The Role of Job Seekers' Expectations on the Effects of Active Labor Market Policies

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Abstract

It has been shown that unemployed workers who anticipate participation in an active labor market policy (ALMP) program adjust their job search behavior. Depending on the expected effect of such a program, they search more intensively to leave unemployment and prevent the treatment or reduce their effort to wait out until the program start. Theoretical considerations suggest that these expectations (with respect to the participation probability and the treatment effect) also influence the job seekers labor market outcomes after the actual treatment has been realized, if there exists an inter-temporal dependency of the unemployeds' behavior. Using German survey data on newly unemployed job seekers, the study shows that participants in long-term training programs who are not aware of the treatment ex ante face significantly lower long-run employment rates compared to their participating counterparts expecting the treatment. A further analysis of the job search behavior is conducted to understand the effect mechanisms. It shows that job seekers who do not expect a treatment also receive less support by their caseworker and fewer information about ALMP programs, which results in a lower willingness to adjust their job search behavior in association with a treatment. A structural model is estimated to account for the endogenous formation of expectations. The findings suggest that adjustments of the search behavior during the unemployment spell create additional search costs and therefore job seekers who have not been sufficiently informed about the possibility of a future program participation choose behavioral patterns that result in lower employment rates once the treatment is realized.

Keywords: Active labor market policy, Treatment effects, Heterogeneity, Expectations, Biased beliefs, Job search

JEL codes: C35, D04, D83, J68

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1 Introduction

Active labor market policies (ALMP) have a long tradition in many Western countries and represent one of the major instruments to reintegrate unemployed job seekers into the labor market. So far, many studies have evaluated the impact of participating in these programs on subsequent labor market outcomes like employment prospects and earnings (see e.g. Card et al., 2010; Kluve, 2010, for an overview of international ALMP studies). Moreover, in recent years several studies also showed that the presence of ALMP programs already has an impact on the job search behavior of unemployed workers even before they actually participate in a program (Black et al., 2003; Rosholm and Svarer, 2008; van den Berg et al., 2009). This paper links these two strands of the literature, by analyzing the impact of job seekers' expectations about a program, measured before participating, on the labor market outcomes after the realization of a treatment. Two dimensions of expectations are assumed to be particularly relevant in the context ALMP programs: 1) the job seeker's perceived probability of participating in a program (given that the she remains unemployed) and 2) the expected returns to treatment with respect to the labor market performance, respectively the individual utility level in general.

For instance, the possibility of participating in a program that is expected to be beneficial provides incentives to reduce the search effort in order to remain unemployed until the treatment can be realized, while the opposite applies for a program that reduces the job seekers expected utility. These opposite effects are empirically documented by several studies that exploit specific eligibility criteria for ALMP programs. On the one hand, several studies document that the presence of compulsory ALMP programs encourages job seekers to leave unemployment earlier to prevent participation, i.e. in the US (e.g. Black et al., 2003), Denmark (e.g. Geerdsen, 2006; Geerdsen and Holm, 2007; Rosholm and Svarer, 2008; Graversen and Van Ours, 2008) or Sweden (e.g. Carling and Larsson, 2005; Hägglund, 2011). Moreover, using self-reported measures, van den Berg et al. (2009) show that German job seekers who generally expect to enter an ALMP program in the future try to prevent participation by setting lower reservation wages and searching harder.[1] However, on the other hand, van den Berg et al. (2014a) show that job seekers reduce their search effort if they are close to reaching the eligibility criteria for job search assistance in the UK, while Crépon et al. (2014) find a negative effect of notifications about imminent training programs on exit rates of French job seekers.[2]

[1] In a subsequent study, Bergemann et al. (2011) show that these findings vary considerably among ethnic groups.

[2] A related strand of the litertaure shows that individuals select themselves into the treatment based on expectations about their future labor market performance (see Ashenfelter, 1978; Heckman and Smith, 1999). This is typically associated with higher reservation wages and a reduction of search intensities, resulting in substantial locking-in effects (see van Ours, 2004; Lalive et al., 2008).

So far, there exists no evidence about the long-term consequences of differences in job seekers' expectations beyond the presence of these *ex ante effects*. However, it can be assumed that expectations about upcoming ALMP program, which are formed early during the unemployment spell, also have an impact on long-term behavioral patterns and therefore also on the *ex post effects* of a program (after the treatment has been realized). For instance, one could argue that adjustments of the search behavior over the course of time are associated with additional search costs. If this is the case, the ex ante effect of the program on the individual behavior also has long-run implications. This could be also related a reduced compliance with program conditions if participants do not expect the treatment ex ante or the choice of different program providers. To test the relevance of such a mechanism, I exploit a unique combination of survey data and administrative records for a sample of newly unemployed job seekers in Germany. The data provide measures of subjective expectations about the individual probability to participate in a program in the near future and the expected effect of a treatment on the employment prospects. I estimate the impact of these two measures on the long-term labor market outcomes after the actual treatment status has been realized. In particular, the analysis focuses on a specific program, long-term training, which generally requires a high level of participants' commitment, creates relatively large costs for the society compared to other ALMP programs and is frequently applied.

The findings show that long-term training programs are less effective when the job seekers are not aware of the treatment ex ante, while participants' expectations about the treatment effect are empirically unrelated to the realized effectiveness of the program. To account for unobserved heterogeneity a difference-in-difference strategy is applied. Therefore, I compare the effects of the belief measures on outcomes of participants in long-term training to effect on a control group of individuals participating in short-term training. The results show that there are no differences with respect to the impact of the expected treatment rate on pre-treatment outcomes of both groups, while it has a positive effect on the post-treatment employment rates of participants in long-term training, but no effect on those participating short-term training. This suggest that the estimated effect highly depends on the characteristics of the specific treatment that is assigned to the job seeker and cannot be explained by general unobserved differences with respect to the individual level of ability or motivation.

In a second step, I exploit detailed information on the individual job search behavior to investigate the actual channels through which subjective expectations affect long-term outcomes. The analysis of the job seekers behavior shows that those who expect a treatment also receive more support by their caseworker, e.g. information about training programs or vacancies, and have a higher willingness to adjust their search behavior in association with a potential ALMP participation. The findings suggest that differences with respect to the perceived treatment probability are induced by the information received from their caseworker, which translates into different behavioral patterns during the treatment and mirrors into long-run employment effects. The higher willingness to adjust the search behavior might be explained by the fact that such an adjustment requires the usage of new search methods, which creates additional costs since job seekers might not be able to exploit learning effects. Finally, I estimate a model of expectation formation that incorporates the fact that job seekers decide about their job search strategy and form expectations and beliefs about a variety of outcomes, e.g. earnings, employment prospects, program participation and treatment effects, simultaneously. This allows me to test the theoretical predictions by connecting the estimated parameters to the realized labor market outcomes. The findings of the structural analysis confirm the interpretation of the reduced-form results. It is shown that the positive effect of the expected treatment probability on participants' labor market outcomes is driven by those individuals who are less likely to adjust their behavior because they have less contact with their caseworker.

The results provide important insights about the optimal assignment process of ALMP programs. Previous findings suggest that it might be attractive for policy makers to exploit the presence of anticipation effects by using specific information treatments in order manipulate job seekers beliefs and induce behavioral changes that would increase the probability of leaving unemployment. However, the analysis shows that influencing job seekers expectations would not only affect short-run exit rates from unemployment, but also has consequences on long-run outcomes, like the program effectiveness, that policy makers should take into account. Moreover, the findings also suggest that the fact that job seekers have insufficient information about future program participation when entering unemployment can partly explain the general inefficiency of ALMPs (e.g. Card et al., 2010). This implies that the optimal unemployment insurance systems should comprise, beside a monitoring and sanctioning system (see Lalive et al., 2005), also intensive counseling by the caseworker about the possibility of future ALMP participation and the development of the optimal search strategy.[3] Finally, the paper also contributes to the recent literature analyzing the consequences of individual perceptions and preferences on the search process during unemployment. For example, Dohmen et al. (2009) find systematical biases in the perception of job finding probabili-

[3]This is in line with recent findings by Altmann et al. (2015), who show in a large-scale field experiment that informing job seekers about search strategies, the consequences of unemployment and labor market opportunities positively affects employment prospects and subsequent earnings, especially for those job seekers who at risk of being long-term unemployed. It is also related to several studies pointing out the importance of counseling unemployed workers (see e.g. Gorter and Kalb, 1996; Behaghel et al., 2014), analyzing the impact of caseworkers on job finding chances in general (see e.g. Behncke et al., 2010a,b), as well as their efficiency when assigning job seekers to ALMP programs Lechner and Smith (2007).

ties, while Spinnewijn (2015) shows that these biased beliefs affect savings decisions, the job search behavior and have consequences for the unemployment insurance system. Results by Caliendo et al. (2015) indicate that job seekers who believe that their outcomes depend on their own actions (internal locus of control) search harder for new jobs, but also have higher reservation wages. Moreover, DellaVigna and Paserman (2005) show that workers who are more impatient search less intensively, while DellaVigna et al. (2017) present first evidence for the presence reference-dependent search behavior with respect to previous income for unemployed job seekers.

The rest of paper is structured as follows. Section 2 discusses the theoretical framework, while Section 3 introduces the *IZA/IAB Linked Evaluation Dataset*, discusses the institutional details and presents the relevant expectation measures in more detail. Section 4 shows estimation results with respect to the impact of subjective expectations on the program effectiveness and the related differences in search characteristics, while Section 5 presents a structural model of the expectation formation process and Section 6 concludes.

2 Theoretical Framework

2.1 Subjective Expectations in a Job Search Model

To understand the role of subjective expectations and show the potential mechanisms through which they affect the individual behavior of unemployed workers, it is useful to consider a job search model where job seekers face the possibility to participate in an ALMP program in the future (see also van den Berg et al., 2009). It is assumed that unemployed individuals search sequentially for new jobs deciding about a specific search strategy s_t, which affects the probability to receive job offers $\lambda(s_t)$ and generates search costs $c(s_t)$.[4] When the agent finds a new job, she would earn a wage which implies the utility ω. For given offers, the job seeker has to decide whether to accept or reject it taking into account that she might potentially has to participate in an ALMP program in the future. Within this framework, particularly two dimensions of subjective beliefs about the occurrence of ALMP programs have an influence on the job seekers expected value. Given that the job seeker remains unemployed, she expects to participate in an ALMP program with probability π, while this program is expected to have an impact on the job seekers utility δ. If $\delta > 0$, the treatment is expected to be beneficial, while, if $\delta < 0$, the individual does not like to participate

[4] In general, the choice of the search strategy could involve decisions with respect to several dimensions, e.g. the level of search effort, the usage of different search methods, reservation wages or a decision on regions/firms where to apply.

per se or it es expected to have an adverse effect on future labor market prospects. Hence, for a given discount rate ρ, the inter-temporal value of being unemployed is given as:

$$V_t^u = -c(s_t) + \rho \left\{ \lambda(s_t)\omega + (1 - \lambda(s_t))(V_{t+1}^u + \pi\delta) \right\}, \tag{1}$$

and the optimal search strategy of an individual who is unemployed has not yet been treated is determined by the following first-order condition:

$$\frac{\partial c(s_t)}{\partial s_t} = \rho \frac{\partial \lambda(s_t)}{\partial s_t}(\omega - V_{t+1}^u - \pi\delta) \tag{2}$$

As already discussed by van den Berg et al. (2009), the presence of a treatment which is expected to be beneficial ($\delta > 0$) provides incentives to choose search strategies that prolong the unemployment spell until the treatment can be realized, while the presence of a program that is considered as a threat ($\delta < 0$) encourages job seekers to choose s that allows them to leave unemployment earlier. The magnitude of this effect depends on the expected probability that the treatment will take place. This can be seen, e.g., assuming that s_t denotes the level of search effort and the job offer arrival rate ($\partial\lambda(s_t)/\partial s_t > 0$, $\partial^2\lambda(s_t)/\partial s_t^2 < 0$), as well as the search costs ($\partial c(s_t)/\partial s_t > 0$ and $\partial^2 c(s_t)/\partial s_t^2 > 0$) have conventional functional forms.

Consequences for Realized Treatment Effects: The baseline framework only explains the impact of subjective beliefs on individuals who have not yet been treated, while consequences for the long-run behavior (after the realization of a treatment) remain unclear. However, there are several reasons to believe that the behavioral adjustment before entering the treatment has also an impact on the individual behavior directly associated to the realization of the treatment. A potential mechanisms, which will be discussed in more detail, implies the presence of inter-temporal efficiency effects, i.e. the search strategy in the current period t depends on the choice of the search strategy in the previous period $t-1$. This inter-temporal relationship can be generated by learning effects, e.g. job seekers learn about their own abilities (see e.g. Falk et al., 2006), specific labor market and firm characteristics (see e.g. Morgan, 1985) or optimal search strategies (see e.g. Krueger and Mueller, 2016), which imply that the adjusted search strategy before entering the treatment in $t-1$, due the presence of an anticipation effect, translates into a different long-term behavior that also influences the employment prospects of actual participants. It can be expected that these learning effects are particularly important when a job seeker enters a labor market program that requires an adjustment of the search strategy due to time constraints during a treatment. This adjustment of the search strategy can be expected to require the usage of new search methods that can be associated with additional costs since job seekers are not familiar with these new search methods. The inter-temporal value of participating in a program is given by:

$$V_t^p = -c^p(s_{t-1}, s_t) + \rho \left\{ \lambda^p(s_t)\omega + (1 - \lambda^p(s_t))V_{t+1}^p \right\}, \tag{3}$$

where λ^p characterizes the job offer arrival rate and c^p the search costs during the treatment. The inter-temporal relation of the job search behavior is illustrated by the fact that search costs depend on the strategy of the current period s_t, but also that of the previous period s_{t-1}. Assuming that the search behavior before participating in the program can be characterized as a function of the job seekers subjective beliefs about the program $s_{t-1} = g(\pi, \delta)$, the optimal search strategy of a participant is determined by:

$$\frac{\partial c^p(s_t, g(\pi, \delta))}{\partial s_t} = \rho \frac{\partial \lambda^p(s_t)}{\partial s_t}(\omega - V_{t+1}^p), \tag{4}$$

which implies that the agent's subjective beliefs before entering a program would have an impact the search behavior during the treatment, while the sign of this effect crucially depends on the functional form of $c^p(s_{t-1}, s_t)$. For instance, if it would be possible to gain from learning effects for high effort levels ($\partial^2 c/\partial s_{t-1}\partial s_t < 0$), $\delta < 0$ and high values of π will lead to an intensive search in both periods an vice versa. However, assuming it can be expected that for specific search methods, maintaining the pre-treatment level of search effort creates excessive costs when entering an ALMP program due to the reduced amount of time that is available for job search during the treatment. Therefore, when $\partial^2 c/\partial s_{t-1}\partial s_t > 0$, $\delta > 0$ and high values π will potentially reduce the search intensity in $t-1$, but allow the job seeker to choose a search strategy that increases the employment prospects after the beginning of the program. For instance, a forward-looking agent who expects a treatment might have incentives to spend effort developing the optimal search strategy along with his/her caseworker (see Appendix A.1 for details). A close relationship between the job seeker and the caseworker might be particularly helpful during the treatment when the caseworker can support the job seeker when allocating the limited time that is available for search activities during the treatment.

It should be noted, there are also reasons to argue that, instead of the search costs, the job offer arrival rate during the treatment is related to the job seekers beliefs before participating. First, it could be the case that participants who are assigned to the program without expecting it ex ante (π is low) or expecting it to have a negative effect ($\delta < 0$) have a stronger distaste for the treatment and therefore reduce their compliance with program conditions. Hence, there would be a direct effect of the expectation measures on the job finding rates of participants $\lambda^p(\pi, \delta, s_t)$ with $\partial\lambda^p/\partial\pi > 0$ and $\partial\lambda^p/\partial\delta > 0$. Finally, a last explanation is directly related to the institutional settings in Germany as discussed in Section 3.2. Given that potential participants typically receive a training voucher and can choose the actual provider of the program by themselves, it can be expected that those job seekers who expect to participate (π is high) have incentives to gather information in order to choose providers that positively affect their job finding prospects. This process of gathering information presumably requires a reduction of the search effort (for employment) before the treatment, which implies that the job offer arrival rate during the treatment depends on the search strategy in both periods: $\lambda^p(s_{t-1}, s_t)$ with $\partial \lambda^p / \partial s_{t-1} < 0$ and $\partial s_{t-1} / \partial \pi < 0$ resulting in a higher program effectiveness for participants who do expect the treatment ex ante.

2.2 Endogenous Formation of Expectations

So far, the mechanism relies on the fact that the agent's expectations are exogenously given. However, job seekers might form their beliefs, i.e. about the participation probability, taking into account the choice of their search strategy, as well as their expectations about related outcomes, e.g. employment prospects and earnings, that affect the expected value functions. In particular, the unemployed might think that they can influence the actual participation probability (conditional on remaining unemployed), e.g. by bargaining with the caseworker, and therefore choose π to maximizes the expected utility. The equilibrium is characterized by the following condition, which implies that the agent equalizes the marginal returns with respect to the search strategy and the expected treatment probability, i.e. $\partial V_t^u / \partial s_t = \partial V_t^u / \partial \pi = 0$:

$$-\frac{\partial c(s_t)}{\partial s_t} + \rho \frac{\partial \lambda(s_t)}{\partial s_t} (\omega - V_{t+1}^u - \pi \delta) = \rho (1 - \lambda(s_t)) \delta. \tag{5}$$

It can be seen that the optimal level of π depends on all other parameters of the model. For instance, the condition implies that for programs that are expected to have a positive effect $\delta > 0$:

$$\frac{\partial \pi}{\partial \delta} > 0 \quad \text{if} \quad \lambda(s_t) + \pi \frac{\partial \lambda(s_t)}{\partial s_t} < 1. \tag{6}$$

This means a higher expected treatment effect encourages job seekers to belief (ceteris paribus) in higher treatment probabilities as this would increase the expected utility when participating in the next period. However, as this would come along with stronger waiting effect (a reduction of the search effort), it implies also a reduction of the job seekers expected utility from the lower job finding prospects. Therefore, an increase of δ will only lead to higher levels of π if the utility loss from the adjusted search behavior is sufficiently low, while the opposite applies if $\delta < 0$.

