The Power of Expectations: Anticipation Effects and the Effectiveness of Active Labor Market Policies

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Abstract

The presence of labor market programs has been shown to influence the individual behavior of unemployed workers even before they enroll. This paper studies how behavioral adjustments due to these anticipation effects influence the program effectiveness after the enrollment by utilizing a unique dataset that provides information regarding the unemployeds' expectations about a future program participation and realized labor market outcomes. It is shown that program participants in long-term training who do not expect a treatment ex ante have significantly lower long-run employment rates than those participants who expect the treatment. An extensive sensitivity analysis shows that the effect is not induced by differences with respect to the selection into the program, but it can be traced back to individuals who have little contact to their caseworker and show limited flexibility with respect to their job search strategy. The findings emphasize the importance of early and intensive counseling by the caseworker about the possibility of a future treatment and the job search strategy in order improve the effectiveness of labor market programs.

Keywords: Active labor market policies, Job search, Expectations, Treatment Effects

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1 Introduction

Expectations about future events and outcomes have shown to be important for determine short-run individual behavior in many area of economics, while little is known about the intertemporal consequences. For instance, various studies show that the presence of active labor market policies (ALMPs) already influences the job search behavior of unemployed workers even before they actually enroll in a program (e.g. Black *et al.*, 2003; Rosholm and Svarer, 2008; van den Berg *et al.*, 2009). At the same time, there exists comprehensive evidence that, for many programs, the actual treatment has only limited success bringing participants back to work (see e.g. Card *et al.*, 2010; Kluve, 2010, for an overview of international ALMP studies).[1] However, due to data limitations, traditional evaluation studies often fail to provide convincing evidence with respect to the underlying effect mechanisms. In order to close this gap, I connect the two currently separated strands of the literature and provide first evidence on the impact of job seekers' expectations about a potential future program enrollment on the effectiveness of a realized treatment later during the unemployment spell. This is particularly interesting since behavioral adjustments of job seekers who anticipate a treatment might influence the selection into a program and, more importantly, also the individual behavior in the long-run. Moreover, I provide evidence for the empirical relevance of several related effect mechanisms that potentially affect the labor market outcomes of program participants and discuss policy implications.

In this context, two dimensions of expectations are likely to be of special relevance (see van den Berg *et al.*, 2009): 1) the job seeker's perceived probability to participate in a program (given that she remains unemployed) and 2) the expected returns to the treatment with respect to the labor market performance, respectively the individual utility level in general. On the one hand, the possibility of participating in a program that is expected to reduce the individual utility level provides incentives to increase the search effort in order to find a new job before the treatment can be realized. This threat effect is empirically documented by studies from 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, 2011) and Sweden (e.g. Carling and Larsson, 2005; Hägglund, 2011) showing that the presence of

[1]In a recent follow-up study, Card *et al.* (2017) show that the effects of training programs, which are the main objective of the following analysis, are typically negative in the short-run, but become more favorable in the medium- and long-run (2-3 years after completion of the program).

compulsory ALMP programs encourages job seekers to leave unemployment. In line with this, van den Berg *et al.* (2009) exploit self-reported expectation measures to show that German job seekers who actually expect to enter an ALMP program in the near future set lower reservation wages and utilize more search channels than those who do not expect to participate. On the other hand, the presence of a program that is assumed to be beneficial would encourage individuals to reduce the search effort in order to remain unemployed until the treatment can be realized. Evidence for such a waiting effect is documented for job search assistance programs in the UK (see van den Berg *et al.*, 2014a) and notifications about imminent training programs in France (see Crépon *et al.*, 2014).[2]

Although the presence of these anticipation (or ex ante) effects has been widely confirmed by previous studies, there have been data limitations that prevented a more detailed analysis of the effect mechanisms and the long-term consequences after the enrollment. For instance, most of the studies analyzing ex ante effects exploit the presence of specific eligibility criteria or notifications about imminent treatments that create heterogeneity with respect to the job seekers expectations about a future treatment without directly observing individual expectations. However, since the program enrollment is typically a deterministic function of these proxies,[3] it is not possible to study their impact on labor market outcomes of program participants. Nevertheless, it can be assumed that the behavioral adjustments due the anticipation of the treatment also affect the individual behavior and outcomes even after the enrollment. For instance, previous results show that the job search process involves sequential stages, e.g. screening of vacancies, collecting information and sending out applications, as well as learning about the optimal search behavior (see e.g. the discussion in Barber *et al.*, 1994). If this is the case, the individual's choice of today's or past search strategy affects the optimal behavior in the future and therefore ex ante effects of ALMP programs would also have implications for long-run outcomes. Since the program participation presents an external shock that reduces the job seeker's time that is available for job search and would require an adjustment of the corresponding search strategy, pre-treatment expectations might be particularly important even when the individual is already enrolled. Moreover, job seekers who

[2]A related strand of the literature 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).

[3]For instance, all program participants meet the eligibility criteria or received a notification in advance.

anticipate that they will enter a program soon might collect information about the content of different potential programs or providers, which helps them to choose the most effective treatment. Finally, also endogenous factors, i.e. heterogeneity with respect to the quality of the caseworker or the possibility to negotiate about the assignment to a program[4] might be related to the job seekers expectations about ALMP programs and long-term labor market outcomes simultaneously.

The empirical analysis is based on a combination of survey and administrative data for a sample of newly unemployed job seekers in Germany. The dataset includes measures of subjective expectations regarding the individual probability to participate in a program in the near future and the expected effect of a treatment on the employment prospects, as well as realized labor market outcomes, including the actual participation in ALMP programs. Directly observing probabilistic expectations, provides the unique opportunity to document the relationship between the two relevant expectation measures and the labor market outcomes of participants in long-term training, a typically ALMP program that aims at improving occupational specific skills. Participation in the program generally requires a high level of participants' commitment as it lasts for several months, creates relatively large costs for the society compared to other ALMP programs and it is frequently applied. The key results show that program participants are substantially more likely to be employed in the long-run (about 10 percentage points) when they do expect the treatment ex ante compared to those participants do not anticipate the treatment. However, participants' expectations about the treatment effect are unrelated to the realized effectiveness of the program.

Moreover, I can test the sensitivity of the results with respect to the potential presence of unobserved heterogeneity, by using a difference-in-difference strategy that compares the impact of the expected assignment probability on the reemployment prospects of participants in two different ALMP programs. Both programs are shown to have similar selection patterns, but differ substantially with respect to the program duration, the participants' commitment to the treatment and therefore also the size of the external shock on the available time. There are no differences with respect to the impact of the expected assignment probability on related beliefs about earnings and employment prospect or pre-treatment outcomes of both groups. However, it has a strong positive effect on the post-treatment employment

[4]For instance, individuals who do not want to participate can try to negotiate with the caseworker and adjust their expectations accordingly.

rates of participants in long-term training, but no effect on those participating short-term training measures. This implies that the estimated effect depends on the characteristics of the specific treatment and cannot be attributed to general unobserved differences, e.g. with respect to the individual level of ability, motivation or the quality of the caseworker, that might be potentially related to the expected assignment probability.

