.0102)	(0.0094)	(0.0099)	(0.0100)	(0.1083)	(0.1102)	(0.1090)	(0.1081)
Duration												
Specification 1: 13 Dummies (standard)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: No time dummies	no	yes	no	no	no	yes	no	no	no	yes	no	no
Specification 3: 5 dummies	no	no	yes	no	no	no	yes	no	no	no	yes	no
Specification 4: 2 variables (duration, duration squared)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)												
Number of applications	2851	2851	2851	2851	7835	7835	7835	7835	2851	2851	2851	2851
Number of unemployed	162	162	162	162	162	162	162	162	162	162	162	162
Estimation (OLS with robust standard errors)												
R-squared	0.1825	0.1717	0.1755	0.1732	0.1178	0.1116	0.1142	0.1122	0.1806	0.1780	0.1788	0.1793
F-value	3.1401	5.7401	4.0171	4.0862	4.8861	9.2781	6.5348	8.9038	0.7125	0.3131	0.5672	0.9727

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Specification 1 contains the following 13 duration dummies: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Specification 3 contains the following 5 duration dummies: 1-2 months (omitted), 3-4, 5-6, 7-12, 13 and more months. Specification 4 contains two continuous variables: duration in weeks and duration in weeks squared. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 7: Sensitivity test 4 – dropping outliers

Estimation without unemployed who show at any stage of their unemployment spells more than 15 applications a week or 5 interviews per week. Unemployed with an overall interview probability above 0.75 are not covered. If the unemployment spell is longer than 2 years, it is cut off after this point.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Overall Effect ALMP	0.0245	0.0430*	0.0003	0.0056	0.0132+	-0.0054	0.1372+	0.2120*	0.0732
(Dummy is 1 after the announcement of the ALMP)	(0.0202)	(0.0215)	(0.0342)	(0.0061)	(0.0069)	(0.0100)	(0.0721)	(0.1018)	(0.1071)
Control variables (duration; application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	6428	3487	2785	17596	9432	7651	6428	3487	2785
Number of unemployed	331	165	157	331	165	157	331	165	157
Estimation (OLS with robust standard errors)									
R-squared	0.1866	0.2278	0.1595	0.1102	0.1429	0.0879	0.2160	0.2243	0.1867
F-value	2.1789	2.2664	2.8293	3.3079	3.2212	4.1352	0.7453	1.0210	0.6505

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Annex 8: Sensitivity test 5 – dropping personal applications with an unusual high success rate

Unemployed who report an overall interview probability above 0.9 for their personal applications are not covered.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Overall Effect ALMP	0.0360+	0.0376+	0.0268	0.0118+	0.0121+	0.0068	0.0732	0.1691	0.0224
(Dummy is 1 after the announcement of the ALMP)	(0.0211)	(0.0218)	(0.0357)	(0.0062)	(0.0071)	(0.0103)	(0.0749)	(0.1044)	(0.1099)
Control variables (duration; application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	6263	3365	2734	17176	9060	7503	6263	3365	2734
Number of unemployed	319	158	152	319	158	152	319	158	152
Estimation (OLS with robust standard errors)									
R-squared	0.1834	0.2332	0.1510	0.1150	0.1500	0.0918	0.2263	0.2299	0.1807
F-value	2.3374	2.2277	3.1856	3.9109	3.1027	4.6701	0.7137	0.9894	0.7103

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Annex 9: Sensitivity test 6 – testing the no anticipation assumption

A dummy variable is added which switches to one in the period from one month before the ALMP announcement to the announcement.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Overall Effect ALMP	0.0496+	0.0414	0.0293	0.0194*	0.0164+	0.0123	0.1611+	0.2349+	0.0192
(Dummy is 1 after ALMP announcement)	(0.0275)	(0.0299)	(0.0482)	(0.0084)	(0.0099)	(0.0141)	(0.0972)	(0.1309)	(0.1527)
Placebo test	0.0283	0.0047	0.0196	0.0124	0.0050	0.0106	0.0962	0.0456	-0.0120
(Effect one month before announcement)	(0.0287)	(0.0299)	(0.0494)	(0.0075)	(0.0090)	(0.0124)	(0.0990)	(0.1264)	(0.1511)
Control variables (duration; application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	6518	3496	2851	17910	9451	7835	6518	3496	2851
Number of unemployed	338	166	162	338	166	162	338	166	162
Estimation (OLS with robust standard errors)									
R-squared	0.2173	0.2748	0.1825	0.1455	0.1864	0.1179	0.2234	0.2245	0.1806
F-value	2.3828	2.2276	3.0741	3.8311	3.0266	4.6669	0.7905	0.9499	0.6713

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).