Moreover, a forward-looking agent will anticipate the inter-temporal effect of the search behavior on the expected value of being treated. Therefore, the expected effect of a treatment is given as a function of the search strategy in the initial period $\delta(s_t)$ and the equilibrium condition changes to

$$-\frac{\partial c(s_t)}{\partial s_t} + \rho \frac{\partial \lambda(s_t)}{\partial s_t}(\omega - V_{t+1}^u - \pi\delta(s_t)) = \rho(1-\lambda(s_t))\left(\delta - \pi\frac{\partial \delta(s_t)}{\partial s_t}\right), \tag{7}$$

where die additional term (compared to equation 5) describes the impact of changing the expected treatment effect δ by adjusting the search behavior. This implies that, in addition to the equation 6, the following condition must be true in order to ensure that $\partial\pi/\partial\delta$ if $\delta > 0$:

$$\frac{\partial \lambda(s_t)}{s_t}\delta > -(1-\lambda(s_t))\frac{\partial \delta(s_t)}{\partial s_t}. \tag{8}$$

This implies that the direct positive effect of the expected treatment effect exceeds the potential negative effect due to the anticipated adjustment of the search strategy.

In summary, the theoretical considerations illustrate that the agent might form her beliefs, in particular with respect to the participation probability, based on the parameters of the expected value functions that are related to the expected treatment effect, but also expectations about earnings and employment prospects. This has two implications for the analysis of the realized treatment effects. First, if there is an inter-temporal relation of the job seekers behavior, the endogenous formation of beliefs might enhance the impact of pre-treatment expectations on the program effectiveness (if condition 6, respectively 8 hold) since the effects of π and δ on the individual behavior during the treatment work into the same direction. However, on the other hand, this might also cause a correlation between the expected treatment rate π and labor market outcomes even if no causal relationship exists, since other factors, that influence the belief formation, might also be related to the actual selection process into the program and the employment prospects. It can be expected that in particular the quality of the caseworker plays a crucial role for the belief formation, the actual assignment process, but also the individual job finding prospects. To account for these endogenous factors, the model presented in Section 5 directly estimates the process belief formation relying on additional measures for expected earnings and job finding rates, as well as the realized job search behavior.

3 Data and Institutional Details

3.1 The IZA/IAB Linked Evaluation Dataset

This study is based on the *IZA/IAB Linked Evaluation Dataset* which includes survey information on individuals who entered unemployment between June 2007 and May 2008 in Germany (see Caliendo et al., 2011). About 17,400 individuals are interviewed shortly after the entry into unemployment (between 7 and 14 weeks). Besides the extensive set of individual-level characteristics (including socio-demographics and personality measure), as well as regional and seasonal information, the individuals are asked a variety of non-standard questions about their subjective assessments on future economic outcomes and job search characteristics. This includes expectations about ALMP participation (see Section 3.3 for details), the search intensity, the usage of different search channels, but also expectations about future earnings and employment prospects.

For the 88% of individuals who agreed, these survey data were then merged to administrative information from the *Integrated Employment Biographies* (IEB) provided by the Institute for Employment Research (IAB).[5] The IEB integrates different sources, e.g., employment history, benefit recipient history, training participation history and job search history and therefore provides detailed information on labor market histories, as well as outcomes such as employment states, earnings, transfer payments and participation in active labor market policies for a period of 30 months after the entry into unemployment. Altogether, this amounts to a total of 15,274 realized interviews.

3.2 Institutional Setting

The combination of survey and administrative data provides an ideal setting to empirically analyze mechanisms discussed before focusing on long-term training which is one of the major ALMP programs. On the one hand, the dataset includes expectation measures for long-term training, as well as information about the actual program participation. On the other hand, the program is frequently assigned to job seekers and requires a high level of participants' commitment since these programs typically last from several months up to one year, while for some degree courses participants might stay in the program for up to three years. The average program duration in the data set is about 6 months.

The program typically aims to improve occupational specific skills in order facilitate the reintegration into the labor market. Although, the usage of these long lasting and expensive measures was reduced related to the major labor market reform in the early 2000s, long-term training is still one of the most important ALMP programs in Germany. Previous studies find positive effects only in the very long-run (e.g. Fitzenberger et al., 2008; Lechner et al., 2011) or even partly negative effects on employment prospects (e.g. Lechner and Wunsch, 2008). In the short-run, these programs are expected to create a relative strong locking-in effect. From 2003 onwards, caseworkers no longer

[5]This study is based on a weakly anonymized sample of the Integrated Employment Biographies by the IAB (V.901).

choose a specific course for the unemployed but hand out a training voucher to the job-seeker. The caseworker defines the objective, the content and the maximum duration of the course, but the unemployed is allowed to find an appropriate provider for herself, respectively not to redeem the voucher (see Bernhard and Kruppe, 2012; Doerr et al., 2014). Moreover, it should be noted that there exist no explicit eligibility criteria for participating in a training program and participation is not mandatory in general. Therefore, the caseworker plays a crucial role. They are instructed to grant a voucher only if the estimated probability that a job seeker will find employment immediately after finishing the program is at least 70%. Hence, it can be expected that caseworkers are the main source of information for the unemployed job seeker. However, as described by Schütz et al. (2011), there exists a wide dispersion with respect to the quality of the job seekers counseling among caseworkers in Germany and the discussion, definition and adjustment of the job seekers targets is often rarely stringent.[6]

For the purpose of the study, the estimation sample is restricted to all individuals who remain unemployed and do not participate in any ALMP program until the first interview takes place and report non-missing information for the relevant expectation measures discussed below. Job seekers are defined as participants if they attend long-term training within the first twelve months after the entry into unemployment. Moreover, I excluded all participants in short-term training measures. This is necessary since the dataset contains no expectation measures for those types of ALMP programs, but it can be expected that some of the participants relate the corresponding questions about their expectations with respect to long-term training to short-term measures by mistake. Therefore, the final estimation sample contains 5,289 individuals, whereof 790 participate in long-term training and 4,499 individuals do not participate in any training program.

3.3 Measuring Expectations and Descriptive Statistics

Expected Treatment Rates: The key variables for the analysis is given by the expected participation probability in ALMP training programs π. This information is measured by the conditional question: *"What do you think is the probability that you will participate in a long-term training scheme within the next 3 months?"* Possible answers range from 0 (very unlikely) up to 10 (very likely) in one digit steps. The distribution of this variable by the actual treatment status is depicted in the left column of Figure 2. In general, most individuals report either zeros, fives or tens, while

[6] Another important aspect of the German UI system with respect to formation of job seekers expectations is the so called integration agreement *(Eingliederungsvereinbarung)* (see e.g. Jacobi and Kluve, 2007; van den Berg et al., 2014b). These compulsory agreements between the employment agency and the unemployed define the job seekers obligations and services that she received by the employment agency in a given period of unemployment, including search activities, as well as ALMP participation. Non-compliance could lead to a reduction of the unemployment benefits.

there is a correlation between the expected and the actual treatment status. For example, about 36% of the participants report ex ante that it is very likely that they will participate, while only about 13% of the non-participants do so. In line with this, about 31% of the non-participants say ex ante that is very unlikely that they will participate, while only 17% of the participants report a zero.

[Insert Figure 2 about here]

Based on this information on the expected participation probability, I construct a binary measure by summarizing the answers 0-4 (π-low), respectively 5-10 (π-high) (see van den Berg et al., 2009, who use the same variable without exploiting information on the actual participation decision).[7] Therefore, participants as well as non-participants are divided into two subgroups, those with low, respectively high expected treatment rates. This leads to four combinations of expected and actual treatment states which are exploited for the main analysis. A sensitivity analysis with respect to the group classification shows that there are only small differences with respect to main outcome variables within these four groups (see Table A.1 in the Appendix).

Expected Treatment Effects: The second important information refers to the expected effect of the treatment δ. To measure this information I exploit the survey question: *"In your opinion, to what extent would your chances of finding new employment be changed by participating in long-term training?"* The answers range from 'improve strongly' to 'worsen strongly' and can be interpreted as a proxy for the expected differences in job finding rates for the treated and non-treated situation. As shown in the right column of Figure 2, in general, only a very few individuals expect these programs to worsen their labor market performance. However, those who participate, are also more likely to belief that the treatment will have a positive impact on their labor market outcomes. For example, only 27% of the non-participants think that training schemes will strongly improve their employment prospects, while 47% of the participants do. Again, both actual treatment groups are divided into two subgroups. For the main analysis, those individuals who report expected treatment effects in the highest category ('improve strongly') are denoted by δ-high while the remaining participants, respectively non-participants, are categorized as δ-low.

Differences in Labor Market Outcomes: Table 1 presents unconditional differences in labor market outcomes separated by pre-treatment expectations and the actual treatment status. In

[7] Note that for the ease of notation, I use the terms 'expecting a treatment', respectively 'not expecting a treatment', to describe individuals, who report expected participation probabilities between 5 and 10, respectively 0 and 4.

particular, I focus on the employment status 30 months after the entry into unemployment, the total number of months spend in employment within this period and the average monthly earnings conditioned on being employed in the corresponding month. From Panel A of Table 1 can be seen that non-participants who expect to participate in a training program face a higher employment probability of about 3 percentage points and spend on average about 1 months more in employment compared to those non-participants who do not expect a treatment. Both differences are statistically significant at the 5-, respectively 1-%-level. The average earnings of those who do expect the treatment are slightly lower, but the difference is not statistically significant. When considering participants the total time spend in employment is substantially lower compared to non-participants.[8] However, more interestingly, there are also strong differences within the group of participants. The employment rate 30 months after the entry is about 11 percentage points higher for those participants who already expect the treatment when entering unemployment compared to those who are not aware of the treatment ex ante, while the cumulated difference over the full observation period is about 1.6 months. The unconditional differences are statistically significant at least at the 5%-level, while, again, there are no significant differences with respect to earnings.

[Insert Table 1 about here]

Moreover, Panel B depicts differences with respect to labor market outcomes between those participants, respectively non-participants, who expect training programs to have a strong positive effect on their labor market performance and those who do not. For none of the outcome variables there is statistically significant differences neither for non-participants nor participants. The latter provides first evidence that participants have only a very poor ability to predict the impact of a training program on their labor market outcomes and suggests that private information about the individual-specific program effectiveness are not the driving force of the observed differences with respect to the expected treatment rate.

4 Baseline Results

4.1 Estimation Strategy

The main objective of the study is to analyze the effects of the job seekers pre-treatment beliefs about ALMP program on labor market outcomes after the realization of the actual treatment

[8]These differences between participants and non-participants are not very surprising since long-term training programs last on average about 6 months and participants are generally expected to reduce their search effort during this period which would result in a locking-in effect. Moreover, it can be expected that there is a negative selection of individuals who stay unemployed until a treatment can be realized which might also contribute to the lower employment rate of participants in general.

status. Therefore, I estimate average treatment effects on the treated (ATT) using a propensity score matching procedure exploiting the categorization of individuals as discussed in the previous section. The propensity score specification accounts for individual heterogeneity with respect to an extensive set of covariates including socio-demographics, household characteristics, labor market histories, regional and seasonal information, as well as personality traits.[9] Given the four combinations of expected and actual treatment states (see Panel A of Table 1), the estimated ATTs refer to the effect of expecting participation in long-term training ex ante (π-high) compared to not expecting the treatment (π-low) given the realized treatment status within 12 months. Moreover, a second set of ATTs is estimated which refers to the effect of expecting long-term training to beneficial (δ-high) compared to a control group which expects the treatment to be less helpful (δ-low) using the categorization shown in Panel B of Table 1. Moreover, I conduct an extensive sensitivity analysis that 1) takes into account the dynamic selection into the treatment and 2) compares participants in different types of ALMP programs over time. Finally, I investigate investigates the relationship between the job seekers ALMP expectations and the job search strategy to provide a more profound understanding of the effect mechanisms. Since the dataset includes information about the current search behavior when entering unemployment, but also the individuals' willingness to change the search behavior in connection with an upcoming ALMP participation, this allows further conclusions with respect to the mechanisms discussed in Section 2.

4.2 The Impact of Expectations on Program Effectiveness

Table 2 presents the estimated ATTs referring to the matched difference between individuals with high and low expectations with respect to π, respectively δ separated for non-participants and participants. There are several possible estimators for the ATT parameters (e.g. Imbens and Wooldridge, 2009), the main analysis focuses on a particular estimator, kernel matching with a bandwidth of 0.06, which is often used when evaluating labor market policies. The propensity scores are estimated using separated pairwise logit models.[10]

Expected Treatment Rates: Panel A of Table 2 shows the effect of expecting a treatment ex ante (π-high v. π-low) separated for non-participants and participants. Column (1) and (3)

[9]Descriptive statistics with respect to these observed characteristics are shown in Panel A of Table A.2 in the Appendix.

[10]Marginal effects for the logit models are shown in Table A.3 in the Appendix and the distribution of the estimated propensity scores is shown in Panel A of Figure A.2. Estimation results for alternative matching algorithms are presented in Table A.4. In each case the group with the higher number of observations is used as the control group in order to minimize issues related to the common support condition. However, the depicted coefficients always refer to the effect of reporting a high expected treatment rate (effect) compared to reporting a low expected treatment rate (effect).

refer to the unconditional differences (as already depicted in Table 1), while column (2) and (4) show the ATTs based on propensity score matching taking into account differences with respect to observed characteristics. For non-participants, expecting participation is associated with a 3.1 percentage point higher employment rate 30 months after the entry into unemployment. The effect is statistically significant at the 10%-level. Moreover, this is related to a difference of 0.9 months with respect to the cumulated time spend in employment which is significant at the 1%-level, while there is no significant effect with respect to the average earnings. The findings for non-participants are in line with the previous results by van den Berg et al. (2009) who show that job-seekers who expect to participate in an ALMP program search harder and set lower reservation wages. This threat effect can be expected to result in higher job finding rates. Moreover, the effect seems to be persistent over time which suggest that the threat of being treated can create positive long-run employment effects.

When regarding participants in long-term training, there is a positive effect of expecting a treatment on the employment probability which is substantially larger than the effect for non-participants. 30 months after the entry into unemployment, the matched difference in employment rates between those participants reporting π-high and π-low is about 9.2 percentage points and statistically significant at the 5%-level. The lower employment probabilities of those who did not expect the treatment mirrors also in a lower cumulated effect over the full observation period of about 1.15 months. However, the effect is statistically insignificant at conventional levels. Again, there is no significant effect on earnings. Moreover, it should be noted that the estimated ATTs, that take into account differences with respect to an extensive set of control variables, are very similar to the unconditional difference. This can be interpreted as evidence that the positive effect of the expected treatment rate on the program effectiveness cannot be explained by structural differences (at least with respect to socio-demographics, labor market histories and personality traits) associated with the expected treatment rate π.

[Insert Table 2 about here]

Expected Treatment Effects: Panel B of Table 2 shows the impact of the expected treatment effect δ on the realized labor market outcomes separated for non-participants and participants according to the group classification in Panel B of Table 1. Again, column (1) and (3) show the unconditional effect of expecting the treatment to be beneficial, while column (2) and (4) show the matching estimates. In can be seen that there are no significant effects of the expected treatment effect for any of the labor market outcomes, neither for participants nor non-participants. Moreover, accounting for individual level characteristics has nearly no impact on the estimated differences. The findings for non-participants are not very surprising given that the expectation measure refers to the impact of an event which does not take place. However, more surprisingly, the expected treatment effect is also unrelated to the actual treatment effect for those who enter long-term training within 12 months.

Comparing the ATTs based on the two expectation measures π and δ allows already to draw conclusions about the underlying effect mechanisms. First of all, the set of estimates presented in Panel B shows that participants have only a limited capacity to predict the impact of the program on their own labor market performance. Although, this may seem surprising at first, the finding is in line with earlier results showing that caseworkers are typically not able to identify job seekers who would benefit most from social programs and statistical assignment rules could improve program efficiency (Frölich et al., 2003; Lechner and Smith, 2007; Caliendo et al., 2008). Assuming that the caseworker is the most relevant source of information about labor market programs for the unemployed, it can be expected that the caseworkers' limited capacity to predict the program efficiency translates into a zero effect of δ on the realized treatment effect. Moreover, the findings can be also related to the discussion about the connection between endogenous belief formation and long-term labor market outcomes in Section 2. For instance, the lower employment rates of those participants who do not expect the treatment ex ante could be explained by the assumption that job seekers have private information about their individual-specific program effectiveness. On the one hand, this would lead to higher expected treatment rates when individuals anticipate that they can influence the likelihood of entering a program, e.g. due to bargaining with their caseworker or not redeeming training vouchers. On the other hand, this private information can be expected to be related to the realized treatment effect. However, the results show that, although π-high and δ-high are positively correlated (the correlation coefficient is about 0.26 and statistically significant), the expected treatment effect is unrelated to the realized treatment effect. Therefore, it can be concluded that subjective beliefs about the program effectiveness are not driving the differences in employment rates with respect to expected treatment rates π.

4.3 Sensitivity Analysis

Accounting for the Elapsed Unemployment Duration: As already discussed in Section 2, there might exist other confounders that are related to the expected treatment rate π and the labor market performance. As pointed out by Biewen et al. (2014), an important factor in the context of training programs is the elapsed unemployment duration before entering a program. Differences with respect to the timing of the treatment between participants with low or high expected treatment rates π could potentially translate into lower long-term employment rates even if both groups otherwise would behave completely identical. Moreover, job seekers who remain unemployed longer and are therefore at the risk of being treated in later periods are likely to represent a selected group of individuals with lower unobserved characteristics. Therefore, a dynamic matching approach following Sianesi (2004) is adopted in order to account for these differences.[11] As shown in Panel A of Table 3 accounting for the elapsed unemployment duration reduces the estimated coefficient for participants in long-term training about 2.5 percentage points, while the remaining effect is still large and statistically significant at the 10%-level. However, it should be noted that there are also exogenous reasons that imply a relationship between π and the elapsed unemployment duration. For instance, individuals who expect the treatment might prepare themselves in a different way before the actual program start or choose different providers which could lead to differences with respect to the timing of the treatment. As this would be a causal consequence of the expected treatment rate π, the dynamic matching procedure will underestimate the actual effect of the pre-program expectations π. The fact that the estimated coefficient is still positive and statistically significant indicates that π indeed has an impact on the program effectiveness beyond the effect induced by delayed program starts.