Finally, the dataset includes a variety of additional information with respect to the individual job search behavior, related expectations, e.g. reemployment prospects and earnings, as well as measures that describe the relationship between the job seeker and the caseworker, which can be utilized to analyze the relevance of different mechanisms. An extensive subgroup analysis shows that the positive effect of expecting a treatment ex ante on the program effectiveness is completely driven by those individuals who have only little contact to their caseworker, are not informed about the treatment and show limited flexibility with respect to their search strategy. Again, this underlines the causal interpretation of the results since endogenous factors, such as the quality of the caseworker or the possibility to negotiate about the assignment probability, are less relevant or not for the subgroups with the strongest effect.

The results have two important implications, as it can be concluded that the ineffectiveness of long-lasting programs, which aim to improve the skills of unemployed workers, can be largely explained by a lack of information that encourages specific job seekers to choose search strategies that are insufficient once they are enrolled in a program. First, this emphasizes that early and intensive counseling by the caseworker about the possibility of a future treatment can improve the long-run outcomes of realized ALMP programs since underestimating the participation probability. Second, the results have important implications that allow to better understand the dynamics of the job search process since the treatment in general presents an external shock that reduces the time available job search. The findings imply that individuals who do not anticipate such a shock and are not able to adjust their behavior over time choose search strategies that are not compatible with the new situation. The paper is 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 (see e.g. Behncke *et al.*, 2010a,b), as well as their efficiency when assigning ALMP programs (Lechner and Smith, 2007). Moreover, it also contributes to the recent literature analyzing the impact of individual perceptions and preferences on the behavior of unemployed workers. For instance, Dohmen *et al.* (2009) find systematical biases in the perception of job finding probabilities that affect saving decisions and the job search behavior (see Spinnewijn, 2015), while Caliendo *et al.* (2015) show 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.

The reminder of the paper is structured as follows. Section 2 shows the theoretical framework, while Section 3 discusses the underlying data and the institutional details. Section 4 shows the empirical strategy and the main estimation. Section 5 analyzes the potential effect mechanisms, while Section 6 concludes.

2 Theoretical Framework

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 van den Berg *et al.*, 2009). Moreover, several additional features are incorporated, which are important when relating individual expectations before starting the treatment to their long-term labor market outcomes after the enrollment. In particular, the model captures four mechanisms: 1) the inter-temporal dependency of the job search behavior, 2) the choice of appropriate program providers, 3) the possibility of negotiating with the caseworker and 4) heterogeneity with respect to the caseworker's quality.

2.1 Subjective Expectations in a Job Search Model

Consider an unemployed individual who searches sequentially for a new job. As in standard job search models, the job seeker decides in each period t about the search strategy s_t, which determines the probability to find a new job $\lambda(s_t)$. Finding a job implies utility ω, which is assumed to always exceed the value of remaining unemployed. Moreover, it is assumed that the job seeker takes into account the possibility of participating in a training program during the unemployment spell. Given that she remains unemployed, she expects to be enrolled in the program in period $t+1$ with probability π. However, in contrast to the baseline model by van den Berg *et al.* (2009), the agent can influence this probability by spending effort into negotiations with the caseworker b_t to increases or decrease the probability of being assigned to a program. Both, the job finding prospects λ and the assignment probability π are subject to the behavior of the caseworker denoted by η. This captures differences with respect to quality, e.g. the ability to find suitable job offers, and preferences, e.g. with respect to ALMP assignment, of the caseworker. Finally, the agent can also invest effort z_t to search for an appropriate provider of a training program that meet her needs and increases the effectiveness of a potential future treatment. The three types of effort are assumed to generate costs $c(s_t, z_t, b_t)$. Hence, for a given discount rate ρ, the inter-temporal value of being unemployed is given as:

$$V_t^u = c(s_t, z_t, b_t) + \rho \left\{ \lambda(s_t|\eta)\omega + (1 - \lambda(s_t|\eta))((1 - \pi(b_t|\eta))V_{t+1}^u + \pi(b_t|\eta)V_{t+1}^p) \right\}, \qquad (1)$$

where V_{t+1}^p denotes the inter-temporal value of being enrolled in a program in the next period.

After the start of the program, the agent no longer faces the possibility of a future treatment, but due to the effort that she has to devote to the treatment, there remains less time for job search, which has implications for the associated search costs (e.g. Spinnewijn, 2013). Moreover, the inter-temporal utility of a participant is also affected by the behavioral choices of the pre-treatment period. First, the effort that the job seeker has invested to search for an appropriate provider is assumed to have a positive impact on the job finding prospects after the program start.[5] Second, it is assumed that the agent's job search behavior of the pre-treatment period s_{t-1} affects the efficiency of her search activities during/after enrollment. For instance, during the search process, 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 the wage offer distribution (see e.g. Burdett and Vishwanath, 1988; Krueger and Mueller, 2011, 2016). Therefore, the decision about the search strategy in period t depends on the agent's experiences in $t-1$. Moreover, job seekers might conduct the search process in sequential stages (see Blau, 1993, e.g.), i.e. screening potential vacancies, gathering information about firms and actually applying, while psychological motives, e.g. related to self-efficacy

[5]For the ease of notation, is assumed that the quality of the provider has positive effect on the fob finding prospects from the first day of the treatment and does not require the successful completion of the treatment.

or reference-dependence, can also generate an inter-temporal connection.[6] Therefore, the inter-temporal value of being treated is given as:

$$V_t^p = c^p(s_t, s_{t-1}) + \rho \left\{ \lambda^p(s_t, z_{t-1}|\eta)\omega + (1 - \lambda^p(s_t, z_{t-1}|\eta))V_{t+1}^p \right\}, \tag{2}$$

where the search cost function $c^p(s_t, s_{t-1})$ indicates the inter-temporal efficiency effects of job search, while λ^p characterizes the job finding prospect after the program start depending on the current search effort and the previous effort spent into the search for a program provider. Again, the job-finding prospect are subject to the behavior of the caseworker η. Within this setting the expected effect of participating in a program on the overall utility level is given by $\delta = V_t^p(s_t, s_{t-1}, z_{t-1}) - V_t^u(s_t, z_t, b_t)$ depending on the agents behavioral choices of the current and the previous period.

2.2 Optimal Behavior of Not-yet Treated Individuals

The optimal behavior of an individual who is unemployed and has not yet been enrolled is characterized by an equilibrium condition, which implies that the agent equalizes the marginal returns with respect to all three types of effort, i.e. $\partial V_t^u/\partial s_t = \partial V_t^u/\partial z_t = \partial V_t^u/\partial b_t = 0$:

$$\begin{aligned}\frac{1}{\rho}\sum_{j\in\{s,z,b\}}\frac{\partial c(s_t,z_t,b_t)}{\partial j_t} &= \frac{\partial \lambda(s_t|\eta)}{\partial s_t}\left\{\omega - (1-\pi(b_t|\eta))V_{t+1}^u - \pi(b_t|\eta)V_{t+1}^p\right\} \\ &+ (1-\lambda(s_t|\eta))\left\{\rho\pi(b_t|\eta)\frac{\partial \lambda^p(s_{t+1},z_t|\eta)}{\partial z_t}(\omega - V_{t+2}^p) + \frac{\partial \pi(b_t|\eta)}{\partial b_t}(V_{t+1}^p - V_{t+1}^u)\right\}\end{aligned} \tag{3}$$