[Insert Table 3 and Figure 3 about here]

Difference-in-Difference Model: As an additional robustness check, I compare the impact of the subjective expectation measures on the realized treatment effects of different ALMP programs. In addition to the long-term training measures discussed before, I also consider individuals who participate in short-term training programs within the first 12 months of the unemployment spell. These programs last from two days up to eight weeks and include job search assistance, computer or language classes and practical training within companies (see e.g. Wolff and Jozwiak, 2007, for an evaluation of these programs). As discussed by Biewen et al. (2014), short-term training programs have similar employment effects in the long-run, but unsurprisingly participation is associated with much shorter locking-in periods compared to long-term training. Therefore, it seems to be reasonable to consider participants in short-term training as a control group to identify behavioral adjustment of participants in long-term training that are induced by differences with respect to the expected treatment rate π. In a first step, I estimate the effect of the expected treatment rate π on the employment status of participants in these programs 30 months after the entry into

[11] The distribution of the start dates is shown in Figure A.1.

unemployment. As shown in Panel B of Table 3, the expectation measure has no influence on the long-term outcomes for these individuals. This can be interpreted as first evidence that the effect of the expected treatment rate π is directly related to the specific characteristics of long-term training.

However, in order to allow the comparison of these two different programs to have causal interpretation it is important to argue that there are no unobserved characteristics that are associated with π, the actual selection into the two programs and the individual labor market outcomes. Therefore, Figure 3 shows a difference-in-difference comparison between participants in short- and long-term training based on the expected treatment π over a period from 10 years before the entry into to unemployment up to the end of the observation period 30 months after the entry. It reveals two important results. First, it can be seen that π has no significant impact on the differences in the average employment rates before the entry into unemployment. This suggests that there are no time-constant unobserved characteristics, e.g. different levels of ability, associated with π that generally affect the employment rates of participants in the two programs differently. Second, about 9 months after the beginning of the unemployment spell π starts to have positive and significant impact on participants in long-term training relative to individuals participating in short-term training. The difference is particularly pronounced twelve months after the entry (about 18 percentage points), but remains on a high level (10 percentage points or larger) over the full observation period. In order to complete the graphical illustration depicted in Figure 3, I also estimate a conditional difference-in-difference-in-difference (DDD) model that can be characterized by the following equation:

$$\Delta Y_i = \beta_0 + \beta_1 D_i + \beta_2 \pi_i^{high} + \beta_3 (D_i \times \pi_i^{high}) + v_i, \tag{9}$$

where ΔY_i refers to the difference between the employment status at the end of the observation period and the average employment rate in the reference period before the entry into unemployment. D_i indicates a dummy that takes the value one for participants in long-term training and zero for individuals participating in short-term training, while π_i^{high} indicates an expected treatment rate of five of higher. The model is estimated using weighted least squares and weights are obtained from propensity score matching based on the covariates discussed before. The coefficient β_3 of the interaction term between the treatment status and the expected treatment rate π then indicates the average differences in ATTs of the expectation measure between participants in long-term and short-term training. Three different reference periods for ΔY_i are utilized, to account explicitly for time-constant unobserved differences: 1) the last 2 years before the entry, 2) the last 5 years and 3) the last 10 years. As shown in Panel C of Table 3 the estimate of β_3 is positive and statistically significant in all three cases. Moreover, the magnitude is always similar (or even larger) compared to the baseline effect depicted in Panel A.

Finally, Panel D presents the estimates of a placebo test. Therefore, I exploit an additional expectation measure that refers to the question: *"When you think of the future, how likely is it from your perspective that you will find a job within the next 6 months?"* Possible answers range from (very) unlikely to (very) likely. To verify the validity of the results, I reestimate equation 9 using the job seeker's answer to this question about her reemployment prospects as the outcome variable. Since both variables are measured in the first wave of the survey before the actual treatment is realized, the expected treatment rate π should be related to the expected reemployment prospects in a similar way for participants in two different training programs. Since this is actually the case, as indicated by the small and insignificant coefficients in Panel D, one can conclude that there exist no unobserved differences that would affect the expectations of both groups of participants differently. In summary, the findings show that the impact the of expected treatment rate π is specific for long-term training programs and is very robust with respect to several types of unobserved heterogeneity that could be potentially related to the individual expectation formation.

4.4 Differences in Search Strategies as Underlying Mechanism

So far, the focus of the empirical analysis was on analyzing the impact of different expectation measures on the labor market outcomes after the realization of a treatment. Although the sensitivity analysis suggest that the results are highly robust with respect to unobserved heterogeneity, a causal explanation for the positive impact of the expected treatment rate on the program effectiveness requires that individuals who expect the treatment ex ante adjust their behavior differently in association with a realized treatment compared to those who do not expect the treatment (see discussion in Section 2). In order to provide (positive) evidence for the presence of such an adjustment and the underlying effect mechanisms, the following section analyzes several characteristics of the individual job search behavior. These measures are obtained during the first interview of the survey which takes place 7 to 14 weeks after the entry into unemployment, but before the actual treatment has been realized. Table 4 shows the matched differences between individuals reporting high and low expected treatment rates with respect to these outcome variables. In line with the baseline results, presented in Panel A of Table 2, the propensity score specification includes an extensive set of control variables and the ATTs of π-high are estimated separately for participants and non-participants.

[Insert Table 4 about here]

Own Job Search Strategy: Panel A presents differences in variables characterizing the job seeker's search strategy with respect to her own personal effort. These search strategies typically comprise several dimensions, like the individual search intensity or the usage of different search methods. The first observed variable characterizes the average weekly number of own job applications (measured between the entry into unemployment and the first interview). There are no significant differences with respect to π neither for participants nor non-participants. A second variable describes the search channels that the job seeker uses for job search. In the literature the number of utilized search channels is exploited as an alternative measure for the search effort (e.g. van den Berg and van der Klaauw, 2006; van den Berg et al., 2009). The results show that, among the non-participants, those who expect a treatment in total use more different search methods than those who do not expect to participate, while there is no difference among the participants. It can be concluded that the initial level of search effort is not a driving factor for the positive effect π on the employment rates of participants. This indicates that unobserved differences, e.g. with respect to the level of motivation, that affect the job seeker's initial search strategy are unlikely to be responsible for the estimated effects presented in Section 4.2.

Adjustment of the Job Search Behavior: As discussed in Section 2, a mechanism that implies a causal relationship between the expected treatment rate π and the labor market outcomes of participants requires that π has implications for the individual behavior after (or related to) the realization of the actual treatment status. In order to test this hypothesis, I exploit the answers to the additional survey question: *"To what extent would your search activities change, when you know that you could/must participate in an ALMP program within the next 2 months?"* Although, the wording of the question implies that the agent adjusts the search behavior already before the treatment actually takes place, it can be expected that the variable measures the behavior adjustment that is immediately related to the treatment assignment. Moreover, it can be also assumed to provide a valid proxy for the flexibility of the agent's search strategy in general and for those who actually enter the program also to provide information regarding the behavior during the treatment.[12]

[12] An obvious interpretation of the question would imply that it reflects the anticipation (threat or waiting) effect of a program. However, it should be noted that a comparision of the individual willingness to adjust the search behavior and the expected treatment effect shows that those job seekers who actually would have incentives to wait out until the treatment (since they expect the treatment to be beneficial) show a higher willingness to increase their search effort (see Table A.5 for details). Since this contradicts theoretical considerations with respect to formation of anticipation effects, it can be concluded that the survey question provides additional information about the agents behavior going beyond the measurement of the anticipation effect.

The results in Panel B show that, among both actual treatment states, those who expect to participate show a 10 percentage points higher willingness to increase their search effort compared to those who do not expect the treatment ex ante. Both effects are statistically significant at the 1%-level. Interestingly, among participants, job seekers who are aware of the treatment are also about 3 percentage points more likely to decrease their search effort (statistically significant at the 5%-level). The findings show that expecting a treatment is associated with being more likely to adjust the search behavior in connection with an ALMP program. This implies that, after the realization of the actual treatment, those individuals who expect to participate ex ante choose a different search strategy than those who do not expect to participate. This supports the idea that the expected treatment rate π has a causal impact on the behavior of actual participants which would explain the higher employment rates of those expect the treatment ex ante.

Contact to Employment Agency: Given that there are no differences with respect to the initial level of search effort (see Panel A), the question arises what mechanism triggers the higher willingness to adjust the search behavior of individuals who expect the treatment. In order to shed more light on this question, the estimates in Panel C take a closer look on variables that characterize the contact between the unemployed job seeker and the employment agency, respectively the responsible caseworker. First, it can be seen that those job seekers who expect a treatment more often utilize the caseworker as a search channel. Participants with π-high have 9 percentage point higher probability to report that the caseworker is one of the search channels. The effect is statistically significant at the 1%-level. Interestingly, the effect is almost of the same size as the effect on the willingness to increase the search effort, as well as the employment probability after 30 months. Moreover, related to this, participants who expect a treatment also receive significantly more job offers by the employment agency, while there is no difference among non-participants. Finally, it can be also seen that expected participation rate is related to information treatments with respect to training program. In this case an information treatment describes a dummy variable which takes the value one if 1) the caseworker has already suggested the job seeker to participate in a training program, 2) the caseworker has already suggested to hand out a training voucher or 3) the job seeker already received a training voucher before the first interview. The results show that, especially participants who expect to participate more often received such an information treatment compared to those who do not expect to participate.

In summary, the findings of this section support the idea that differences with respect to expected treatment rate π are induced by the information that the job seeker receives by the caseworker.

Although this seems to be unrelated to the initial effort that future participants spend into search activities before the treatment, it leads to higher willingness to adjust the search behavior once the treatment has been realized. In line with the theoretical discussion in Section 2, this mechanism provides an explanation for the positive effect of the expected treatment rate on the employment rates of participants. For instance, it can be expected that during participation in a program job seekers have less time available for job search and the necessary adjustment of the search strategy requires the usage of new search methods. It seems to be plausible that those job seekers who already take into account the possibility of a future treatment at the beginning of the unemployment spell face lower costs of adjusting their behavior as they already had the chance to become familiar with these methods. This effect might be even stronger given that expecting a treatment is associated with a closer connection to the caseworker who can be helpful when developing the optimal search strategy.

5 A Model of Endogenous Expectations

So far, the empirical analysis established two innovative results. First, there is a positive effect of the expected treatment rate π on the long-run employment rates of participants in long-term training. Second, expecting a treatment is related to having a stronger connection to the caseworker, being more often informed about potential treatments and a higher willingness to adjust the search behavior in association with an ALMP program. These findings suggest that differences in the relationship, and therefore also the exchange of information, between the caseworker and the job seeker before participating in a program affects the unemployeds expected treatment probability, as well as their behavior over time, and leads to differences in labor market outcomes after the realization of the treatment. Although the sensitivity analysis in Section 4.3 shows that the findings are robust with respect to different types of unobserved heterogeneity, the empirical analysis does so far not take into account that unemployed individuals form their beliefs about the treatment probability, as well as other economic outcomes and decide about specific job search strategies simultaneously as discussed theoretically in Section 2.2. In the following, I present an empirical model that represents this endogenous formation of expectations. It is assumed job seekers take their decision about π and choose a search strategy based on the expected value functions depending on their expectations about the treatment effect, reemployment prospects and earnings. While the model itself does not rely on realized labor market outcomes, in a second step, the estimated parameters of the model are directly connected to the realized treatment effects of long-term training. This analysis provides direct evidence with respect to the underlying mechanisms suggested by the reduced-form estimates of Section 4.4.

5.1 Economic Framework

Baseline Model: It is assumed that the agent maximizes her expected inter-temporal utility over a three-period horizon.[13] In the first period t_0, all agents are unemployed and have to decide about a search strategy s_u that is characterized by the average weekly number of own job applications measured at the first interview. This search strategy implies immediate costs of the form: $c_u(s_u) = \kappa_u s_u^2$ (see e.g. van den Berg and van der Klaauw, 2006). Moreover, the agent forms expectations about her labor market status in the subsequent period t_1 facing three options. First, she expects to find a new job with probability λs_u, which is associated with the utility $\log(\omega)$,[14] with ω denoting the expected monthly net income. It is assumed that the agent keeps the job in the final period t_2 and receives the same level of utility. Second, when not finding a job with probability $(1 - \lambda s_u)$, she expects to participate in a training program with probability π, which would imply a different search strategy s_p due to different search costs $c_p(s_p) = \kappa_p s_p^2$ and the agent expects that the treatment changes the returns in t_2 by the factor δ. Third, with probability $(1 - \lambda s_u)(1 - \pi)$ the agent expects to remain unemployed without entering a program. Therefore, the search costs and expected returns would be the same as in the initial period.

Inter-temporal Adjustment of Search Behavior: In order to incorporate the fact that the individual beliefs are related to the long-run behavior, it is assumed that expecting a treatment in t_1 is associated 1) with the expectation that the agent needs to adjust her own behavior between t_0 and t_1 and 2) with the prospect that this adjustment creates additional costs. The first assumption seems to be reasonable given that the treatment reduces the time that is available for job search activities, which could require an adjustment of the search strategy. However, the crucial question is whether the agent assumes that the adjustment of the search behavior creates additional costs going beyond the direct impact of the new search strategy (indicated by the search costs $\kappa_p s_p^2$ and job finding prospects $\lambda_p s_p$). From a theoretical perspective, the presence of these additional costs can be justified since the adjustment of the search strategy is likely to be associated with a change

[13] This assumption is motivated, on the one hand, by the availability of survey data, but on the other hand, also by the underlying economic issue that comprises one period before, during and after the potential treatment.

[14] It is assumed that the expected job finding probability λ contains an expected baseline rate which is estimated within the model and an individual-specific part which is predicted from an ordered probit estimation (see Table A.6) of the individual characteristics X on the expected job finding rate within the next 6 months measured on a scale from 1 ('very likely') to 4 ('very unlikely'). The distribution of the expected job finding rate and the expected earnings is depicted in Figure A.3b and A.3c.

of the search methods that can be assumed to create actual costs since job seekers might be less effective when they are not familiar with these methods. A related explanation could be derived from prospect theory (see Kahneman and Tversky, 1979). Assuming that the search strategy, and therefore also the amount of leisure time, in the initial period t_0 defines an agent's reference point for her future behavior, it can be expected that an increase of the search effort creates disproportionately high costs when the agent is habituated to her reference-level of leisure time. The effect can be expected to be particularly important given that the program participation per se reduces the available leisure time. Moreover, this might be also related to the agents willingness to comply with the program conditions, since one way of maintaining the reference-level of leisure time is to spend less effort into activities that are directly related to treatment.

Therefore, it is assumed that job seekers who expect to adjust their search behavior take into account that this adjustment will create additional costs $\kappa_a \eta$, where κ_a denotes the expected marginal adjustment costs and η characterizes the extent of the behavioral adjustment. As already discussed in Section 4.4, the dataset provides the information whether the agent expects to change her search behavior when the treatment is imminent, which can be assumed to provide a valid measure for the expected behavioral adjustment over time (see Panel B of Table 4). As the question directly relates to the presence of an ALMP program it is reasonable to assume that only those individuals who expect to enter a program also expect to actually adjust their behavior in connection with it.[15] While the survey question provides an indicator whether the agent will adjust her behavior or not, I propose two alternative ways in oder to determine the magnitude of the effort adjustment, which is particularly relevant to obtain a measure for the expected search effort during the treatment s_p. First, the magnitude of the expected adjustment is estimated by using information from the second wave of the survey (which takes place about 12 months after the entry). Changes of effort levels are obtained for 438 individuals who participate in a training program between the first and the second interview and predictions for the full sample are generated based on OLS estimates.[16] Hence, the adjustment costs are given as: $\kappa_a \eta = \kappa_a (s_p - s_u)^2$. This refers to the baseline model in the following. As an alternative, I exploit only the information whether the individual will the increase search effort and estimate the additional parameter η that characterizes the magnitude

[15]It should be noted that the formulation of the survey question implies that the agent adjusts the search behavior already before the treatment. However, since the model does not take into account whether the agent actually participates in a program or not, but rather illustrates the process of expectation formation, it is secondary at which point in time the behavioral adjustment is expected to take place. Nevertheless, it is shown in Table A.5 that the willingness to increase the search effort is positively related to the expected treatment effects, which suggests that the willingness to adjust the search behavior is not a manifestation of a potential threat effect and therefore might contain information regarding the agents expected behavior during the treatment.

[16]See also Table A.6 for the results of the corresponding OLS estimation and Figure A.3d for the distribution of the expected effort change based on these estimates.

of this adjustment within the model. Hence, the search effort during the treatment is defined as $s_p = s_u + \eta$. It should be noted that, for this alternative model, the adjustment costs occur only if the agent expects to increase the search effort. This reflects the fact that an effort reduction (which is associated with more leisure time) is unlikely to imply the application of new search methods or to affect the agent's utility negatively due to reference-dependent preferences.

5.2 Econometric Specification

Within this framework the agent forms her beliefs about the treatment probability π, which is given by an ordinal outcome variable that takes values $j = 1, ..., J$ (see e.g. Cunha et al., 2007; Greene and Hensher, 2010), according to the following rule:

$$P(\pi = j) = P(\zeta_j \geq \Delta V(s_u, s_p) > \zeta_{j-1}), \tag{10}$$

where ΔV characterizes the difference of expected values between the situation where the agent expects a treatment in period t_0 and the situation where she does not. For a given discount rate ρ, this expected utility difference over the three-period horizon is given as:

$$\Delta V(s_u, s_p) = \rho(1 - \lambda s_u) \left\{ \rho\lambda \log(\omega)(\delta s_p - s_u) - (\kappa_p s_p^2 - \kappa_u s_u^2 + \kappa_a \eta) \right\}. \tag{11}$$

The factor before the brackets denotes the discounted probability that the agent is still unemployed in period t_1 and therefore faces the possibility of being treated. The first term inside the brackets denotes the expected discounted utility difference between the treated and non-treated situation with respect to labor market returns, while the last term characterizes differences with respect to search costs. Moreover, ζ captures the agents expectations about all other factors, e.g. the influence of the caseworker when choosing the search strategy. Therefore, the log-likelihood is given by:

$$\ln \mathcal{L} = \sum_{i=1}^{N} \sum_{j=1}^{J} \pi_{ij} \ln \left\{ \Phi(\zeta_j - \Delta V_i(\kappa_u, \kappa_p, \kappa_a, \lambda, \delta)) - \Phi(\zeta_{j-1} - \Delta V_i(\kappa_u, \kappa_p, \kappa_a, \lambda, \delta)) \right\}, \tag{12}$$

where Φ denotes the cdf of the normal distribution. Moreover, I allow for individual heterogeneity with respect to the parameters κ_u and κ_p depending on the observed characteristics X:

$$\kappa_u = \gamma_u X + \varepsilon_u \qquad \text{and} \qquad \kappa_p = \gamma_p X + \varepsilon_p. \tag{13}$$

In total, I estimate four different versions of the model. As discussed before, in the baseline model, the level of search effort during the treatment is imputed from wave 2 information for those who participate in a training program, while in the alternative model an additional parameter η is estimated which denotes the magnitude of the adjustment of the search effort for those who report that they will change their search behavior when entering a program. Moreover, for both versions of the model, I additionally include unobserved heterogeneity by allowing for two different types of agents with high, respectively low, levels of utility cutoffs ζ. This can be expected to capture differences with respect to factors that are not included into the model, e.g. unobserved ability differences or the quality of the caseworker.

Finally, it is assumed that, during the first meetings with the caseworker, the job seeker receives specific information about potential future activities, e.g. program participation or employment prospects in general. This set of received information Z is assumed to influence the agent's specific search strategy and therefore also the level of the adjustment costs that will arise once she enters a program:

$$\kappa_a = \gamma_a Z_i + \varepsilon_a. \tag{14}$$

The vector Z contains several variables indicating whether the job seeker utilizes the caseworker as a search channel, the number of job offers she received from the agency, as well as indicators for whether she received an information treatment with respect to training programs, respectively other ALMP programs, or a job offer for full- or part-time employment.[17]

It is important to note that the model is estimated only based on the agent's search behavior and expectations measured during the first interview and does not rely on realized labor market outcomes or the actual program participation. Therefore, the estimated parameters refer to the agent's expectations about search costs, reemployment probabilities and treatment effects. The main objective of the estimation procedure is to identify the set of parameters κ_a that can be interpreted as agent's expected costs of adjusting the search behavior when entering a training program, respectively the impact of the employment agency on these expected costs. It can be argued that these parameters are relevant in the context of the search model proposed in Section 2 since the agent's decision about the behavior during the treatment is taken only based on her expectations about costs that will arise in the future.

5.3 Parameter Estimates

For the estimation of the parameters, I consider $J = 3$ potential level of individual expected treatment probabilities ($\pi_1 = \mathbb{1}\{\pi \in (0,3)\}$, $\pi_2 = \mathbb{1}\{\pi \in (4,6)\}$ and $\pi_3 = \mathbb{1}\{\pi \in (7,10)\}$). This reflects the fact that the empirical distribution of π has three peaks at zero, five and ten (see Figure 2). The finer segregation of π (compared to the baseline analysis of Section 4) takes into

[17]Descriptive statistics with respect to these information treatments can be obtained in Panel B of Table A.2 in the Appendix.

account that a substantial group of job seekers report values that reflect uncertainty about the future treatment status.[18]

The estimation results for the parameters of the model are presented in Table 5. The first set of estimates characterizes the search cost function, where κ_a refers to the job seekers expected adjustment costs. The estimates of the constant suggest that a job seeker who had no contact to the employment agency (until the first interview) expects to face substantial costs when adjusting the search strategy in association with an imminent training program. Although, the estimated coefficients are about three times larger in the alternative (compared to the baseline) models, the effect is statistically significant in all four cases. Moreover, the findings show that specific information treatments that the job seeker received by the employment agency affect these adjustment costs. Most importantly, informing the job seeker about the availability of training programs reduces the level of the adjustment costs significantly. For the two alternative models this reduction is even larger than the constant indicating that job seekers who have been already informed about these programs, e.g. by receiving a training voucher, do not expect any adjustment costs. Moreover, since the parameters κ_u and κ_p denoting the search costs during unemployment, respectively the treatment, depend on individual characteristics X, average values for these two parameters are depicted in Table 5.[19] For all models, the expected search costs are on average higher during the program which is reasonable given that participating in a training program is time-consuming and job seekers have less time available for job search. It should be noted that there might exists external factors, e.g. the influence of the caseworker or the threat of sanctions, which would encourage the agent to spend effort into job search activities even if the expected returns in terms of future earnings and employment prospects are relatively low. As I do not take these external factors into account explicitly, they are captured implicitly by smaller values of the search cost parameters.

[Insert Table 5 about here]

The second set of parameters refers to the expected returns to job search. It should be noted that all estimated parameters have the sign as expected and are of reasonable size. The baseline hazard rate λ^{base} characterizes the expectation of an average agent that she would find a new job

[18]It should be noted that this finer segregation (compared to Section 4) is possible since the analysis is conducted without conditioning on the actual treatment status. Moreover, this allows to include also individuals who participate in short-term training within the first 12 months after the entry. The findings are qualitatively similar when excluding those individuals. Results are available upon request. Finally, individuals from the highest/lowest percentile of the expected income distribution are excluded in order to avoid a strong impact of a few individuals who report implausible high/low values for this variable.

[19]Full estimation results are shown in Table A.7 in the Appendix.

between two periods given that she sends out one application per week.[20] Moreover, the estimates for the expected treatment effects δ_1, respectively δ_2, suggest that those agents who expect the training program to have a (very) positive effect expect a utility increase of about 54% (107%) in the baseline model without unobserved heterogeneity. While the estimates are similar for the alternative model, allowing for unobserved heterogeneity suggests even larger expected benefits of the treatment. At first sight this effect appears large, however it should be noted that this might also capture whether the individual expects to like participation per se. Moreover, it can also be expected that the caseworker affects the job seeker's perception of the program positively. Finally, the alternative model provides also an estimate for the parameter η which denotes the magnitude of the expected effort adjustment during the program which is about 0.60 to 0.67 applications per week. This is substantially larger than the corresponding prediction for the baseline specification exploited from participants observed changes with respect to the search behavior between wave 1 and 2 which is about 0.21 applications per week.

When interpreting the results, it should be noted that all parameters refer to the job seekers perception of search costs, respectively their expectations about labor market outcomes. Therefore, it is difficult to evaluate whether the estimated parameters are realistic or not. In order assess the quality of the model, two measures are presented that allow the comparison to the predictions of an simple ordered probit model estimating the effect of the covariates X on the ordinal variable π_j. First, a likelihood ratio test shows that the ordered probit model is rejected in favor of all four versions of the proposed model. Moreover, I calculate a hitrate which refers to share of correctly predicted values.[21] Again, all four versions of the proposed model predict the observed outcomes substantially better than the ordered probit model. The hitrate increases between 5 and 8 percentage points, while it is larger for the alternative compared to the baseline model.

5.4 Adjustment of the Search Behavior and Labor Market Outcomes

The estimated parameters of the model show that, when deciding about their search strategy, job seekers consider the appearance of adjustment costs once they enter a training program during the unemployment spell. Moreover, these costs can be directly influenced by the caseworker through various information treatments. Although, this is an interesting finding per se, an open question remains whether the expectancy of these adjustment costs has also implications for realized labor

[20] It should be noted that in this context the definition of a period refers to respondents interpretation of the survey question on the expected treatment rate as depicted in Figure 2.

[21] It is given as the mean of a variable which takes for each individual-choice combination the value one if the actual value is one (zero) and the predicted value of the model is greater or equal (smaller) than the sample average and zero otherwise : $\frac{1}{NJ}\sum_{i=1}^{N}\sum_{j=1}^{J}\pi_{ij}\mathbb{1}\left\{P_{ij}\geq\bar{P}_j\right\}+(1-\pi_{ij})\mathbb{1}\left\{P_{ij}<\bar{P}_j\right\}$.

market outcomes and, in particular, the effectiveness of training programs. This question is of special relevance as it directly relates the theoretical discussion about the inter-temporal adjustment of the search behavior to the positive effect of the expected treatment rate π on the employment rates of participants and would provide the employment agency a tool to improve the effectiveness of training programs.

In order to directly test this mechanism, the estimated model is utilized to generate predictions about the level of the adjustment costs κ_a, given the set of available information Z. Based on these predictions a dummy variable indicating whether the adjustment costs are above/below the sample median is defined and each of the four groups analyzed in Section 4 —given by the combinations of expected and actual treatment states— is divided into a subgroup with a high, respectively low, level of adjustment costs. Table 6 shows ATTs for the outcome variable regular employed in month 30 separated for these subsamples with low/high levels of expected adjustment costs. Since the number of observations for the groups of participants becomes relatively small due to the additional sample split, the group of non-participants with a low expected treatment rates (π-low) is used as the unique reference group and differences with respect to the estimated ATTs are calculated.

[Insert Table 6 about here]

In the first specification ('unconditional'), the adjustment cost κ_a-low, respectively κ_a-high, are assumed to characterize individuals who report that they will, respectively will not, adjust their search behavior when the treatment is imminent. This specification provides a reference level where adjustment costs are endogenously predicted based on the observed willingness to adjust the search behavior. In the second specification the adjustment costs are predicted based on the baseline model, while in the third specification the alternative model is utilized. In both cases, I choose the model which allows for unobserved heterogeneity. The findings show no clear pattern for non-participants which is not very surprising, given that the effects of π are generally small and non-participants do not actually have to adjust their behavior. More interestingly, in all three specifications, the positive effect of π on the employment probability of participants is completely driven by those individuals who are assumed to have a high level of adjustment costs. Although, this pattern is more pronounced when using the baseline model, in all cases the difference between those participants π-high and π-low is large and statistically significant for individuals with high adjustment costs, while it is close to zero and insignificant for individuals with low adjustment costs. For instance, using the alternative model the estimated difference is about eight times larger for the group with high adjustment costs compared to the group with low adjustment costs.

5.5 Discussion of Economic Implication

The key result of the empirical analysis shows that the job seekers' expectations about the likelihood to participate in the near future is positively related to the effectiveness of realized long-term training programs later during the unemployment spell. The crucial question that arises from this finding is whether the connection between the expected treatment probability and the program effectiveness reflects a causal relationship or the endogenous formation of expectations and differences with respect to the selection into the program. To answer this question, the comparison with participants in short-term training provides evidence that the revealed connection is very specific for long-term training and can not be explained by the fact that job seekers who expect to participate are generally different from those who do not expect a treatment. Moreover, it should be noted that it is unlikely that estimated effects can be explained by different selection patterns induced by anticipation effects. This can be concluded based on two argument. First, as shown empirically, the expected treatment effect has no impact on the realized program effectiveness, which implies that heterogeneity with respect to the expected treatment effect is not the driving factor influencing the expected treatment rate and the outcomes of participants simultaneously. Second, it can be argued that the presence of a threat effect (as indicated by the employment effects of the expected treatment rate on non-participants) implies that those job seekers who expect a treatment and end up in the program are those who fail to find employment and have on average a lower level of unobserved abilities compared to job seekers who do not expect a treatment. Therefore, it can be assumed that the selection into the treatment based on expected participation probabilities would imply a downward bias for the estimated effects of π and the latter would be interpreted as a lower bound.[22]

The second part of the empirical analysis aims to shed light on the underlying mechanisms by considering the job search behavior and estimating a structural model of the expectation formation process. The findings provide a direct link between the theoretical discussion of Section 2 and the baseline estimates of Section 4. First, it is shown that job seekers take into account that adjusting the search behavior when entering a training program creates significant additional costs. It can be concluded that participants who correctly predict their treatment status ex ante choose search patterns that are more efficient when the treatment is realized. Second, the size of the adjustment costs can be influenced by the employment agency, respectively the caseworker, by using different information treatments for unemployed workers. Finally, the level of the adjustment costs, and,

[22]See also Table A.8, which shows that the positive effect of π is substantially stronger for those participants who expect the treatment to be less beneficial. This underlines the interpretation that the positive effect of π is not the consequence of different selection patterns due to the threat/waiting effect.

therefore, the job seekers willingness to choose more efficient search strategies during the treatment is directly connected to the positive effect of the expected treatment π on the program effectiveness. For participants who face high costs of adjusting their job search strategy, the expected treatment rate before participating has a strong positive effect on the long-term employment probability, while there is no effect on those participants who face low levels of adjustment costs. This is particularly important as it points out that the employment agency can easily improve the effectiveness of training programs by informing potential participants about upcoming treatments early during the unemployment spell.

An important question remains, how the employment agency can effectively implement these information strategies that influence the job seekers' expectations about future treatments and reduce the expected costs of adjusting the search behavior. It should be noted that, in 2003, Germany already implemented a reform which can be expected to affect the job seekers perception of the individual-specific treatment probability by switching from caseworker assignment to a voucher system. Before 2003, participants had been assigned to a specific training program by their caseworker, while after the reform, which has been introduced in the context of the Hartz reforms (see e.g. Jacobi and Kluve, 2007; Caliendo and Hogenacker, 2012, for an overview), job seekers are free to choose a training provider in the market. Therefore, potential participants receive a training voucher which defines the maximum duration, the target of the program and its costs. The voucher is valid for up to 3 months. However, since job seekers are free not to redeem the voucher, the new system can be expected to reduce the difference between the job seeker's perceived and the actual treatment probability and therefore increases the likelihood that potential participants choose the optimal search strategy given the future treatment status. This argument is supported by the fact that previous studies find a positive effect of the introduction of the voucher system on labor market outcomes (see e.g. Rinne et al., 2013). However, in the present sample only about 23% of the participants already received a voucher between the entry into unemployment and the first interview, while another 15% of the participation have been informed about the possibility of participating in a training scheme by their caseworkers. These numbers indicate that the majority of participants already spent several months into job search activities before discussing a participation in a training programs with the caseworker. It can be expected that the presence of such a time lag reduces their willingness to adjust their search behavior.

6 Conclusion

Previous studies have shown that the possibility of a future participation in an ALMP program encourages job seekers to change their search behavior. Either they search more intensively to leave unemployment and prevent a treatment that is expected to lower their utility level or they reduce the search effort to wait out until the beginning of a beneficial treatment. This studies connects these former results on the presence of anticipation effects to the vast literature that analyzes the impact of ALMP programs on post-treatment labor market outcomes by combining survey measures on job seekers subjective expectations about ALMP programs and administrative data on actual program participation in Germany.

In particular, I analyze the effect of two self-reported expectation measures, obtained directly at the into unemployment, on long-term labor market outcomes after the realization of the actual treatment status. The main results show that the expected probability to participate in a training program in the near future has a strong positive effect on the long-term employment probabilities of individuals who actually participate in a long-term training program later during the unemployment spell. However, the expected effect of the program has no impact on the realized treatment effect. Theoretical considerations suggest that positive effect of the expected treatment rate on the program effectiveness would be due to a causal relationship if the job seekers' beliefs about the future treatment have an impact on the participants' behavior once the actual treatment has been realized. This comprises the job search behavior during the treatment, the compliance with program conditions and the choice of program providers. The latter might be of special relevance in the case of Germany since unemployed workers have a high degree of autonomy when choosing providers for long-term training programs. However, an alternative explanation would imply that the expected participation probability is related to unobserved characteristics that in turn would have an impact on the labor market performance.

In order to understand the effect mechanisms, a comprehensive analysis of the job search behavior is conducted. The findings show that the expected treatment rate is indeed related to the job search strategy. Although there are no differences with respect to the number of job applications or the choice of participants search channels, unemployed workers who expect a treatment are more likely to exploit the help of their caseworker, i.e. they receive more job offers from the employment agency and more often receive information about training programs. Moreover, this is associated with a higher willingness to adjust the search behavior when an ALMP program is imminent. These findings suggest that the perceived treatment probability indeed has a causal effect on the program effectiveness by affecting the search strategy during the treatment. This interpretation is supported by an extensive sensitivity analysis. The results turned out to be highly robust with respect to several potential confounders including the timing of the treatment and unobserved characteristics like the job seeker's ability to correctly predict future economic outcomes or motivation. Moreover, a placebo test, considering participants in short-term training courses, shows that the finding is strongly related to a specific treatment with a sufficient program duration.

Finally, a structural model of the individual process of expectation formation is estimated taking into account that job seekers decide about their search strategy and form expectations about various labor market outcomes, e.g. program participation, employment prospects and earnings, simultaneously. The parameter estimates show that job seekers take into account the fact that an adjustment of the search strategy, when entering a training program creates, significant additional costs. For instance, these costs might occur since the reduced time that is available for job search during the treatment requires the adoption of new search methods. It is further shown that the size of the adjustment costs can be influenced by the employment agency by informing the job seeker about potential future treatments, while the positive effect of the expected treatment rate on the program effectiveness is driven by the group of participants facing adjustment costs above the sample median.

The findings of the paper give new insights into the job search process of unemployed workers and indicate that the German System of ALMP programs provides substantial room for improvement when assigning job seekers to ALMP programs. For very costly long-term training programs, it seems to be important that potential participants receive the information about future treatment very early during the unemployment spell. For instance, informing job seekers about the possibility of a future treatment or awarding a training voucher reduces the degree of uncertainty and allows potential participants to choose the optimal search pattern, which in turn increases the program effectiveness once the treatment has been realized. However, it should be also noted that facing the threat of being treated might also encourage job seekers to leave unemployment early which implies that some degree of uncertainty could also have positive implications for the welfare state.

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Tables and Figures

Table 1: Unconditional Differences in Labor Market Outcomes by Expectations and Actual Treatment Status

	Non-participants			Participants		
A. Expected treatment rate	$\pi-$low	$\pi-$high	$P-$value	$\pi-$low	$\pi-$high	$P-$value
No. of observations	2,222	2,277		223	567	
Regular employed in month t_{30}	0.540	0.571	0.035	0.480	0.589	0.005
Cumulated effect ($\sum_{t=0}^{30}$, months)	12.848	13.801	0.002	9.399	11.011	0.020
Average earnings (€ /month)	1,095	1,037	0.104	1,323	1,141	0.232
	Non-participants			**Participants**		
B. Expected treatment effect	$\delta-$low	$\delta-$high	$P-$value	$\delta-$low	$\delta-$high	$P-$value
No. of observations	3,244	1,208		416	367	
Regular employed in month t_{30}	0.559	0.547	0.474	0.553	0.561	0.813
Cumulated effect ($\sum_{t=0}^{30}$, months)	13.311	13.361	0.889	10.469	10.605	0.829
Average earnings (€ /month)	1,075	1,034	0.317	1,263	1,086	0.194

Note: Percentage share unless indicated otherwise. $P-$values measured based on two-tailed t-tests on equal means.