The left-hand side denotes changes of the search costs with respect to the three types of effort, while the first term on the right-hand side characterizes the marginal returns when increasing the job search effort. As already discussed by van den Berg *et al.* (2009), assuming that the job offer arrival rate ($\partial\lambda/\partial s_t > 0$, $\partial^2\lambda/\partial s_t^2 < 0$), as well as the search costs ($\partial c/\partial s_t > 0$ and $\partial^2 c/\partial s_t^2 > 0$) have conventional functional forms, this has several implications for the optimal search strategy. The presence of a treatment that is expected to

[6] Although all these explanations would apply for all job seekers independently of their treatment status, it can be expected that these inter-temporal effects become particularly important in a situation where the job seeker is enrolled in a labor market program that requires an adjustment of the search strategy due to time constraints during a treatment. For instance, this adjustment could involve the usage of different search methods, which triggers additional costs due to the inter-temporal component.

be sufficiently beneficial $\delta > \delta^*$ 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 $\delta < \delta^*$ encourages job seekers to choose a strategy s_t that allows them to leave unemployment earlier. Moreover, the magnitude of this effect depends on the expected probability that the treatment will take place. If the latter is sufficiently high $\pi > \pi^*$, it implies a positive relationship between the expected treatment effect δ and the level of search effort.[7] The second term of Equation 3 denotes the marginal return with respect to effort spent into search activities for an appropriate program provider z_t, while the last term of Equation 3 represents the returns with respect to the level of effort spent into negotiating with the caseworker b_t.

2.3 Implications for Treated Individuals

After the beginning of the program, the agent no longer faces the possibility of a future treatment. However, the behavioral choices in the pre-treatment period, which have been influenced by her expectations about π and δ, affect the optimal behavior even after the program start. In the following, I will discuss four potential mechanisms that potentially relate the pre-treatment expectations to the program effectiveness.

Inter-temporal adjustment of the job search behavior: First, an inter-temporal relation of search strategies, e.g. through the search costs c, implies that the optimal strategy of an individual who is enrolled in period t is determined by:

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

where the search behavior in the pre-treatment period is a function of the job seekers subjective expectations $s_{t-1} = g(\pi(b_{t-1}|\eta), \delta)$. Therefore, the altered search strategy in $t-1$, due to the anticipation effect, translates into a different long-term behavior that also influences the employment prospects of individuals who are already enrolled in the program. The sign of this effect depends on the functional form of $c^p(s_t, s_{t-1})$. For instance, assuming

[7] The critical values for the expected treatment effect and the expected assignment probability are given as: $\delta^* = -(1-\lambda(s_t|\eta))\frac{\partial\lambda^p/\partial z_t}{\partial\lambda/\partial s_t}(\omega - V^p_{t+2})$ and $\pi^* = -(1-\lambda(s_t|\eta))\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t}$. Note that, in contrast to the model by van den Berg *et al.* (2009), $\pi^* \neq 0$ and $\delta^* \neq 0$, since job seekers take into account the possibility of changing the assignment probability by bargaining with their caseworker and increasing the program effectiveness by spending effort into the choice of an appropriate program provider (see Appendix B for details).

$\partial^2 c/\partial s_{t-1}\partial s_t < 0$, which would imply that job seekers benefit from high effort levels in the previous period, e.g. due to learning effects or a good preparation of applications, low expectations about the effectiveness of the treatment $\delta < \delta^*$ in combination with high values of π lead to an intensive search in both periods, as well as good employment prospects and vice versa. However, if $\partial^2 c/\partial s_{t-1}\partial s_t > 0$, $\delta > \delta^*$ in combination with high values of π will 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. This could be the case if initially high effort levels create excessive costs after the program start due to the reduced amount of time that is available. For instance, job seekers who applied for many vacancies before being enrolled could not manage to show up at all the corresponding interviews. This would have implications in the short-run as the job seekers will not get the specific job, but also in the long-run as it reduces the job seekers reputation and therefore also the future employment prospects.

The presence of such a mechanism crucially depends on the assumption that the search behavior in $t-1$ affects the choice of the optimal search strategy in t. Therefore, it should be noted that the economic and psychological literature provide several explanations for the presence of such an inter-temporal relationship. First, it is often argued that the search process involves different stages, i.e. starting with the screening of potential offers, followed by the acquisition of detailed information about firms and vacancies and the actual application (see e.g. Rees, 1966; Osborn, 1990; Blau, 1993). If this is the case, deviations from the initial search strategy, due to a reduction of the available time for job search during the treatment, are particularly costly due to the inter-temporal dependence of this search process. For instance, this could imply that job seekers applied at particular firms before the treatment, but could not take the chance to show up at the job interview if they are enrolled in a program. Beside direct consequences, e.g. the wasted effort spent into the application, this might also has negative long-run implications for the job-finding prospects by reducing the job seekers reputation for future applications. Moreover, psychological motives, like self-efficacy (see e.g. van Ryn and Vinokur, 1992; Saks and Ashforth, 1999; Moynihan *et al.*, 2003) or reference-dependent preferences (see e.g. Kahneman and Tversky, 1979; Kőszegi and Rabin, 2006) can also justify the presence of additional costs that appear when individuals change their job search strategy over time.

Choice of program providers: A second mechanism that would imply a causal relationship between the pre-treatment expectations and the program effectiveness requires that participants have a say in the choice of the program provider, respectively the actual type of treatment. If this is the case, job seekers who expect to participate (π is high) have incentives to gather information and search for program providers, i.e. invest higher levels of z_{t-1}. This is likely to have a positive effect on their job finding prospects once the treatment has been started, i.e. $\partial \lambda^p / \partial z_{t-1} > 0$ and results in a higher program effectiveness for participants who expect the treatment ex ante. Note that this is true only if $\delta < \delta^*$, which implies that the marginal returns with respect to the provider search $\partial \lambda^p / \partial z_t$ are sufficiently large relative to the marginal returns to job search $\partial \lambda / \partial s_t$. In general, the effect is particularly relevant, when job seekers are deeply involved into the assignment process. As discussed in Section 3.2 this is actually the case, since a potential program participant in Germany typically receives a training voucher and can choose the actual provider of the program by herself.

Bargaining with the caseworker: Third, job seekers might assume that they can influence the actual participation probability (given that they would remain unemployed), e.g. by bargaining with the caseworker. As discussed before, they choose the level of bargaining b_t that maximizes the expected utility. In particular, assuming that the increase in the marginal costs of bargaining is sufficiently low (see Appendix B.4 for details), it implies:

$$\frac{\partial b_t}{\partial \delta} > 0 \quad \text{if} \quad \pi > \pi^* \tag{5}$$

for programs that are expected to have a sufficient positive effect $\delta > \delta^*$ and vice versa. On the one hand, a higher expected treatment effect encourages job seekers to negotiate more intensively (ceteris paribus) with the caseworker to increase the assignment probability, as this would increase the expected utility from participating in the next period. However, as a higher level of π 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 in δ will lead to higher levels of b_t if the utility loss from the adjusted search behavior is sufficiently low, while the opposite applies if $\delta < \delta^*$. The presence of this bargaining mechanism could cause a correlation between the expected treatment rate π and labor market outcomes even if no causal relationship exists. However, it is important to note that this is only the case, if the expected treatment effect is (positively) related to the actual effect of the program. Therefore, the possibility to negotiate with the caseworker would imply that high levels of π are related to better labor market outcomes even in absence of causal effect on the individual behavior during the treatment or the choice of the program provider.