Table 2: The Impact of Expectations on Average Treatment Effects on the Treated (ATT)

	A. Expected treatment rate π-high v. π-low			
	Non-participants		Participants	
	(1)	(2)	(3)	(4)
Outcome variable				
Regular employed in month t_{30}	**0.0313**	*0.0306*	***0.1092***	**0.0924**
	(0.0148)	(0.0163)	(0.0411)	(0.0402)
Cumulated effect ($\sum_{t=0}^{30}$, months)	***0.9532***	***0.8795***	**1.6115**	1.1456
	(0.3136)	(0.3382)	(0.7052)	(0.7195)
Average earnings (€ /month)	-58.2	-52.9	-181.4	-131.3
	(35.8)	(37.2)	(151.7)	(233.2)
No. of observations	4,499	4,499	790	790
Treated off support		0		2
Mean standardized bias	7.73	0.68	9.65	1.44
	B. Expected treatment effect $\hat{\delta}$-high v. $\hat{\delta}$-low			
	Non-participants		Participants	
	(1)	(2)	(3)	(4)
Outcome variable				
Regular employed in month t_{30}	-0.0120	-0.0125	0.0084	-0.0042
	(0.0167)	(0.0176)	(0.0356)	(0.0354)
Cumulated effect ($\sum_{t=0}^{30}$, months)	0.0496	0.1215	0.1362	-0.0593
	(0.3550)	(0.3592)	(0.6309)	(0.6434)
Average earnings (€ /month)	-40.6	-4.2	-176.7	144.5
	(40.5)	(36.0)	(136.1)	(128.2)
No. of observations	4,499	4,499	790	790
Treated off support		0		0
Mean standardized bias	6.15	0.58	9.00	1.97
Control variables				
Socio-demographic characteristics	No	Yes	No	Yes
Household characteristics	No	Yes	No	Yes
Labor market histories	No	Yes	No	Yes
Regional and seasonal information	No	Yes	No	Yes
Personality traits	No	Yes	No	Yes

Note: Depicted are average treatment effects on the treated (ATT) as the difference in mean outcomes between treated and matched controls using Epanechnikov kernel propensity score matching with bandwidth 0.06. Standard errors are in parentheses and based on bootstrapping with 399 replications. Treated and controls are defined based on π, respectively δ, separated for non-participants and participants. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table 3: Sensitivity Analysis: Addressing the Potential Endogeneity of Expectations

	Exp. treatment rates π-high v. π-low
Regular employed in month t_{30}	
A. Long-term training (N=790)	
Baseline effect	**0.0924**
	(0.0411)
Dynamic treatment assignment	*0.0671*
	(0.0384)
B. Short-term training (N=1,681)	
Baseline effect	-0.0035
	(0.0231)
Dynamic treatment assignment	0.0005
	(0.0259)
C. Conditional DDD model with reference level...	
...avg. employment rate last 2 years	**0.1232**
	(0.0521)
...avg. employment rate last 5 years	**0.1016**
	(0.0500)
...avg. employment rate last 10 years	*0.0892*
	(0.0498)
D. Placebo test (difference-in-difference)	
Expected employment probability within 6 months	
high	-0.0130
	(0.0437)
very high	0.0040
	(0.0448)
Control variables	
Socio-demographiccharacteristics	Yes
Household characteristics	Yes
Labor market histories	Yes
Regional and seasonal information	Yes
Personality traits	Yes

Note: Panel A and B show matched differences between treated/non-treated with π-high and treated/non-treated with π-low using Epanechnikov kernel propensity score matching with bandwidth 0.06. Standard errors are in parentheses and based on bootstrapping with 399 replications. Panel C and D show differences in ATTs between participants in long-term training and short-term training based on weighted least squares regression using propensity score weights obtained in Panel A and B. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table 4: Matched Differences wrt Job Search Behavior and Expected Returns

	Exp. treatment rates π-high v. π-low	
	Non-participants	Participants
	(1)	(2)
A) Own job search strategy in t_0		
Average weekly number of own applications	0.0111	-0.4776
	(0.0765)	(0.4058)
Total number of utilized search channels (10=high, 0=low)	***0.2099***	-0.0215
	(0.0488)	(0.1603)
B) Adjustment of job search behavior		
Expected change of search behavior when ALMP program is imminent		
will increase search efforts	***0.0984***	***0.0979***
	(0.0139)	(0.0337)
will reduce search effort	-0.0034	**0.0310**
	(0.0052)	(0.0148)
C) Contact to employment agency		
Utilizing caseworker as search channel	***0.0644***	***0.0911***
	(0.0112)	(0.0344)
Average weekly number of offers by employment agency	0.0176	***0.0586***
	(0.0165)	(0.0287)
Information treatment received	***0.0434***	***0.2650***
	(0.0088)	(0.0320)
No. of observations	4,499	790
Control variables		
Socio-demographic characteristics	Yes	Yes
Household characteristics	Yes	Yes
Labor market histories	Yes	Yes
Regional and seasonal information	Yes	Yes
Personality traits	Yes	Yes

Note: Depicted are matched differences between treated/non-treated with π-high and treated/non-treated with π-low using Epanechnikov kernel propensity score matching with bandwidth 0.06. Standard errors are in parentheses and based on bootstrapping with 399 replications. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table 5: Structural Parameters of Expected Value Function

		Baseline Model		Alternative Model	
		(1)	(2)	(3)	(4)
Parameters of Search Cost Function					
Adjustment costs	κ_a				
Constant		***0.2098***	**0.2680**	***0.6146***	***0.7839***
		(0.0678)	(0.1063)	(0.1566)	(0.1785)
Utilizing caseworker as search channel		-0.1079	-0.1478	-0.1120	-0.0548
		(0.0682)	(0.1153)	(0.1286)	(0.1586)
Information treatment received					
Training program		**-0.1305**	**-0.2258**	***-0.7681***	***-1.0685***
		(0.0664)	(0.1091)	(0.2250)	(0.3031)
Other ALMP program		-0.0692	-0.1556	-0.3644	*-0.6329*
		(0.1004)	(0.2023)	(0.2245)	(0.3397)
Job offer received					
Full-time employment		***0.1954***	**0.2062**	0.1190	0.2055
		(0.0644)	(0.1026)	(0.1279)	(0.1700)
Part-time employment		0.0373	*0.2283*	-0.2249	-0.2986
		(0.0833)	(0.1261)	(0.1816)	(0.2519)
Average weekly number of offers by employment agency		***-0.2743***	***-0.6398***	-0.1980	*-0.6609*
		(0.1023)	(0.2179)	(0.2164)	(0.3435)
Search costs in unemployment (avg.)	κ_u	0.1079	0.1835	0.0903	0.0468
		(0.0699)	(0.1138)	(0.1296)	(0.1684)
Search costs in training program (avg.)	κ_p	**0.1543**	**0.2431**	0.1423	0.1059
		(0.0680)	(0.1138)	(0.1296)	(0.1684)
Parameters of Expected Return Function					
Expected baseline hazard	λ^{base}	***0.0752***	***0.0912***	***0.1018***	***0.0950***
		(0.0114)	(0.0047)	(0.0065)	(0.0047)
Expected treatment effect					
positive	δ_1	***0.5434***	***0.6125***	***0.5362***	***0.7007***
		(0.0780)	(0.0615)	(0.0435)	(0.0614)
very positive	δ_2	***1.0777***	***1.8021***	***0.9707***	***1.6899***
		(0.1090)	(0.1251)	(0.0548)	(0.1371)
Expected change of search effort	μ			***0.6000***	***0.6585***
				(0.1405)	(0.1379)
Utility cutoff 1	ζ_1	-0.0117		***0.0828***	
		(0.0218)		(0.0253)	
	ζ_1^{low}		***-0.4729***		***-0.3206***
			(0.0575)		(0.0547)
	ζ_1^{high}		***2.5005***		***2.4947***
			(0.1654)		(0.1762)
Utility cutoff 2	ζ_2	***0.6183***		***0.7226***	
		(0.0229)		(0.0263)	
	ζ_2^{low}		***0.4394***		***0.5731***
			(0.0371)		(0.0389)
	ζ_2^{high}		***5.8692***		6.4322
			(1.5989)		(5.9892)
Share of high cutoff individuals	q^{high}		***0.7368***		***0.7514***
			(0.0174)		(0.0174)
Discount factor (fixed)	ρ	0.9500	0.9500	0.9500	0.9500
No. of observations		6,239	6,239	6,239	6,239
log-Likelihood		-6,404.9	-6,369.4	-6,314.7	-6,295.2
LR test (χ^2)		320.5	391.6	500.9	1948.4
		{0.000}	{0.000}	{0.000}	{0.000}
Hitrate					
absolute		0.8345	0.8326	0.8611	0.8545
difference		0.0538	0.0519	0.0804	0.0738
Unobserved heterogeneity		No	Yes	No	Yes

Note: Depicted are Maximum-Likelihood Estimates. The LR-test and the hitrate difference refer to a comparison to an ordered probit model based on covariates X. The hitrate is defined as: $\frac{1}{NJ}\sum_{i=1}^{N}\sum_{j=1}^{J}\hat{\pi}_{ij}\mathbb{1}\left\{P_{ij} \geq \bar{P}_j\right\} + (1-\hat{\pi}_{ij})\,\mathbb{1}\left\{P_{ij} < \bar{P}_j\right\}$. Standard errors are shown in parenthesis; $p-$values in brackets. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table 6: Adjustment Costs, Expectations and Program Effectiveness

	Exp. treatment rates π-high v. π-low			
	Non-participants		Participants	
	κ_a-low (1)	κ_a-high (2)	κ_a-low (3)	κ_a-high (4)
Regular employed in month $t+30$				
A. Unconditional	-0.0194	***0.0562***	0.0091	***0.1221***
	(0.0204)	(0.0170)	(0.0754)	(0.0452)
No. of observations	1,539	2,960	262	528
B. Baseline Model	*0.0331*	0.0270	-0.0021	***0.2265***
	(0.0187)	(0.0242)	(0.0543)	(0.0604)
No. of observations	2,579	1,920	519	271
C. Alternative Model	0.0193	0.0301	0.0173	***0.1495***
	(0.0227)	(0.0212)	(0.0626)	(0.0579)
No. of observations	2,080	2,419	446	344
Control variables				
Socio-demographic characteristics	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes	Yes

Note: Differences in ATTs between treated/non-treated with π-high and treated/non-treated with π-low separated by the level of predicted adjustment costs. Epanechnikov kernel propensity score matching with bandwidth 0.06. Standard Errors in parenthesis are obtained based on bootstrapping with 399 replications. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.
The adjustment costs κ_a are obtained from the ML estimation depicted in Table 5 for the baseline, respectively the alternative model. κ_a-low (κ_a-high) denote prediction below (above) the sample median. For the unconditional case, κ_a-low (κ_a-high) characterizes individuals who report that they will (not) adjust their search behavior when the treatment is imminent.

Figure 1: Empirical Setting and Economic Framework

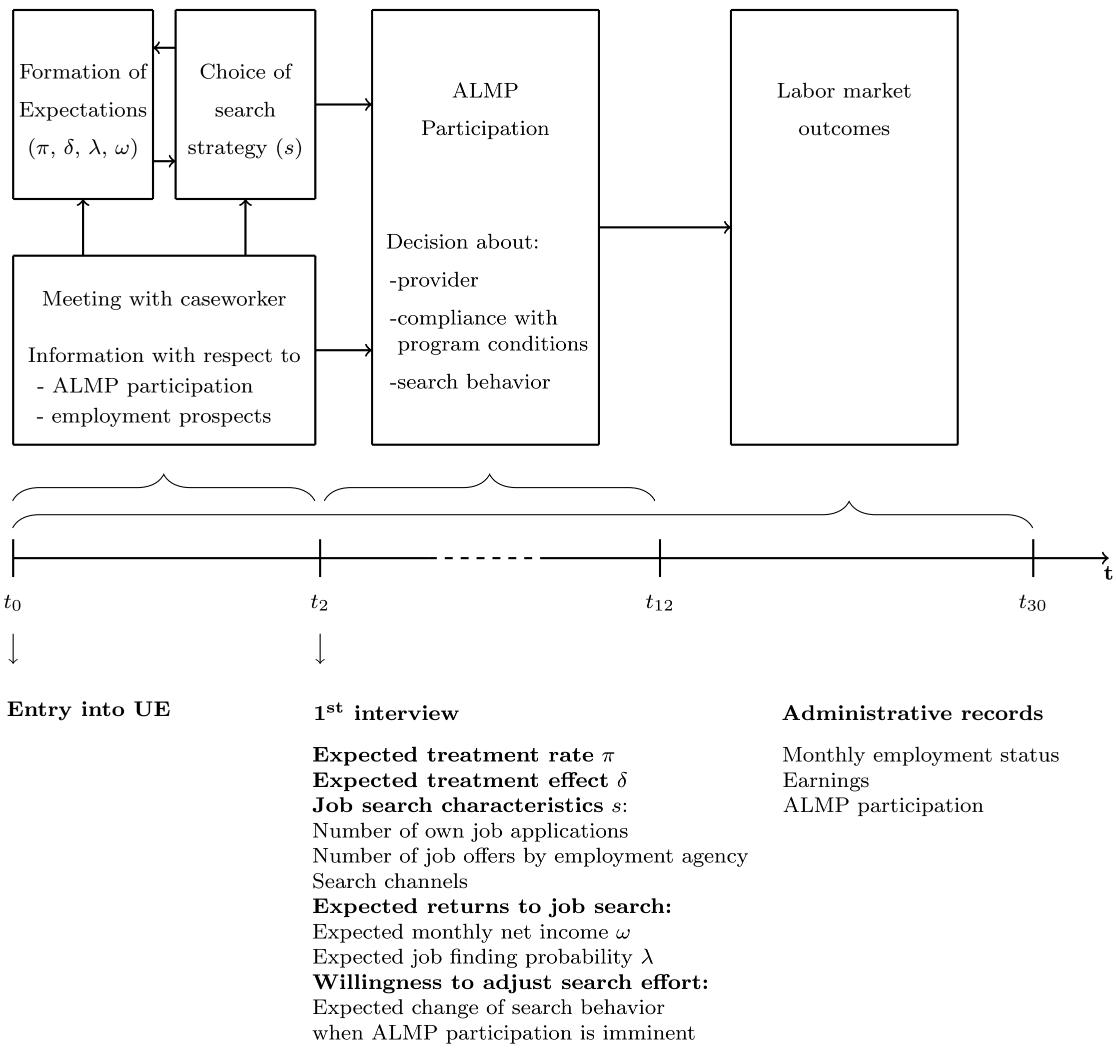
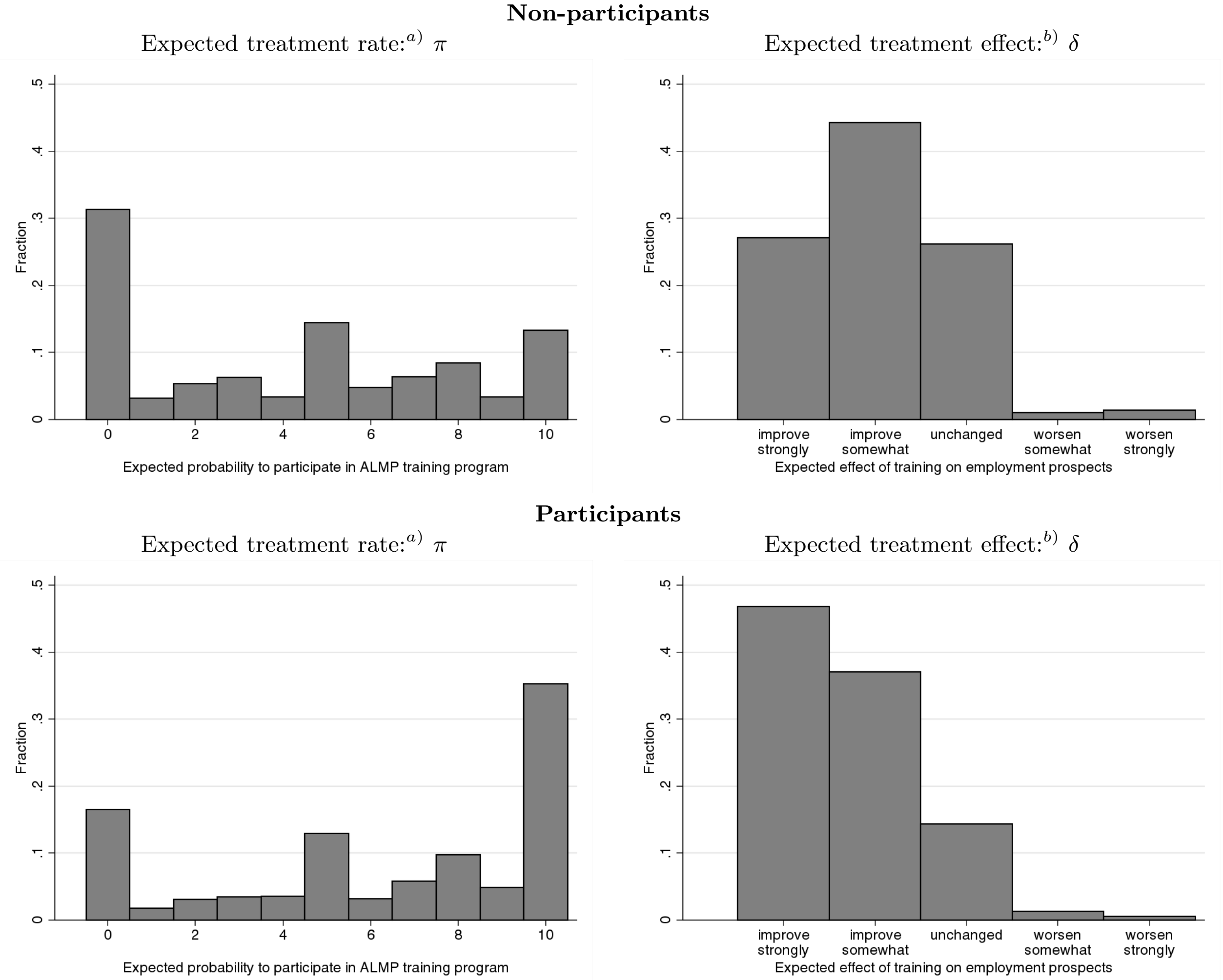
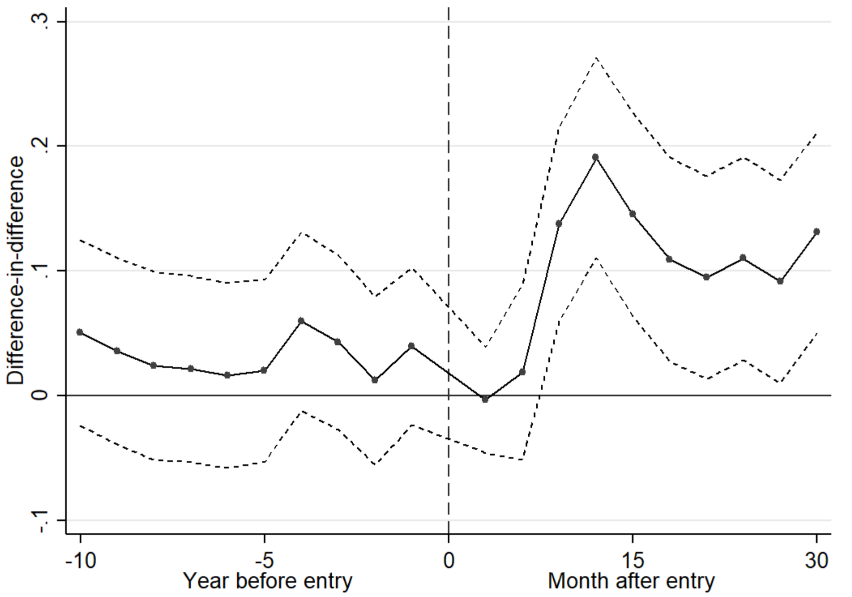


Figure 2: Distribution of Expectations by Actual ALMP Participation



[a] Depicted are answers to the question: *"Assuming that you are still unemployed during the next 3 months. What is the probability that you will participate in a training scheme?"* 0 = very unlikely; 10 = very likely.
[b] Depicted are answers to the question: *"In your opinion, to what extent would your chances of finding new employment be changed by participation in a training scheme?"* 1 = improve strongly, 2 = improve somewhat, 3 = remain unchanged, 4 = worsen somewhat, 5 = worsen strongly.