Caseworker quality: Another crucial element that influences the formation of job seekers expectation is the behavior of the caseworker, who is the main source of information about ALMP programs. Moreover, the caseworker is also responsible to issue the training voucher, which is a precondition for participating in long-term training. Assuming that there are differences with respect to the quality and the experience of the caseworker η in identifying potential participants who benefit from the treatment, high-quality caseworkers are more likely to assign training vouchers only to those individuals who experience a positive treatment effect. At the same time, having contact to a caseworker with higher quality gives job seekers the possibility to form more accurate expectations, which means that those who end up in the program also expect higher levels of π ex ante. Moreover, even without having the capacity to identify successful candidates for a treatment ex ante, caseworkers with higher quality can provide better assistance during participation and are more successful in offering promising job vacancies. This implies that participants who are attended by better caseworkers are more likely to expect the treatment ex ante and are more successful in the labor market independently of the treatment.

3 Data and Institutional Details

3.1 The IZA/IAB Linked Evaluation Dataset

The empirical analysis 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; Eberle *et al.*, 2017). 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 behavior, but also expectations about future earnings and employment prospects, as well as measures that describe the relationship between the unemployed and the caseworker, respectively the employment agency (see also Figure A.1 in the Appendix for a graphical illustration of the empirical setting).

For the 88% of individuals who agreed, these survey data are merged to administrative information from the *Integrated Employment Biographies* (IEB) provided by the Institute for Employment Research (IAB).[8] 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 15,173 realized interviews.

3.2 Institutional Settings and Estimation Sample

The combination of survey and administrative data provides an ideal setting to empirically analyze the mechanisms discussed before focusing on long-term training, which is one of the major ALMP programs in Germany. 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 the average program duration in the data set is about six 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

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

locking-in effect. From 2003 onwards, caseworkers no longer choose a specific course for the unemployed but hand out a training voucher to the job seeker (see e.g. Rinne *et al.*, 2013). 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.*, 2017). Moreover, it should be noted that there exists 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, caseworkers are the main source of information for the unemployed job seeker. However, as described by Schütz *et al.* (2011b), 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.[9]

Although the main objective of the study is to analyze the impact of expectations for participants in long-term training, I will additionally consider individuals participating in short-term training measures (see e.g. Wolff and Jozwiak, 2007) as a control group for the difference-in-difference analysis discussed in Section 4.1. These programs, last from two days up to eight weeks, while an individual's time spent in short-term training programs is limited to twelve weeks in total. In contrast to traditional long-term measures the courses aim to improve general employability or serve a test of occupation-specific abilities. This includes job search assistance, computer or language classes and special programs for certain hard-to-place workers (see Osikominu, 2012, for a general comparision of short- and long-term training programs).

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

[9]It should be noted that within the German UI unemployed workers are obliged to sign so-called integration agreements *(Eingliederungsvereinbarung)* (see e.g. Jacobi and Kluve, 2007; van den Berg *et al.*, 2014b), which defines the job seekers obligations and the services that she receives by the employment agency in a given period of unemployment, including search activities, as well as ALMP participation. Since non-compliance could lead to a reduction of the unemployment benefits, program participation might be mandatory for some job seekers who have signed the agreement. However, at the moment of the fist interview, when expectations are measured, only about 16% of the estimation sample, respectively 19% of those participate within a year, have already signed an integration agreement, while in general less than half of the integration agreements specify participation in an ALMP program (see Schütz *et al.*, 2011a).

below. Job seekers are defined as participants if they attend long-term training within the first 12 months after the entry into unemployment. The main estimation sample includes 707 participants in long-term training. Additionally, I also consider 1,457 participants in short-term training programs and 4,301 individuals who do not participate in any training program within the first year of the unemployment spell.

3.3 Measuring Expectations and Descriptive Statistics

Expected assignment probability: The first key variable for the analysis is given by the subjectively expected probability that the respondent will participate in a long-term training program π. This information is measured by the conditional question: *"Assuming that you are still unemployed during the next three months. What do you think is the probability that you will participate in a long-term training scheme within this period?"* Possible answers range from zero (very unlikely) up to ten (very likely). The distribution of this variable by the actual treatment status is depicted in the left column of Figure 1. In general, most individuals report the answers zero, five or ten, while there is a correlation between the expected and the actual treatment status. For example, about 35% of the participants report ex ante that it is very likely that they will participate, while only about 14% of the non-participants do. In line with this, about 30% of the non-participants say ex ante that is very unlikely that they will participate, while only 17% of the participants report a zero. Based on this information about the expected participation probability, I construct a binary measure, which divides the sample into a group who expects the treatment summarizing answers 5-10 (π-high) and a group who does not expect the treatment containing answers 0-4 (π-low) (see van den Berg *et al.*, 2009, who use the same variable without exploiting information on the actual participation decision).

[Insert Figure 1 about here]

Expected treatment effect: The second variable 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 are measured on a 5-point scale ranging from 'improve strongly' to 'worsen strongly' and can be interpreted as a proxy for the expected differences in job finding rates between the treated and non-treated situation. As shown in the right column of Figure 1, 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 assume that the treatment will have a positive impact on their labor market outcomes. For example, only 28% of the non-participants think that these training schemes will strongly improve their employment prospects, while 46% 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.[10]

Differences in labor market outcomes: The main focus of the study is on the differences in labor market outcomes with respect to the two expectation measures for individuals who actually participate in the program. Moreover, I will also show the corresponding effects of subjective expectations for the group of non-participants, since the comparison of the effects allows me to derive some first conclusions about the underlying the effect mechanisms. The unconditional differences with respect to the main outcome variables are presented in Table 1. In particular, I focus on the employment status 12, respectively 30 months after the entry into unemployment and the average monthly earnings given that the individual was employed in the corresponding month within the full observation period of 30 months after the entry.

[Insert Table 1 about here

Most interestingly, as shown in Panel A of Table 1, participants who expects the treatment ex ante have substantially higher employment rates than those who do not anticipate the treatment. The difference between the two groups of participants is about 13 percentage points, statistically significant at the 1%-level and relatively constant over time, while there are no significant differences with respect to average earnings. When comparing participants to non-participants, it can be seen that the employment rates of participants are generally lower 12 months after the entry, which is not surprising given that the treatment is typically associated with a strong locking-in effect. However, at the end of the observation period the

[10] I also tested alternative classifications, while the overall conclusion remains unaffected. The results are available upon request.

group of participants who expects the treatment ex ante has a higher employment rate than both groups of non-participants, while participants who do not expect the treatment have substantially lower employment rates than all other groups. Moreover, there are only minor differences within the group of non-participants. 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 for neither participants nor non-participants.

4 Expectations and the Program Effectiveness

4.1 Empirical Strategy

Selection on observables: The first objective of the empirical analysis is to estimate the impact of participants' pre-treatment ALMP expectations with respect to the assignment probability π and the treatment effect δ on labor market outcomes after the realization of the actual treatment status. In a first step, I estimate the impact of the two measures by applying a selection-on-observables identification strategy that is motivated by the richness of the survey and administrative data. The effects are estimated separately for participants in long-term training and non-participants. Assuming that the conditional independence assumption (CIA), is fulfilled, this identifies the causal effect of the expectation measure $k \in \{\pi, \delta\}$:

$$\gamma_{dk} = E[Y_{ik}^{high}|D = d] - E[Y_{ik}^{low}|D = d],$$

where $d \in \{0, 1\}$ characterizes the treatment status (either participant of non-participants), while Y_{ik}^{high} denotes the outcome if individual i reports a high level regarding the expectation measure k and Y_{ik}^{low} denotes the outcome if i has low expectations regarding k. Since the validity of this estimation strategy depends on the availability of control variables, I condition on a rich set of socio-demographic and household characteristics, regional and seasonal information, as well as differences with respect personality traits, i.e. the 'Big Five' factors and locus of control. Moreover, I also take into account detailed labor market histories, including characteristics of the previous job and (un)employment experiences within the last ten years before the entry into unemployment, which has been shown to be particularly important in the context of training programs (Mueser *et al.*, 2007; Lechner and Wunsch, 2013; Biewen *et al.*, 2014; Caliendo *et al.*, 2017). To estimate γ_{dk} based on these control variables, I use inverse probability weighting (IPW) with weights obtained from probit estimations.[11]

Difference-in-difference model: Although the dataset provides a comprehensive set of control variables, there might exist unobserved characteristics that are related to the job seekers subjective expectations and affect their outcome variables simultaneously. For instance, differences with respect to the level of intrinsic motivation, ability or the interaction between the job seeker and caseworker might be related to an individual's expectations and the subsequent labor market outcomes. To account for the presence of unobserved heterogeneity, I additionally estimate a difference-in-difference (DID) model. Therefore, I compare the impact of the subjective expectation measures on labor market outcomes for participants in two different types of ALMP programs. The treatment group participates in long-term training, the program of interest, while the control group participates in an alternative program, which is called short-term training. The model is characterized by the following equation:[12]

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 \pi_i^{high} + \beta_3 (D_i \times \pi_i^{high}) + v_i, \tag{6}$$

where Y_i denotes the outcome variable of interest, 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 assignment probability of five of higher. Again, the model is estimated by weighted least squares, where weights are obtained from IPW based on the covariates discussed before. The coefficient β_3 of the interaction term between the treatment status and the expected assignment probability π then indicates the difference in average treatment effects of the expectation measure between participants in long-term and short-term training.

While the objective is to identify the causal effect on the participants in long-term training as discussed before, individuals who participate in short-term training programs serve as a control group. As discussed by Biewen *et al.* (2014), short-term training programs have

[11] Additional estimates of γ_{dk} based on ordinary least squares (OLS) are shown as a sensitivity analysis in Appendix A.

[12] For the convenience of presentation, the following discussion focuses on the impact of the expected assignment probability π. The corresponding results for the expected treatment effect δ can be found in Appendix A.

similar employment effects in the long-run, but, unsurprisingly, participation is associated with much shorter locking-in periods compared to long-term training. The validity of this estimation strategy requires two assumptions. First, all endogenous factors, which might be important, are related to the expectations of both groups of participants in a similar way. Second, there is no causal effect of the pre-treatment expectations on the post-treatment labor market outcomes for participants in short-term training. The latter seems to be reasonable, because, due to the shorter program duration from two days up to eight weeks, there is no need for strong adjustments of the job search behavior if an individual is enrolled in the program. Moreover, the system of training vouchers does not apply for short-term training programs, which means that potential participants have no free choice of the program provider and therefore have no (or only small) incentives to invest effort into the search for an appropriate program provider.

Balancing tests: The crucial assumption for the validity of the identification strategy is that all endogenous factors, like the relevance of the caseworker and the selection into the treatment, are similarly related to the expectation measures for both programs. To justify this assumptions, I present several tests that strongly support the validity of this assumption. First, Table 2 shows a balancing test with respect to observed covariates that, even in the unconditional specification only four out of 53 coefficients are statistically significant at the 5%-level, which indicates that the expected assignment probability is similarly related to both types of participants. When applying IPW, no statistically significant differences can be found.

[Insert Table 2]

As a second test to justify the underlying assumption of the DID model, I conduct a placebo test, which considers various measures of related expectations that are obtained before the individual enters the program as the outcome of equation 6. In particular, this comprises the expected reemployment probability within the next six months, the log expected monthly net income and the expected influence of the employment agency on the job finding prospects.[13] Since all variables are measured at the first interview before individuals

[13] The expected reemployment probability is measured on a four-digit scale from 'very low' to 'very high'. The joint distribution of the expected reemployment probability, the expected income and the expected influence of the employment agency for both groups of participants are shown in Figure A.1 in Appendix A.

are enrolled in a program, the expected assignment probability π should have a similar impact for both types of participants if there are no unobserved differences between the two groups that are related to π, while any difference would suggest that there exist unobserved factors that would challenge the identifying assumptions of the DID. The specific variables are particularly informative in this context since, as the job seekers expectations about labor market outcomes are one of the main determinants of the job search effort and are therefore strongly related to the selection into the program. Moreover, the assumed influence of the employment agency on the job finding prospects provides a proxy for the quality of the caseworker. Since differences with respect to the selection into the program and the quality of the caseworker can be assumed to be the two major threats the identification strategy the placebo test provides a powerful test regarding the underlying assumptions. As shown in column 3 of Table 3, there are no statistically significant differences with respect to the impact of π on the related expectation measures of the two groups, which provides strong support for the validity of the DID model.

[Insert Table 3 about here]

Finally, Figure 2 graphically illustrates the difference-in-difference comparison between participants in short- and long-term training based on the expected assignment probability π for employment rates over a period from ten years before the entry into to unemployment up to the end of the observation period 30 months after the entry. It reveals several important results. First, it can be seen that π has no significant impact on the differences in the average yearly employment rates before the entry into unemployment and there is no particular trend within the ten-year period before the entry into unemployment. This suggests that time-constant unobserved characteristics, e.g. different levels of intrinsic motivation or ability, associated with the expected assignment probability π are similar for both groups of participants and there is no evidence for the presence of time-varying unobserved factors. The latter is particularly important as it shows that the common-trend assumption is fulfilled, which allows me to estimate a difference-in-difference-in-difference (DDD) model. Therefore, I consider ΔY_i as the outcome variable, which refers to the difference between the outcome variable of interest, e.g. the employment rate at a particular point in time, and the corresponding pre-treatment outcome measured before the entry into unemployment, e.g. average employment rate in a given reference period.

[Insert Figure 2 about here]

4.2 Baseline Results

Table 4 presents the estimated average treatment effects of having high levels of expectations with respect to π (Panel A), respectively δ (Panel B). In both cases, the effects are separated for participants and non-participants. While column (1) and (3) refer to the unconditional differences (as already depicted in Table 1), column (2) and (4) show the results based on IPW taking into account differences with respect to observed characteristics.