Figure 3: Difference-in-Difference Comparison of Participants in Long-term and Short-term Training based on Expected Treatment Rates π



Note: Depicted are unconditional differences-in-differences between participants in long-term training and short-term training with high, respectively low expected treatment rates π over time (solid line) and the corresponding 90% confidence interval (dashed line). The left-hand side shows differences-in-differences in average yearly employment rates for the last 10 years before the entry into unemployment. The right-hand side shows differences-in-differences in monthly employment rates for a period of 30 months after the entry into unemployment.

A Appendix

A.1 Technical Details on Theoretical Framework

Search strategy of not-yet treated job seeker: The optimal search strategy of an individual who has not yet been participating is characterized by the first order condition of 1 with respect to s_t:

$$\frac{\partial c^p(s_t, g(\pi, \delta))}{\partial s_t} = \rho \frac{\partial \lambda^p(s_t)}{\partial s_t}(\omega - V_t^p), \tag{A.1}$$

and the relationship between the job seekers beliefs about π, respectively δ, and the search strategy is given:

$$\frac{\partial s_t}{\partial \pi} = \frac{\rho \frac{\partial \lambda(s_t)}{\partial s_t}\delta}{-\frac{\partial^2 c(s_t)}{\partial s_t^2} + \frac{\partial^2 \rho \lambda(s_t)}{\partial s_t^2}(\omega - V_{t+1} - \pi\delta)} \tag{A.2}$$

$$\frac{\partial s_t}{\partial \delta} = \frac{\rho \frac{\partial \lambda(s_t)}{\partial s_t}\pi}{-\frac{\partial^2 c(s_t)}{\partial s_t^2} + \frac{\partial^2 \rho \lambda(s_t)}{\partial s_t^2}(\omega - V_{t+1} - \pi\delta)} \tag{A.3}$$

Assuming $\partial \lambda(s_t)/\partial s_t > 0$, $\partial^2 \lambda(s_t)/\partial s_t^2 < 0$, $\partial c(s_t)/\partial s_t > 0$ and $\partial^2 c(s_t)/\partial s_t^2 > 0$, this implies

$$\frac{\partial s_t}{\partial \pi}\begin{cases} > 0 \text{ if } \delta < 0 \\ < 0 \text{ if } \delta > 0 \end{cases} \qquad \text{and} \qquad \frac{\partial s_t}{\partial \delta} < 0, \tag{A.4}$$

where the latter is always true since $\pi \in [0, 1]$.

Search strategy of treated job seeker: The optimal behavior of an individual after entering the program is characterized by the first order condition 3 with respect to s_t:

$$\frac{\partial c^p(s_t, g(\pi, \delta))}{\partial s_t} = \rho \frac{\partial \lambda^p(s_t)}{\partial s_t}(\omega - V_t^p), \tag{A.5}$$

and the impact of the job seekers beliefs on the search strategy is given as:

$$\frac{\partial s_t}{\partial \pi} = \frac{\rho \frac{\partial^2 c^p(s_t, g(\pi,\delta))}{\partial s_t s_{t-1}} \frac{\partial g(\pi,\delta)}{\partial \pi}}{-\frac{\partial^2 c^p(s_t)}{\partial s_t^2} + \frac{\partial^2 \rho \lambda^p(s_t)}{\partial s_t^2}(\omega - V_{t+1}^p)} \tag{A.6}$$

$$\frac{\partial s_t}{\partial \delta} = \frac{\rho \frac{\partial^2 c^p(s_t, g(\pi,\delta))}{\partial s_t s_{t-1}} \frac{\partial g(\pi,\delta)}{\partial \delta}}{-\frac{\partial^2 c^p(s_t)}{\partial s_t^2} + \frac{\partial^2 \rho \lambda^p(s_t)}{\partial s_t^2}(\omega - V_{t+1}^p)}, \tag{A.7}$$

where $s_{t-1} = g(\pi, \delta)$ is defined based on equation 2 with

$$\frac{\partial g(\pi, \delta)}{\partial \pi}\begin{cases} > 0 \text{ if } \delta < 0 \\ < 0 \text{ if } \delta > 0 \end{cases} \qquad \text{and} \qquad \frac{\partial g(\pi, \delta)}{\partial \delta} < 0. \tag{A.8}$$

Assuming that $\partial^2 c^p(s_t, s_{t-1})/\partial s_t s_{t-1} > 0$, this implies the following relationship between the job seekers beliefs and the search behavior after the beginning of the program:

$$\frac{\partial s_t}{\partial \pi}\begin{cases} < 0 \text{ if } \delta < 0 \\ > 0 \text{ if } \delta > 0 \end{cases} \qquad \text{and} \qquad \frac{\partial s_t}{\partial \delta} < 0 \tag{A.9}$$

Endogenous formation of beliefs: Assuming that a not-yet treated job seeker decides about π and s_t simultaneously, the first-order conditions are given as:

$$\frac{\partial V_t^u}{\partial \pi} = \rho(1-\lambda(s_t))\delta = 0 \tag{A.10}$$

$$\frac{\partial V_t^u}{\partial s_t} = -\frac{\partial c^p(s_t, g(\pi,\delta))}{\partial s_t} + \rho\frac{\partial \lambda^p(s_t)}{\partial s_t}(\omega - V_t^p) = 0. \tag{A.11}$$

Assuming that an equilibrium is characterized by $\partial V_t^u/\partial s_t = \partial V_t^u/\partial \pi$, the relationship between the expected treatment rate and the expected treatment effect is given as:

$$\frac{\partial \pi}{\partial \delta} = -\frac{\frac{\partial \lambda(s_t)}{\partial s_t}\pi - (1-\lambda(s_t))}{\frac{\partial \lambda(s_t)}{\partial s_t}\delta} \tag{A.12}$$

Hence,

$$\frac{\partial \pi}{\partial \delta}\begin{cases} > 0 \text{ if } \operatorname{sgn}(\delta)\left[\lambda(s_t) + \frac{\partial \lambda(s_t)}{\partial s_t}\pi\right] < \operatorname{sgn}(\delta) \\ < 0 \text{ if } \operatorname{sgn}(\delta)\left[\lambda(s_t) + \frac{\partial \lambda(s_t)}{\partial s_t}\pi\right] > \operatorname{sgn}(\delta) \end{cases} \tag{A.13}$$

Assuming additionally that the job seeker take into account the inter-temporal relation of search costs, and thus the fact that the realized treatment effect depends on the search strategy in the pre-treatment period, the first order conditions are given as:

$$\frac{\partial V_t^u}{\partial \pi} = \rho(1-\lambda(s_t))\delta = 0 \tag{A.14}$$

$$\frac{\partial V_t^u}{\partial s_t} = -\frac{\partial c^p(s_t, g(\pi,\delta))}{\partial s_t} + \rho\frac{\partial \lambda^p(s_t)}{\partial s_t}(\omega - V_t^p) + \pi\frac{\partial \delta(s_t)}{\partial s_t} = 0. \tag{A.15}$$

Therefore, the relationship between the expected treatment rate and the expected treatment effect is given as

$$\frac{\partial \pi}{\partial \delta} = -\frac{\frac{\partial \lambda(s_t)}{\partial s_t}\pi - (1-\lambda(s_t))}{\frac{\partial \lambda(s_t)}{\partial s_t}\delta + (1-\lambda(s_t))\frac{\partial \delta)(s_t)}{\partial s_t}}, \tag{A.16}$$

while

$$\frac{\partial \lambda(s_t)}{s_t}\delta > -(1-\lambda(s_t))\frac{\partial \delta(s_t)}{\partial s_t} \tag{A.17}$$

ensures that A.13 holds.

A.2 Supplementary Tables and Figures

Table A.1 presents a sensitivity analysis with respect to categorization based on the expected treatment rate π. Instead of two levels (as in the main analysis) it is assumed that there are five levels of beliefs. Three groups are given by the points zero, five and ten (including the majority of observations), while two additional categories summarize the intermediate answers 1-4, respectively 6-9. Since the size of the five groups of participants becomes relatively, non-participants who report a very low expected treatment rate ($\pi = 0$) are used as the unique reference group and ATTs on the labor market outcomes, as well as the willingness to increase the search effort, are estimated with respect to this reference group. It can be seen that the main difference appears at the threshold $\pi \geq 5$ supporting the group classification used for the main analysis.

Table A.2 shows descriptive statistics with respect to observed characteristics separated by the expected treatment rate π and the realized treatment status.

Table A.3 shows average marginal effects for the logit model utilized to estimate the propensity score specifications based on the expected treatment rate π and the realized treatment status.

Table A.4 shows estimated ATTs based on alternative matching procedures, including four types of kernel matching with different bandwidths (0.006, 0.02, 0.06 and 0.2), two types of radius matching with a caliper of 0.02, respectively 0.1, and one-to-four nearest neighbor matching.

Table A.5 compares the willingness to adjust the search behavior for different levels of expected treatment effects.

Table A.6 shows the OLS estimates for the adjustment of the search effort between wave 1 and 2 for individuals participating in a ALMP program in this period. The estimates are utilized to predict the magnitude of the effort adjustment using the baseline model in Section 5.

Table A.7 shows the full set of estimates for the parameters of the search cost functions corresponding to the average values presented in Table 5.

Table A.1: Sensitivity Analysis: Alternative Categorization with Respect to Expected Treatment Rate $\hat{\pi}$

		Non-participants			Participants		
		ATT	SE	Obs.	ATT	SE	Obs.
A. Regular employed in month t_{12}							
Expected treatment rate							
very low:	$\hat{\pi} = 0$	ref.		1,411	***-0.2313***	(0.0437)	130
medium low:	$\hat{\pi} \in (1, 4)$	-0.0110	(0.0204)	811	***-0.2421***	(0.0524)	93
medium:	$\hat{\pi} = 5$	-0.0159	(0.0253)	650	**-0.1150**	(0.0578)	102
medium high:	$\hat{\pi} \in (6, 9)$	*0.0412*	(0.0220)	1,027	***-0.1684***	(0.0406)	186
very high:	$\hat{\pi} = 10$	0.0263	(0.0260)	600	***-0.0983***	(0.0346)	279
B. Regular employed in month t_{30}							
Expected treatment rate							
very low:	$\hat{\pi} = 0$	ref.		1,411	-0.0501	(0.0484)	130
medium low:	$\hat{\pi} \in (1, 4)$	-0.0009	(0.0230)	811	-0.0751	(0.0484)	93
medium:	$\hat{\pi} = 5$	0.0052	(0.0250)	650	0.0405	(0.0566)	102
medium high:	$\hat{\pi} \in (6, 9)$	*0.0427*	(0.0221)	1,027	0.0182	(0.0435)	186
very high:	$\hat{\pi} = 10$	0.0026	(0.0267)	600	0.0426	(0.0359)	279
C. Cumulated effect ($\sum_{t=0}^{30}$, months)							
Expected treatment rate							
very low:	$\hat{\pi} = 0$	ref.		1,411	***-3.6468***	(0.8645)	130
medium low:	$\hat{\pi} \in (1, 4)$	-0.1110	(0.4503)	811	***-3.5267***	(1.0492)	93
medium:	$\hat{\pi} = 5$	0.0466	(0.5057)	650	*-2.0435*	(1.0801)	102
medium high:	$\hat{\pi} \in (6, 9)$	***1.2576***	(0.4477)	1,027	***-2.9553***	(0.8405)	186
very high:	$\hat{\pi} = 10$	0.3763	(0.5570)	600	***-1.7988***	(0.6798)	279
D. Cumulated earnings ($\sum_{t=0}^{30}$, in €)							
Expected treatment rate							
very low:	$\hat{\pi} = 0$	ref.		1,411	***-4888.0***	(1430.6)	130
medium low:	$\hat{\pi} \in (1, 4)$	-478.2	(792.7)	811	-1867.7	(1903.8)	93
medium:	$\hat{\pi} = 5$	-1156.6	(774.7)	650	*-2741.6*	(1633.1)	102
medium high:	$\hat{\pi} \in (6, 9)$	*1184.5*	(706.7)	1,027	***-3533.4***	(1228.7)	186
very high:	$\hat{\pi} = 10$	124.7	(838.0)	600	*-2017.2*	(1080.1)	279
E. Average earnings (€/month)							
Expected treatment rate							
very low:	$\hat{\pi} = 0$	ref.		1,411	344.6	(310.2)	130
medium low:	$\hat{\pi} \in (1, 4)$	-76.0	(53.9)	811	43.5	(160.8)	93
medium:	$\hat{\pi} = 5$	***-168.4***	(54.3)	650	28.8	(126.4)	102
medium high:	$\hat{\pi} \in (6, 9)$	-59.6	(54.4)	1,027	38.1	(121.8)	186
very high:	$\hat{\pi} = 10$	-58.0	(60.8)	600	81.3	(81.1)	279
F. Will increase search effort when ALMP program is imminent							
Expected treatment rate							
very low:	$\hat{\pi} = 0$	ref.		1,411	-0.0259	(0.0390)	130
medium low:	$\hat{\pi} \in (1, 4)$	0.0145	(0.0212)	811	-0.0194	(0.0514)	93
medium:	$\hat{\pi} = 5$	***0.0598***	(0.0231)	650	0.0480	(0.0562)	102
medium high:	$\hat{\pi} \in (6, 9)$	***0.0951***	(0.0225)	1,027	0.0516	(0.0397)	186
very high:	$\hat{\pi} = 10$	***0.1154***	(0.0264)	600	***0.0939***	(0.0345)	279

Note: Depicted are average treatment effects on the treated (ATT) as the difference in mean outcomes between treated and matched controls using Epanechnikov kernel propensity score matching with bandwidth 0.06. In each case the control group contains non-participants with very low expected treatment rates $\hat{\pi} = 0$ (with $N = 1,411$), while the depicted number of observations refers to the corresponding treatment group only. Standard errors are in parentheses and based on bootstrapping with 399 replications. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table A.2: Descriptive Statistics by Expectations and Treatment Status

	Non-participants			Participants		
Expectations	$\hat{\pi}-$low	$\hat{\pi}-$high	$P-$value	$\hat{\pi}-$low	$\hat{\pi}-$high	$P-$value
No. of observations	2,222	2,277		223	567	
A. Baseline control variables X						
Socio-demographic characteristics						
Female	0.48	0.47	0.52	0.46	0.55	0.03
Age in years	36.64	33.69	0.00	37.05	36.89	0.84
A-level qualification	0.31	0.23	0.00	0.30	0.27	0.36
University degree	0.25	0.17	0.00	0.21	0.21	0.83
German citizenship	0.96	0.94	0.00	0.97	0.94	0.09
Migration background	0.12	0.18	0.00	0.15	0.17	0.61
Searching for full-time employment	0.65	0.68	0.05	0.70	0.60	0.01
Household characteristics						
Married (or cohabiting)	0.41	0.36	0.00	0.36	0.44	0.05
Two children or more	0.13	0.13	0.95	0.14	0.18	0.19
Partner is full-time employed	0.45	0.44	0.54	0.40	0.50	0.02
Substantial problems with childcare	0.09	0.09	0.97	0.07	0.11	0.05
Labor market history						
UI benefit recipient	0.76	0.78	0.17	0.76	0.81	0.07
Last daily income in €	49.17	46.18	0.00	50.96	47.84	0.27
Employment status before unemployment						
Regular employed	0.65	0.63	0.12	0.72	0.66	0.14
Subsidized employed	0.07	0.06	0.20	0.07	0.06	0.56
Last job was full-time	0.95	0.96	0.19	0.96	0.95	0.95
Months regular employed						
in last year	7.71	8.25	0.00	7.88	8.34	0.22
in last 5 years	32.69	34.95	0.00	33.83	36.15	0.14
in last 10 years	48.72	50.08	0.11	51.50	53.39	0.42
Months unemployed						
in last year	1.25	1.03	0.00	1.17	0.83	0.04
in last 5 years	9.56	7.17	0.00	10.77	7.65	0.00
in last 10 years	12.76	9.69	0.00	13.17	10.07	0.00
Regional and seasonal information						
Region						
West-Germany and local UE rate ≤6%	0.24	0.25	0.33	0.21	0.29	0.09
West-Germany and local UE rate >6%	0.40	0.47	0.00	0.43	0.44	0.64
East-Germany and local UE rate ≤12%	0.15	0.13	0.02	0.12	0.11	0.54
East-Germany and local UE rate >12%	0.21	0.15	0.00	0.24	0.16	0.01
Time between entry into UE and interview						
8 weeks	0.26	0.26	0.62	0.26	0.25	0.76
9 weeks	0.20	0.23	0.01	0.21	0.23	0.55
10 weeks	0.17	0.16	0.12	0.21	0.18	0.43
11 weeks	0.16	0.16	0.86	0.16	0.17	0.67
12 weeks	0.10	0.08	0.04	0.09	0.07	0.32
13 weeks	0.04	0.04	0.75	0.02	0.04	0.08
14 weeks	0.06	0.06	0.89	0.04	0.05	0.64
Personality traits						
Openness	4.96	5.14	0.00	4.88	4.99	0.25
Conscientiousness	6.23	6.28	0.03	6.21	6.34	0.04
Extraversion	5.15	5.24	0.01	4.95	5.11	0.07
Neuroticism	3.75	3.72	0.46	3.75	3.80	0.58
Locus of Control	5.04	5.06	0.44	5.00	5.01	0.88
B. Information variables Z						
Utilizing caseworker as search channel	0.64	0.72	0.00	0.62	0.71	0.02
Average weekly number of job offers by employment agency	0.21	0.25	0.00	0.14	0.20	0.13
Information treatment received						
Training program[a)]	0.12	0.20	0.00	0.23	0.49	0.00
Other ALMP program[b)]	0.06	0.10	0.00	0.05	0.07	0.49
Job offer received						
Full-time employment	0.32	0.37	0.00	0.29	0.36	0.05
Part-time employment	0.10	0.12	0.07	0.08	0.10	0.26

Note: Percentage share unless indicated otherwise. $P-$values measured based on two-tailed t-tests on equal means. Personality traits are measured with different items on a 7-Point Likert-Scale.
[a)] Includes application training, programs to improve employment prospects and training vouchers (either received or offered).
[b)] Includes workfare programs, job creation schemes and start-up subsidies to become self-employed.

Table A.3: Estimation of Propensity Scores: Marginal Effects of Pairwise Logit Models for π

	A. Expected treatment π-high v. π-low		**B. Realized treatment** Treated v. non-treated		**C. Realized treatment** Treated v. non-treated	
	Non-participants	Participants	π-low	π-high	Correct prediction	Incorrect prediction
	(1)	(2)				
Female	-0.0052	0.0077	0.0086	0.0221	0.0152	0.0089
Age (Ref.: 16-24 years)						
25-34 years	**-0.0550**	-0.0203	0.0243	***0.0750***	*0.0545*	*0.0350*
35-44 years	***-0.1093***	**-0.1301**	-0.0042	***0.1498***	***0.0967***	0.0229
45-55 years	***-0.1314***	-0.0300	0.0189	***0.1242***	*0.0558*	*0.0572*
School leaving degree (Ref.: None)						
Lower sec. degree	-0.0170	0.0357	0.0150	0.0473	0.0426	0.0165
Middle sec. degree	-0.0247	-0.0001	0.0117	0.0693	0.0606	0.0165
(Spec.) Upper sec. degree	*-0.0927*	0.0936	0.0193	0.0683	0.0149	0.0574
Higher education (Ref.: None)						
Internal/external prof. training	-0.0055	-0.0170	-0.0019	0.0002	-0.0028	0.0018
University degree	**-0.0667**	-0.0648	-0.0252	0.0159	-0.0313	-0.0076
German citizenship	-0.0224	0.1646	0.0448	-0.0058	-0.0140	0.0522
Migration background	***0.0853***	0.0553	*0.0446*	-0.0120	*0.0514*	0.0247
Married or cohabiting	-0.0106	-0.0306	**-0.0292**	-0.0098	-0.0146	*-0.0218*
Children (Ref.: None)						
One child	0.0050	0.0391	0.0205	0.0087	0.0125	0.0181
Two children or more	0.0235	0.0344	0.0374	0.0156	0.0333	0.0270
Problems with childcare	0.0107	-0.0362	-0.0213	-0.0134	0.0019	-0.0194
Partner is full-time employed	0.0220	-0.0408	-0.0040	-0.0066	0.0200	-0.0114
Searching for full-time employment	**0.0393**	**0.0740**	***-0.0517***	0.0111	-0.0196	-0.0043
Region (Ref.: West & UE rate 0-6%)						
West & UE rate 6+%	*0.0322*	0.0462	0.0163	-0.0284	-0.0026	0.0071
East & UE rate 9-14%	-0.0201	0.0677	-0.0028	*-0.0481*	**-0.0586**	0.0048
East & UE rate 15+%	**-0.0589**	**0.1312**	0.0283	-0.0130	**-0.0463**	**0.0578**
Entry into unemployment (Ref.: 2nd quarter 2007)						
3rd quarter 2007	0.0166	-0.1062	***-0.0534***	-0.0134	-0.0028	***-0.0559***
4th quarter 2007	0.0011	*-0.1022*	-0.0350	0.0178	0.0188	-0.0279
1st quarter 2008	0.0293	-0.0997	-0.0385	0.0083	0.0340	*-0.0422*
2nd quarter 2008	0.0071	-0.1002	-0.0196	0.0264	0.0364	-0.0182
Time to interview (Ref.: 7 weeks)						
8 weeks	0.0796	-0.1082	-0.0181	-0.0027	0.0766	-0.0527
9 weeks	*0.1151*	-0.1381	-0.0168	0.0055	0.1093	-0.0622
10 weeks	0.0570	-0.0864	-0.0120	0.0350	0.0959	-0.0367
11 weeks	0.0879	-0.1132	-0.0236	0.0064	0.0994	-0.0612
12 weeks	0.0393	-0.0587	-0.0206	-0.0190	0.0465	-0.0463
13 weeks	0.1046	***-0.2591***	-0.0528	0.0357	0.1457	**-0.0917**
14 weeks or more	0.0843	-0.1472	-0.0439	0.0116	0.0763	*-0.0746*
Unemployment benefit recipient	0.0273	***-0.1089***	-0.0114	0.0336	**0.0505**	-0.0202
Last daily income in €	*-0.0005*	0.0005	0.0000	-0.0001	-0.0004	0.0002
Employment status before unemployment (Ref.: Other)						
Regular employment	-0.0017	*0.0790*	0.0190	-0.0074	-0.0125	0.0233
Subsidized employment	-0.0023	0.1062	0.0085	-0.0442	-0.0308	0.0138
Last job was full-time employment	-0.0076	0.0081	0.0052	0.0433	0.0273	0.0073
Months in employment						
in last year	0.0011	-0.0031	-0.0022	-0.0028	-0.0008	-0.0026
in last 5 years	0.0008	-0.0034	0.0004	0.0020	*0.0023*	-0.0001
in last 10 years	0.0003	0.0023	0.0003	-0.0010	-0.0008	0.0003
Months in unemployment						
in last year	-0.0008	0.0021	-0.0056	**-0.0114**	**-0.0114**	-0.0053
in last 5 years	-0.0014	0.0011	*0.0017*	**0.0031**	0.0017	**0.0019**
in last 10 years	**-0.0022**	0.0028	-0.0007	**-0.0023**	***-0.0037***	0.0001
Openness (standardized)	***0.0328***	-0.0028	-0.0016	**0.0192**	0.0040	*-0.0121*
Conscientiousness (standardized)	0.0094	-0.0277	0.0018	*0.0150*	**0.0223**	-0.0021
Extraversion (standardized)	-0.0054	-0.0122	**-0.0135**	-0.0124	*-0.0158*	**-0.0146**
Neuroticism (standardized)	-0.0120	-0.0062	-0.0023	0.0042	-0.0031	-0.0021
Locus of control (standardized)	-0.0064	0.0054	-0.0009	-0.0061	-0.0077	0.0010
Observations	4499	790	2445	2844	2789	2500
Hitrate	0.6012	0.6392	0.5992	0.5960	0.6131	0.6404
log-Likelihood	-2976.9	-432.3	-721.8	-1359.2	-1344.0	-702.1

Note: Depicted are average marginal effects for a sequence of logit models comparing each combination of expected and actual treatment states. Panel A estimates probability of expecting the treatment conditioning on the realized treatment status. Panel B estimates the probability of actually participating conditioning on the expected treatment status. Panel C estimates the probability of actually participating conditioning on having correct, respectively incorrect expectations. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table A.4: Sensitivity Analysis: Alternative Matching Algorithms

	Exp. treatment rates $\hat{\pi}$-high v. $\hat{\pi}$-low	
	Non-participants	Participants
	(1)	(2)
A. Regular employed in month t_{30}		
Kernel matching ($bw = 0.006$)	*0.0275*	**0.1009**
	(0.0154)	(0.0460)
Kernel matching ($bw = 0.02$)	**0.0302**	*0.0801*
	(0.0152)	(0.0434)
Kernel matching ($bw = 0.06$)	*0.0306*	**0.0924**
	(0.0163)	(0.0411)
Kernel matching ($bw = 0.2$)	*0.0254*	**0.0958**
	(0.0150)	(0.0390)
Radius matching ($c = 0.02$)	*0.0278*	**0.0956**
	(0.0150)	(0.0398)
Radius matching ($c = 0.1$)	**0.0303**	*0.0773*
	(0.0151)	(0.0430)
Nearest neighbor matching (1:4)	0.0246	**0.1020**
	(0.0177)	(0.0497)
B. Cumulated effect ($\sum_{t=0}^{30}$, months)		
Kernel matching ($bw = 0.006$)	***0.8923***	1.2314
	(0.3393)	(0.8080)
Kernel matching ($bw = 0.02$)	***0.9173***	0.9517
	(0.3331)	(0.7641)
Kernel matching ($bw = 0.06$)	***0.8795***	1.1456
	(0.3382)	(0.7195)
Kernel matching ($bw = 0.2$)	**0.8115**	*1.2867*
	(0.3262)	(0.6644)
Radius matching ($c = 0.02$)	***0.8449***	*1.1765*
	(0.3291)	(0.6847)
Radius matching ($c = 0.1$)	***0.9154***	0.9413
	(0.3331)	(0.7566)
Nearest neighbor matching (1:4)	**0.8943**	1.0930
	(0.3782)	(0.8609)
No. of observations	4,499	790
Control variables		
Socio-demographic characteristics	Yes	Yes
Household characteristics	Yes	Yes
Labor market histories	Yes	Yes
Regional and seasonal information	Yes	Yes
Personality traits	Yes	Yes

Note: Depicted are average treatment effects on the treated (ATT) as the difference in mean outcomes between treated and matched controls using alternative matching algorithms: Epanechnikov kernel propensity score matching with bandwidth (bw) 0.006, 0.02, 0.06 and 0.2; radius matching with a caliper (c) of 0.02 and 0.1; one-to-four nearest neighbor matching. Standard errors are in parentheses and based on bootstrapping with 399 replications. Treated and controls are defined based on $\hat{\pi}$ separated for non-participants and participants. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table A.5: Willingness to Adjust Search Effort and Expected Treatment Effects

	$\hat{\delta}-$low	$\hat{\delta}-$high	$P-$value
A. Non-participants			
No. of observations	3,291	1,208	
Expected adjustment of search behavior			
will increase search effort	0.27	0.41	0.00
will keep search effort constant	0.70	0.55	0.00
will decrease search effort	0.03	0.04	0.31
B. Participants			
No. of observations	423	367	
Expected adjustment of search behavior			
will increase search effort	0.22	0.35	0.00
will keep search effort constant	0.74	0.58	0.00
will decrease search effort	0.04	0.07	0.06

Note: Depicted are answers to the question: *"To what extent would your search activities change when you know that you could/must participate in an ALMP program within the next 2 months?"* Percentage share unless indicated otherwise. $P-$values measured based on two-tailed t-tests on equal means.

Table A.6: Estimation Results: Expected Change of Search Effort and Job Finding Prospect

	OLS		Ordered Probit	
	Expected change of search effort[a]		Expected job finding probability[b]	
	Coef.	SE	Coef.	SE
Female	0.0684	(0.2341)	***-0.2451***	(0.0361)
German citizenship	-0.6638	(0.5924)	-0.1034	(0.0822)
Migration background	0.4237	(0.4086)	**-0.1116**	(0.0524)
Age (Ref.: 16-24 years)	ref.		ref.	
25-34 years	-0.3520	(0.3898)	***0.1523***	(0.0520)
35-44 years	-0.5802	(0.4169)	0.0647	(0.0582)
45-55 years	*-0.6903*	(0.4132)	***-0.2509***	(0.0600)
School leaving degree (Ref.: None)	ref.		ref.	
Lower sec. degree	0.9883	(0.6197)	0.0536	(0.0983)
Middle sec. degree	0.5751	(0.6182)	0.0508	(0.0989)
(Spec.) Upper sec. degree	0.8901	(0.6652)	0.1360	(0.1029)
Higher education (Ref.: None)	ref.		ref.	
Internal/external prof. training	-0.0164	(0.4317)	-0.0021	(0.0547)
University degree	-0.0401	(0.5187)	0.0365	(0.0678)
Married or cohabiting	*-0.4394*	(0.2631)	***-0.2067***	(0.0388)
Children (Ref.: None)	ref.		ref.	
One child	0.0532	(0.2817)	0.0105	(0.0428)
Two children or more	*0.6591*	(0.3886)	-0.0323	(0.0536)
Problems with childcare	-0.0132	(0.3670)	**-0.1368**	(0.0586)
Partner is full-time employed	-0.2665	(0.2392)	*0.0630*	(0.0348)
Searching for full-time employment only	-0.0267	(0.2421)	***0.2907***	(0.0367)
Region (Ref.: West-Germany & UE rate 0-6%)	ref.		ref.	
West-Germany & UE rate 6+%	0.3281	(0.2617)	***-0.0991***	(0.0382)
East-Germany & UE rate 9-14%	0.4421	(0.3408)	**-0.1219**	(0.0523)
East-Germany & UE rate 15+%	0.2488	(0.3193)	***-0.2485***	(0.0488)
Entry into unemployment (Ref.: 2nd quarter 2007)	ref.		ref.	
3rd quarter 2007	0.5349	(0.5514)	-0.0582	(0.0664)
4th quarter 2007	0.3095	(0.5429)	**0.1281**	(0.0650)
1st quarter 2008	-0.0553	(0.5714)	0.0624	(0.0722)
2nd quarter 2008	0.6438	(0.5509)	0.0719	(0.0707)
Time between UE and interview (Ref.: 7 weeks)	ref.		ref.	
8 weeks	-0.6349	(0.7258)	-0.1675	(0.1228)
9 weeks	-0.9016	(0.7518)	-0.1480	(0.1252)
10 weeks	-0.6497	(0.7602)	*-0.2472*	(0.1278)
11 weeks	-0.5647	(0.7822)	*-0.2371*	(0.1303)
12 weeks	0.1751	(0.8483)	-0.1983	(0.1350)
13 weeks	*-1.6069*	(0.9425)	-0.1140	(0.1484)
14 weeks or more	-0.6067	(0.9074)	-0.1849	(0.1407)
Unemployment benefit recipient	-0.1073	(0.2721)	0.0549	(0.0412)
Last daily income in €	0.0021	(0.0036)	0.0007	(0.0006)
Employment status before unemployment (Ref.: Other)	ref.		ref.	
Regular employment	-0.1163	(0.2851)	***0.1509***	(0.0423)
Subsidized employment	*0.9244*	(0.4704)	*0.1103*	(0.0662)
Months in employment				
in last year	0.0270	(0.0338)	***0.0168***	(0.0049)
in last 5 years	-0.0103	(0.0169)	-0.0003	(0.0024)
in last 10 years	0.0104	(0.0100)	-0.0002	(0.0015)
Months in unemployment				
in last year	-0.0386	(0.0614)	***0.0231***	(0.0086)
in last 5 years	**-0.0388**	(0.0153)	***-0.0068***	(0.0024)
in last 10 years	**0.0209**	(0.0102)	-0.0005	(0.0018)
Openness (standardized)	0.0282	(0.1096)	***0.0578***	(0.0166)
Conscientiousness (standardized)	*-0.2242*	(0.1172)	-0.0000	(0.0169)
Extraversion (standardized)	0.0158	(0.1110)	***0.0460***	(0.0172)
Neuroticism (standardized)	0.0634	(0.1091)	*-0.0276*	(0.0165)
Locus of control (standardized)	0.1221	(0.1055)	***0.1149***	(0.0168)
Constant	0.3406	(1.3248)		
cut 1			***-1.9565***	(0.1967)
cut 2			***-1.2507***	(0.1952)
cut 3			0.0008	(0.1948)
No. of Observations	438		6,037	
(Pseudo-)R^2	0.1436		0.0614	
log-Likelihood	-897.8785		-5974.5477	
No. of observations	438		6,037	

Note: Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.
[a] The expected change of search effort is given as the trend adjusted difference between the average weekly number of own job applications in wave 1 and wave 2 for those actually participating in an ALMP program in between.
[b] The expected job finding probability is given as a four-point item ranging from 'very unlikely' to 'very likely'.