Panel A of Table 4 shows the effect of expecting a treatment ex ante (π-high v. π-low). It can be seen in column 1 and 2, that there is a strong positive effect of expecting a treatment on the employment probabilities of participants in long-term training. Twelve months after the entry into unemployment, those participants who anticipated the treatment are 12.1 percentage points more likely to be regular employed relative to those who do not expect to participate. The effect is statistically significant at the 1%-level. Although the effect is slightly lower (10.3 percentage points) 30 months after the entry, expecting the treatment ex ante still has a strong positive influence on the program effectiveness, which is statistically significant at the 5%-level. There is no significant effect on average monthly earnings. Moreover, column 3 and 4 show the corresponding results for those individuals who do not participate in a training program. The effects of the expected assignment probability on non-participants are small and statistically insignificant on employment rates and average earnings when using IPW. This is interesting, as it implies that the positive effect of the expected assignment probability π is unlikely to be the consequence of the potentially endogenous formation of expectations. In particular, the higher employment rates of participants who expect the treatment ex ante cannot be traced back to the fact that a high expected assignment probability is generally related to more favorable unobserved characteristics, since otherwise there would be also a positive effect on non-participants.

[Insert Table 4 about here]

Panel B of Table 4 shows the impact of the expected treatment effect δ on the realized labor market outcomes according to the group classification in Panel B of Table 1. In can be seen that there are no significant effects of the expected treatment effect for any of the labor market outcomes of non-participants, which is not very surprising given that the expectation measure refers to the perception of the impact of an event that does not take place. More interestingly, the expected treatment effect is also unrelated to the actual treatment effect for those who enter long-term training within a year after becoming unemployed. This indicates 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, the caseworkers' limited capacity to predict the program efficiency is likely to translate into a zero effect of δ on the realized treatment effect.

4.3 Difference-in-Difference Model

The right-hand side of Figure 2 shows the unconditional difference-in-difference over time for the whole outcome period of 30 months after the entry into unemployment. It can be seen that there is a strong positive and statistically significant effect of the expected assignment probability π on participants in long-term training relative to those individuals participating in short-term training.

In addition to the graphical presentation of Figure 2, which shows the unconditional differences-in-differences, Table 5 shows the results of the DID model for the expected assignment probability π using IPW.[14] While the first column replicates the baseline results for long-term training, the second column shows the impact of the expected assignment probability π on participants in short-term training. It can be seen that, in contrast to long-term training, π has negative effect on the employment probability after 12 month of about 6.8 percentage points, no effect on the employment probability after 30 months and also no statistically significant negative effect on the average monthly earnings. When using the DID approach (see column 3), this results in a positive employment effect of π on participants in long-term training relative to participants in short-term training of about 18.9 percentage

[14] The corresponding DID results for the impact of the expected treatment effect δ are presented in Table A.4 in the Appendix A.

points after 12 months and of about 10.3 percentage points 30 months after the beginning of the unemployment spell. The effects are statistically significant at the 1%-, respectively 10%-level. Moreover, columns 4 and 5 show the findings for conditional DDD models, which additionally account for two levels of baseline employment rates in the last two (column 4), respectively five (column 5) years before the individual became unemployed. This is assumed to account for time-constant unobserved differences related to π. It can be seen that for both models the employment effects are positive, statistically significant and similar (or even larger) compared to the baseline results. Again, there is no significant effect on average earnings, where I exploit previous income before unemployment as the reference level for the DDD model.

In summary, the results show that the estimated effects of π on the labor market outcomes of participants are particularly program-specific. This is important as it supports the validity of baseline results. The presence of unobserved heterogeneity, e.g. with respect to the level of intrinsic motivation, ability or the quality of the caseworker, that could potentially contribute to the positive effect of π on participants in long-term training would also lead to a positive effect of π on individuals who participate in short-term training (and in consequence to a zero effect for the DID model). Since this is not the case, it can be concluded that unobserved characteristics, which might be generally related to the participants' expectations, are not responsible for the positive effect of the expected assignment probability on the effectiveness of long-term training programs. As already discussed in Section 4.1, the validity of this strategy is supported by the fact that the expected assignment probability π is similarly related to pre-treatment outcomes, i.e. past employment rates, related expectations measured at the beginning of the unemployment spell and other individual-level characteristics, for both types of participants.

5 Effect Mechanisms

The following section analyzes the underlying mechanisms actually triggering the effect of the expected assignment probability π on the program effectiveness. Therefore, I exploit a variety of additional information with respect to variables related to the individual behavior, expected and actual program characteristics, as well as the contact between the job seeker and the caseworker. These variables are directly connected to the potential mechanisms discussed theoretically in Section 2. With exception of the program characteristics, all measures are obtained during the first interview of the survey, which takes place 7 to 14 weeks after the entry into unemployment, but before program enrollment.

5.1 Observed Differences with respect to Potential Mechanisms

In a first step, the results in Table 6 show the differences with respect to the set of additional information between individuals reporting high and low expected assignment probabilities. The first set of variables (see Panel A), focuses on characteristics of the search strategy regarding the job seeker's own personal effort. The first variable denotes 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. Again, this underlines the interpretation that unobserved differences, e.g. with respect to the level of intrinsic motivation, which might affect the job seeker's initial search strategy are unlikely to be responsible for the effect of π on the program effectiveness. Moreover, 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?"*. This is particularly interesting as it reflects on the one hand whether the job seekers wants to participate or not, but on the other hand it proxies also the elasticity of the job search strategy and reflects her ability or willingness to react to external factors and adjust the job search behavior over time.[15] Interestingly, those who expect to participate show a 7.8 percentage points higher willingness to adjust their search behavior compared to those who do not expect the treatment ex ante. The difference is statistically significant at the 10%-level, which suggests that participants who already expect to participate ex ante also (expect to) adjust their behavior differently over the course of time and particularly in connection with the realization of the treatment.

[INSERT TABLE 6 ABOUT HERE]

[15] Comparing the 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, the variable is likely to reflect the ability or willingness to react to external factors rather than the preferences for participating in an ALMP program.

Panel B presents differences with respect to expected and actual program characteristics. It can be seen that those who anticipate the treatment start the program about 1.5 months earlier compared to those who do not anticipate the treatment, but there are no differences with respect to the program duration. The latter indicates that both groups participate in similar types of long-term training programs. Moreover, participants who expect the treatment ex ante also have 22 percentage points higher likelihood to assume that the program will be very helpful with respect to their job finding chances.

Finally, Panel C shows differences regarding the relationship between the job seeker and the responsible caseworker. Unsurprisingly, the expected assignment probability π is positively associated with the likelihood that the participant has already been informed about the treatment by caseworker at the moment of the first interview. [16] The difference between the two groups if participants amounts 22 percentage points and is statistically significant at the 1%-level. Moreover, participants who expect the treatment more often exploit the help of the caseworker during the search process, i.e. have 10.5 percentage point higher probability to report that the caseworker is one of the search channels. The effect is statistically significant at the 5%-level. However, there are no significant differences with respect to the number of job offers received from the employment agency.

5.2 Relevance of Potential Mechanisms

In a second step, Table 7 shows the estimation results of a subgroup analysis with respect to the additional information, which provide proxies for the relevance of the different effect mechanisms. In particular, the variables are connected to five potential channels: 1) the inter-temporal adjustment of the search behavior, 2) the choice of the program provider, 3) bargaining with the caseworker, 4) the caseworker quality and 5) difference with respect to program characteristics. I will outline the underlying ideas during the following discussion. The estimation sample is divided with respect to the variables presented in Table 6 and separated effects of the expected assignment probability π on the employment status 30

[16] This 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. 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.

months after the entry into unemployment are estimated. For all continuous variables, the sample is divided at the median of the corresponding variable.

[Insert Table 7 about here]

Adjustments of job search strategies: For the first set of subgroup analyses (presented in Panel A), the sample is dived based on the job search characteristics and a personality trait, the individual locus of control, that is highly related. It can be seen that the effect of the expected assignment probability π is very similar when dividing the sample with respect the number of applications sent out before the first interview (see column 1 and 2), while there is strong heterogeneity with respect to the elasticity of the search behavior (see column 3 and 4). The positive effect of π on the employment probability of participants is completely driven by those individuals who will not adjust their job search behavior in association with a treatment, while the effect is negative (although not significant) for participants who assume that they will adjust their search strategy. This has interesting implications since it supports the notion that the participants ability to adjust the job search behavior over time is an important determinant of the program effectiveness. In particular, those individuals who have a very inelastic search behavior suffer from underestimating the participation probability as they rely on a search strategy that is not compatible with the treatment. However, for those individuals who can easily adjust their job search behavior to the new situation, i.e. participating in a program, the inter-temporal relation of the search strategy is weak and therefore pre-treatment expectations have no impact on the program effectiveness. To further investigate this interpretation, I also divide the estimation sample with respect to individual locus of control (column 5 and 6). While individuals with an internal locus (sense) of control believe that life's outcomes are due to their own efforts, those with an external locus of control believe that life outcomes are determined by external factors (see Rotter, 1966; Gatz and Karel, 1993). The variable is particularly interesting since it can be assumed that individuals with an internal locus of control, who assume that their own choices are highly relevant, have a strong incentive to adapt their search behavior the new situation of the treatment, while individuals with an external locus of control are unlikely to change their search behavior over time. Previous evidence has shown that an internal locus of control is associated with significantly higher earnings (see Andrisani, 1977; Heineck and

Anger, 2010; Semykina and Linz, 2007) and more intensive job search (see McGee, 2015; Caliendo *et al.*, 2015). The findings of the subgroup analysis show that the effect of the pre-treatment expectations π is completely driven by those individuals who have an external locus of control and therefore do not believe that their own decisions affect their outcomes. This shows that having a correct perception about the likelihood to participate is important for participants who are less likely to adapt their behavior and underlines the importance of the inter-temporal decision regarding the job search strategy.

Timing of the treatment and program characteristics: Differences with respect to the timing of the treatment between participants with low or high expected assignment probabilities π could potentially translate into lower long-term employment rates even if both groups otherwise would behave completely identical. To test the relevance of differences with respect to the program start, Figure 3 shows the impact of the expected assignment probability π for participants on the cumulated exit rate from unemployment for the first 18 months after the beginning of the treatment. Figure 3a shows the unconditional impact of the expected assignment probability π for participants in long-term training, while Figure 3b presents the conditional DID based on IPW taking into account observed differences with respect to the covariates included in the baseline specification. The results show that the expected assignment probability has a positive and significant effect on the likelihood that a participant in long-term training leaves unemployment, which is particularly pronounced nine months after the program start. The magnitude of the effect is similar compared to the baseline results, which implies that π indeed has an impact on the program effectiveness beyond the mechanical effect that would be induced by delayed treatment starts. It should be noted that the timing of the treatment, respectively the elapsed unemployment duration, could is likely to be a function of the expected assignment probability π. For instance, individuals who expect the treatment might prepare themselves differently, which could lead to differences with respect to the timing of the program start. As this would be a causal consequence of the participant's expectations, conditioning on the timing of the program start would underestimate the actual effect of the expected assignment probability π and therefore the results presented in Figure 3 should be interpreted as a lower bound.

[Insert Figure 3 about here]

Moreover, Panel B of Table 7 shows the effect heterogeneity of the treatment effects with respect to the program characteristics. It is shown that the effect of the expected assignment probability π only appears for participants who start the treatment relatively late during the unemployment spell (see column 7 and 8), as well as those who do not stay in the program for a particular long period (see column 9 and 10). Both findings support the idea that the expected assignment probability has a causal effect on the inter-temporal adjustments of the search behavior. First, those who enter the treatment later during the unemployment spell have invested more time into the search process before starting the treatment, which might reduce their willingness or ability to adjust their search methods to the new situation of the treatment. Second, the strong effect on those with a shorter program duration suggest that subjective expectations affect the individual behavioral in particular at the beginning of the program, while participants who underestimate the assignment probability ex ante can adjust their behavior in the long-run, which makes pre-treatment expectations less relevant.

Related expectations and bargaining with the caseworker: Another potential mechanism implies that job seekers have incentives to invest effort into negotiations with the caseworker in order to increase or decrease the assignment probability depending on their perception about the impact of the treatment on their utility level. For instance, individuals who expect the treatment to be beneficial might negotiate with the caseworker more intensively and hence expect a higher assignment probability π. Therefore, column 9 and 10 show separate estimates of π on the employment probability of participants who expect the treatment to be particularly beneficial and those who do not. It is shown that there is strong positive effect of the expected assignment probability for those who expect the treatment to be less beneficial ($\delta-$low, column 11), while there is no effect on those who expect the treatment to have a strong positive impact ($\delta-$high, column 12). This means that those participants who actually have weaker incentives to bargain with the caseworker and to adjust their expectations about the assignment probability are responsible for the effect of π on the employment probability.[17] It can be concluded that the endogenous adjustment

[17] It should be noted that only very few individuals expect the treatment to have a negative impact on their labor market outcomes. Therefore, it can be assumed that δ-low characterizes individuals who generally believe that the treatment has a smaller impact on their labor market performance and have only small incentives to actively influence the assignment process and adjust the expectations about π accordingly.

of the expected assignment probability due to bargaining with the caseworker (or by not redeeming the training voucher) is unlikely to contribute to the estimated effect.

Choice of program providers and caseworker quality: The positive effect of the expected assignment probability could be also a consequence of unobserved differences with respect to the program provider or the caseworker quality. The first is particularly relevant, since participants can influence quality of a training program by searching for an appropriate provider in advance. It seems reasonable that those job seekers who expect to be assigned to the program invest more effort into the search for the optimal provider and the positive effect of π might be the consequence of their success. However, since the training voucher defines the exact program characteristics, like the objective of the program, the maximum duration and its costs, the detailed search for a program provider can start only after the job seeker received a voucher or has been at least informed by the caseworker about the possibility to participate. It should be noted that receiving a voucher is a precondition participating, but individuals are free not to redeem the voucher. Hence, it can be assumed that those who already received the corresponding information but do not expect to participate intend not to redeem to voucher and therefore would have no incentives to search for a provider, while those who received the information and expect to participate have the strongest incentives to invest effort into the provider search. Therefore, I estimate separate effects of π for a subsample who has not received any information treatment before the first interview (column 13) and a sample who has been informed about the possibility of participating (column 14). Interestingly, the positive effect of the expected assignment probability only shows up for those who have not received an information treatment before reporting their expectations about the assignment probability. Assuming that the incentives to search for an appropriate provider are the strongest after the caseworker has informed the individual about the treatment, it implies that the choice of the program provider is unlikely to be the mechanism that generates the positive effect of the expected assignment probability.