Table A.7: Estimation of Search Cost Parameters

	Baseline I		**Baseline II**		**Alternative I**		**Alternative II**	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Search costs in unemployment: κ_u								
Female	*-0.0430*	(0.0245)	-0.0540	(0.0443)	*-0.0817*	(0.0442)	-0.0534	(0.0538)
Migration background	-0.0329	(0.0279)	-0.0598	(0.0481)	-0.0516	(0.0557)	-0.0909	(0.0735)
Age (Ref.: 16-24 years)	ref.		ref.		ref.		ref.	
25-34 years	***-0.1126***	(0.0355)	**-0.1630**	(0.0638)	-0.0067	(0.0621)	0.0035	(0.0783)
35-44 years	-0.0417	(0.0403)	-0.0319	(0.0738)	0.0747	(0.0723)	0.0981	(0.0912)
45-55 years	-0.0368	(0.0437)	0.0124	(0.0767)	0.1322	(0.0860)	*0.1861*	(0.1043)
School leaving degree (Ref.: None)	ref.		ref.		ref.		ref.	
Lower sec. degree	-0.1054	(0.0912)	-0.2186	(0.1482)	-0.0102	(0.1201)	-0.1024	(0.1473)
Middle sec. degree	-0.0843	(0.0922)	-0.2190	(0.1520)	0.0606	(0.1215)	-0.0545	(0.1478)
(Spec.) Upper sec. degree	-0.0204	(0.0956)	-0.1332	(0.1568)	0.0864	(0.1295)	-0.0124	(0.1571)
Higher education (Ref.: None)	ref.		ref.		ref.		ref.	
Internal/external prof. training	-0.0090	(0.0314)	-0.0173	(0.0675)	-0.0367	(0.0702)	0.0682	(0.0931)
University degree	-0.0532	(0.0535)	-0.0553	(0.0945)	-0.0967	(0.0940)	-0.0223	(0.1182)
Married or cohabiting	**0.0729**	(0.0289)	*0.0960*	(0.0496)	-0.0041	(0.0462)	0.0046	(0.0576)
Unemployment benefit recipient	0.0317	(0.0283)	0.0672	(0.0521)	0.0733	(0.0550)	0.0933	(0.0689)
Last daily income in €	-0.0000	(0.0004)	0.0004	(0.0008)	-0.0001	(0.0008)	0.0008	(0.0009)
Months in employment								
in last year	-0.0013	(0.0031)	0.0027	(0.0058)	-0.0029	(0.0053)	-0.0007	(0.0069)
in last 5 years	-0.0010	(0.0017)	-0.0025	(0.0030)	0.0037	(0.0030)	0.0037	(0.0037)
in last 10 years	0.0002	(0.0012)	0.0009	(0.0021)	-0.0035	(0.0021)	*-0.0045*	(0.0026)
Time to interview (Ref.: 7 weeks)	ref.		ref.		ref.		ref.	
8 weeks	-0.0797	(0.0758)	-0.0843	(0.1134)	-0.0329	(0.1453)	-0.0501	(0.1630)
9 weeks	-0.0296	(0.0764)	0.0230	(0.1240)	-0.0150	(0.1466)	-0.0269	(0.1640)
10 weeks	-0.0186	(0.0774)	0.0178	(0.1184)	0.0130	(0.1488)	0.0159	(0.1667)
11 weeks	-0.0732	(0.0755)	-0.0998	(0.1106)	-0.0827	(0.1500)	-0.0849	(0.1695)
12 weeks	-0.0955	(0.0763)	*-0.2220*	(0.1148)	0.0381	(0.1586)	-0.0784	(0.1824)
13 weeks	0.0654	(0.1025)	*0.3276*	(0.1854)	0.0583	(0.1855)	0.0489	(0.2134)
14 weeks or more	-0.1300	(0.0838)	-0.2031	(0.1318)	-0.0990	(0.1621)	-0.1544	(0.1844)
Openness (standardized)	-0.0139	(0.0121)	-0.0110	(0.0238)	-0.0200	(0.0230)	-0.0162	(0.0289)
Conscientiousness (standardized)	0.0174	(0.0108)	0.0256	(0.0173)	0.0157	(0.0217)	0.0234	(0.0259)
Extraversion (standardized)	0.0120	(0.0125)	0.0224	(0.0239)	-0.0289	(0.0247)	-0.0423	(0.0304)
Neuroticism (standardized)	*0.0220*	(0.0130)	0.0416	(0.0263)	0.0106	(0.0224)	0.0404	(0.0313)
Locus of control (standardized)	0.0155	(0.0131)	*0.0402*	(0.0227)	**0.0490**	(0.0243)	**0.0696**	(0.0327)
Constant	**0.2983**	(0.1243)	**0.4338**	(0.1898)	0.1033	(0.1960)	0.0011	(0.2240)
Search costs in training program: κ_p								
Female	**-0.0545**	(0.0232)	*-0.0721*	(0.0408)	**-0.0910**	(0.0394)	-0.0665	(0.0466)
Migration background	**-0.0535**	(0.0254)	**-0.0974**	(0.0422)	-0.0670	(0.0476)	*-0.1079*	(0.0633)
Age (Ref.: 16-24 years)	ref.		ref.		ref.		ref.	
25-34 years	**-0.0787**	(0.0337)	*-0.1020*	(0.0592)	0.0373	(0.0536)	0.0572	(0.0668)
35-44 years	-0.0155	(0.0382)	0.0117	(0.0690)	0.1018	(0.0639)	0.1240	(0.0792)
45-55 years	-0.0117	(0.0417)	0.0496	(0.0733)	*0.1477*	(0.0775)	**0.1890**	(0.0913)
School leaving degree (Ref.: None)	ref.		ref.		ref.		ref.	
Lower sec. degree	-0.1230	(0.0943)	*-0.2663*	(0.1467)	-0.0267	(0.1057)	-0.1242	(0.1303)
Middle sec. degree	-0.1114	(0.0957)	*-0.2818*	(0.1506)	0.0188	(0.1068)	-0.1039	(0.1305)
(Spec.) Upper sec. degree	-0.0522	(0.0983)	-0.1902	(0.1541)	0.0553	(0.1148)	-0.0401	(0.1392)
Higher education (Ref.: None)	ref.		ref.		ref.		ref.	
Internal/external prof. training	0.0003	(0.0284)	0.0136	(0.0576)	-0.0184	(0.0577)	0.0876	(0.0786)
University degree	-0.0269	(0.0509)	-0.0021	(0.0857)	-0.0568	(0.0810)	0.0099	(0.1011)
Married or cohabiting	**0.0622**	(0.0277)	*0.0774*	(0.0470)	-0.0195	(0.0400)	-0.0189	(0.0495)
Unemployment benefit recipient	0.0258	(0.0264)	0.0609	(0.0481)	0.0603	(0.0479)	0.0758	(0.0598)
Last daily income in €	-0.0001	(0.0004)	0.0003	(0.0007)	-0.0001	(0.0007)	0.0006	(0.0008)
Months in employment								
in last year	-0.0008	(0.0029)	0.0035	(0.0054)	-0.0016	(0.0046)	0.0004	(0.0061)
in last 5 years	-0.0017	(0.0016)	-0.0038	(0.0029)	0.0026	(0.0026)	0.0025	(0.0032)
in last 10 years	0.0003	(0.0011)	0.0012	(0.0020)	-0.0030	(0.0019)	*-0.0038*	(0.0023)
Time to interview (Ref.: 7 weeks)	ref.		ref.		ref.		ref.	
8 weeks	-0.0678	(0.0674)	-0.1018	(0.0985)	-0.0415	(0.1268)	-0.0870	(0.1390)
9 weeks	-0.0304	(0.0680)	-0.0060	(0.1096)	-0.0393	(0.1276)	-0.0722	(0.1392)
10 weeks	-0.0161	(0.0694)	0.0017	(0.1042)	-0.0046	(0.1297)	-0.0258	(0.1408)
11 weeks	-0.0707	(0.0672)	-0.1183	(0.0952)	-0.0917	(0.1313)	-0.1167	(0.1459)
12 weeks	-0.0741	(0.0666)	**-0.2094**	(0.0957)	0.0338	(0.1374)	-0.0925	(0.1556)
13 weeks	0.0707	(0.1039)	*0.3249*	(0.1846)	0.0142	(0.1571)	-0.0024	(0.1746)
14 weeks or more	-0.1051	(0.0757)	-0.1674	(0.1170)	-0.0865	(0.1417)	-0.1325	(0.1573)
Openness (standardized)	-0.0135	(0.0114)	-0.0228	(0.0224)	-0.0204	(0.0197)	-0.0248	(0.0242)
Conscientiousness (standardized)	0.0152	(0.0097)	0.0174	(0.0152)	0.0131	(0.0189)	0.0141	(0.0221)
Extraversion (standardized)	0.0071	(0.0118)	0.0164	(0.0223)	-0.0296	(0.0216)	*-0.0444*	(0.0267)
Neuroticism (standardized)	**0.0303**	(0.0126)	**0.0600**	(0.0250)	0.0197	(0.0195)	*0.0500*	(0.0271)
Locus of control (standardized)	*0.0231*	(0.0124)	***0.0563***	(0.0211)	**0.0532**	(0.0217)	***0.0775***	(0.0287)
Constant	***0.3609***	(0.1231)	***0.5495***	(0.1792)	0.1867	(0.1737)	0.1263	(0.1958)

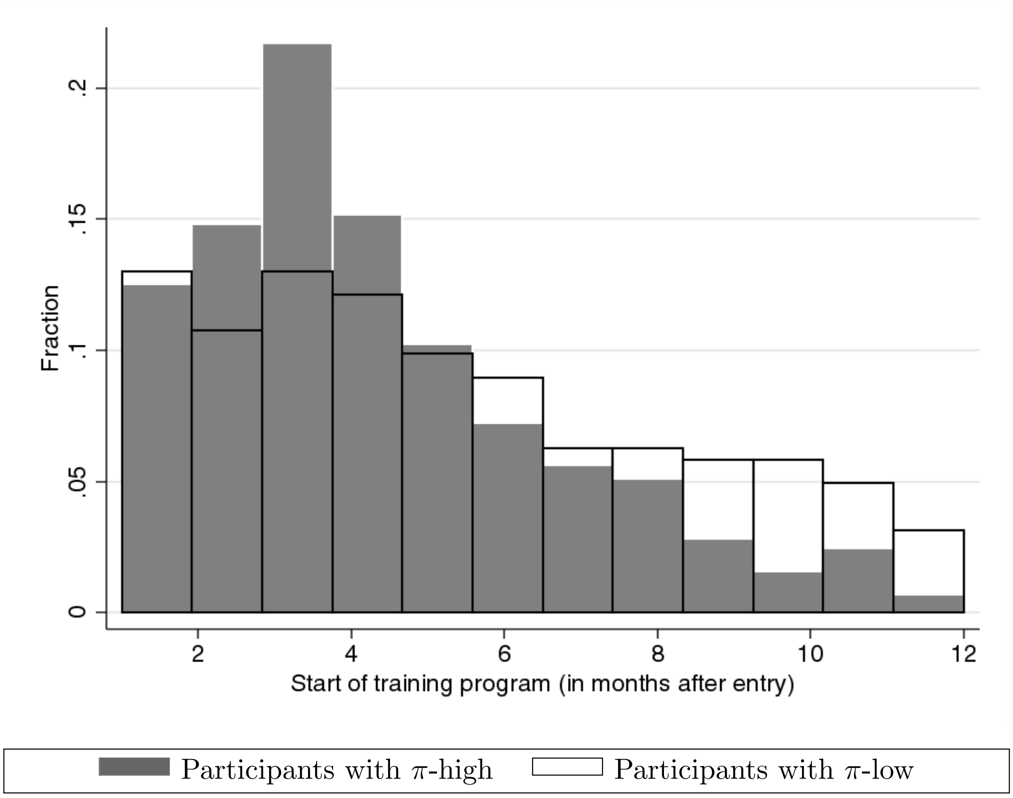
Note: Depicted are parameters of individual characteristics on search costs in unemployment, respectively training programs, using Maximum Likelihood estimation. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Table A.8: Simultaneous Impact of Expected Treatment Rates π and Expected Treatment Effects δ

	Exp. treatment rates π-high v. π-low			
	Non-participants		Participants	
	δ-low (1)	δ-high (2)	δ-low (3)	δ-high (4)
Outcome variable				
Regular employed in month t_{30}	**0.0441**	0.0208	***0.1459***	0.0208
	(0.0183)	(0.0338)	(0.0493)	(0.0759)
Cumulated effect ($\sum_{t=0}^{30}$, months)	***0.9662***	0.9616	**1.9961**	0.6142
	(0.3922)	(0.7096)	(0.9049)	(1.3603)
Average earnings (€/month)	-68.5	42.2	-226.1	97.1
	(46.1)	(65.0)	(278.3)	(156.6)
No. of observations	3,291	1,208	423	367
Control variables				
Socio-demographic characteristics	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes	Yes

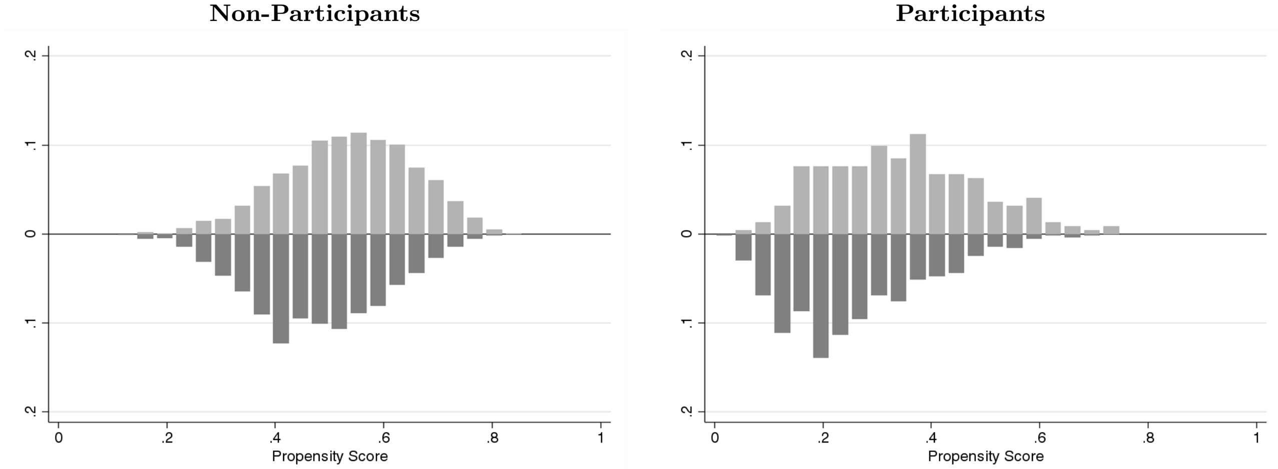
Note: Differences in ATTs between treated/non-treated with π-high and treated/non-treated with π-low separated by the expected treatment rate δ. Epanechnikov kernel propensity score matching with bandwidth 0.06. Standard Errors in parenthesis are obtained based on bootstrapping with 399 replications. Italic numbers: $p < 0.10$; bold numbers: $p < 0.05$; italic and bold numbers: $p < 0.01$.

Figure A.1: Distribution of Start Dates in Training Programs



Note: Depicted are months of program starts t_p for participants in long-term training separated by the expected treatment status π. Mean values: $\bar{t}_p(\pi\text{-high}) = 4.198$; $\bar{t}_p(\pi\text{-low}) = 5.220$; $p-$value$= 0.000$. Two-sample Kolmogorov-Smirnov Test: $D = 0.157$; $p-$value$= 0.001$.

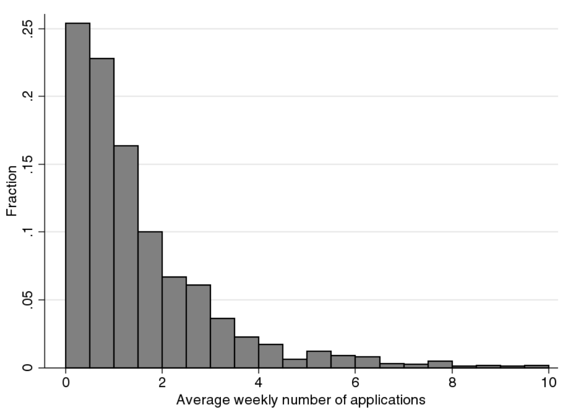
Figure A.2: Propensity Score Distributions



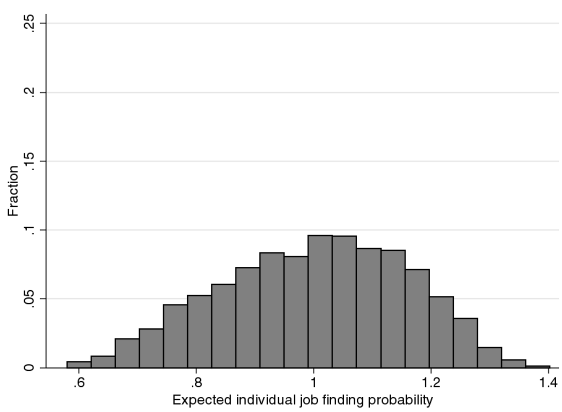
Note: Depicted are propensity score distributions for separated for treated and controls using different choice models. The group with the larger sample size is always defined as the control group (non-participants: π-low; participants: π-high), while the group with the smaller sample size is defined as the treatment group (non-participants: π-high; participants: π-low).

Figure A.3: Distribution of Search Characteristics and Expectations

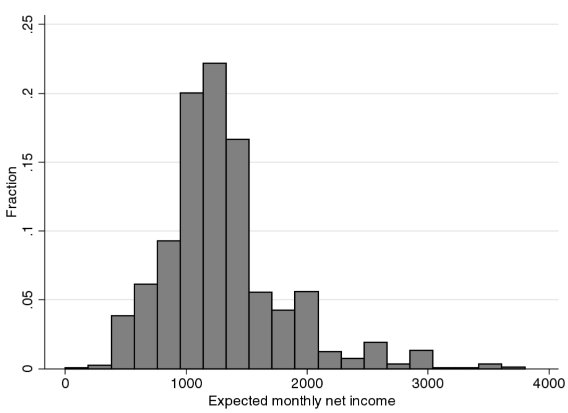
(a) Realized search effort at first interview: s_u



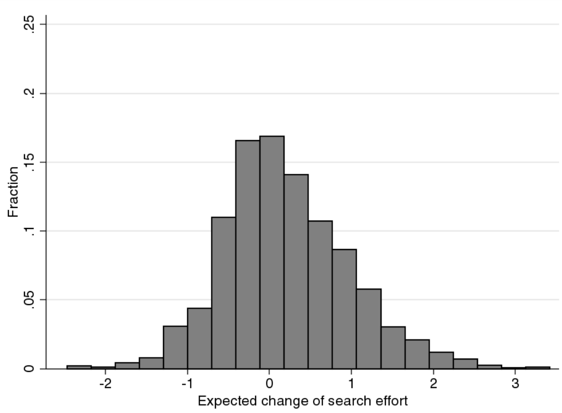
(b) Expected job finding rate (individual-specific)



(c) Expected net income: ω



(d) Expected change of search effort: $s_p - s_u$



Note: Depicted are the distributions of the main search characteristics and expectation measures utilized for the estimation of the expected value functions. While search effort (a) and the expected income (c) are directly observed in the data, the predictions of the expected job finding rates (b) and the expected change of the search effort (d) are obtained from estimates depicted in Table A.6.