Finally, the quality of the caseworker could influence the job seekers expectations and labor market outcomes simultaneously without the differences in expectations having a causal effect on the individual behavior. Therefore, Table 7 also shows results for a subgroup who reports that they do not utilize the caseworker as a search channel (column 13) and a subgroup who does use the caseworker (column 14), as well as a subgroup who received only a few number of offers per week (below the sample median; column 15) and another who received a high number of offers (above the sample median; column 16). Both variables characterize the relationship between the caseworker and the job seeker, while it can be assumed that the caseworker quality is more important for the formation of expectations and the realized labor market outcomes in the subgroups that have a particular strong connection to the caseworker. However, the estimation results show that the positive and significant effect of the expected assignment probability π occurs only on those groups who are assumed to have a relatively loose connection to the caseworker (see column 13 and 15). Although, the findings show that the relationship between the job seeker and the caseworker is related to the expected assignment probability and generally important for the estimated effects, it can be concluded that the caseworker quality is unlikely to provide a source of unobserved heterogeneity that would question the causal interpretation of the baseline results. It rather seems to be the case that a close relationship to the caseworker reduces the impact of the expected assignment probability on the program effectiveness.

5.3 Summary and 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 long-term training programs realized later during the unemployment spell. The comparison with participants in short-term training provides evidence that the revealed connection is specific for long-lasting programs and cannot 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 is unlikely that the estimated effects can be explained by different selection patterns induced by anticipation effects for two reasons. First, as shown empirically, the expected treatment effect has no impact on the realized program effectiveness, which implies that private information with respect to the program effectiveness are not the driving factor influencing the expected assignment probability and the outcomes of participants simultaneously. Second, there is no significant effect of the expected assignment probability on the employment rate of non-participants, which makes it very unlikely that the actual selection into the program based on the expected assignment probability is related the level of unobserved abilities.

The second part of the empirical analysis aims to shed light on the underlying mechanisms by considering various additional information regarding the job search behavior, the connection between the job seeker and the caseworker, as well as program characteristics. This allows me to test the relevance of several mechanisms such as the role of caseworker quality, the endogenous formation of expectations due to bargaining with the caseworker, the choice of program providers and the inter-temporal adjustment of the job search strategy.

I can show that anticipating the treatment is only important for a specific group of participants who seem less prepared for the treatment. In particular, these job seekers have little contact with the caseworker, do not expect the treatment to be particularly beneficial and have not been informed about the treatment ex ante. Moreover, the have a very inelastic search strategy and little intrinsic incentives to optimize their own behavior with respect to the reduced amount of time that is available due to the treatment. These findings have two important implications. First, it is unlikely that the quality of the caseworker, the choice of a program provider or endogenous adjustments of the expected assignment probability due to bargaining with the caseworker can explain the results since the effects only appear for subgroups where these channels are less likely to play a role. Second, the results are in line with a job search model, where individuals who anticipate the treatment adjust their search behavior. For some individuals, the job search strategies are inter-temporally connected, which implies that differences with respect to the pre-treatment behavior (due differences in expectations) translate into behavioral differences after the enrollment. This is particularly important as it points out that the employment agency can improve the effectiveness of training programs by informing potential participants about upcoming treatments early during the unemployment spell.

An important question remains how policy makers can effectively implement information strategies that influence the job seekers' expectations about future treatments and encourage them to be prepared for the treatment. It should be noted that, in 2003, Germany already implemented a reform that 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 three 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 those who actually end up as participants already spent several months into job search activities before discussing a participation in a training program with the caseworker. It can be expected that the presence of such a time lag reduces the flexibility of their job search behavior, while an early awarding of vouchers would lead to efficiency gains.

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 study 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.

Therefore, I analyze the effects of two self-reported expectation measures, obtained directly at the entry 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 program effectiveness for 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. In order to account for the potential endogeneity of expectations, I control for a rich set of individual background information and conduct a difference-in-difference analysis that compares the impact of the expected assignment probability on the effectiveness of two training programs of different length. While the expected participation probability is unrelated to differences with respect to pre-treatment outcomes and expected employment rates, 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 provides strong evidence for the causal interpretation of the results.

In order to understand the underlying effect mechanisms, I analyze a comprehensive set of additional information that can be directly connected to the potential channels. A subgroup analysis shows that the impact of the expected assignment probability on the labor market outcomes is limited to a particular group of participants that has no contact to the caseworker, does expect the treatment to be beneficial and shows no flexibility with respect to their search behavior. Although, these findings underline the importance of the caseworker when developing the optimal strategy for participating in a program and searching for a new job, it also implies that differences with respect to the quality of the caseworker or the relationship between the job seeker and the caseworker cannot explain the positive effect of the expected assignment probability. Rather, job seekers who are not yet treated seem to choose different search strategies if they are not prepared for the program, which translates into a different search behavior after the start of treatment. Explanations for such an intertemporal dependency of search strategies can be either related to the cognitive processes, e.g. learning about optimal behavior and sequential stages of job search, or psychological motives, e.g. related self-efficacy or reference-dependent preferences.

The findings of the paper give new insights into the job search process of unemployed workers and provide evidence for a mechanism that can explain to a substantial extent the ineffectiveness of ALMP programs, in particular programs that require a high level of participants commitment. For very costly long-term training programs, it is shown to be important that potential participants receive the information about future treatments very early during the unemployment spell.

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Tables and Figures

Table 1: Descriptive Statistics: Labor Market Outcomes by Expectations and Realized Treatment Status

	Participants			Non-participants		
A. Expected assignment probability	$\pi-$low	$\pi-$high	$P-$value	$\pi-$low	$\pi-$high	$P-$value
No. of observations	206	501		2,163	2,138	
Regular employed in month						
$t+12$	0.25	0.38	0.00	0.53	0.55	0.07
$t+30$	0.50	0.63	0.00	0.57	0.59	0.27
Average monthly earnings in €	1,246	1,093	0.32	1,014	987	0.36
	Participants			Non-participants		
B. Expected treatment effect	$\delta-$low	$\delta-$high	$P-$value	$\delta-$low	$\delta-$high	$P-$value
No. of observations	382	325		3,171	1,130	
Regular employed in month						
$t+12$	0.33	0.36	0.36	0.53	0.55	0.22
$t+30$	0.58	0.59	0.79	0.58	0.57	0.54
Average monthly earnings in €	1,218	1,042	0.21	999	1,006	0.83

Note: Percentage share unless indicated otherwise. $P-$values measured based on two-tailed t-tests on equal means. Outcome variables are measured relative to the month of entry into unemployment t.

Table 2: Difference-in-Difference Model: Balancing Test wrt Observed Covariates

	Effect of expected assignment probability π-high v. π-low			
	Unconditional		IPW	
	Coef.	SE	Coef.	SE
Female	0.0928*	(0.0498)	0.0535	(0.0572)
Age				
16-24 years	-0.0092	(0.0414)	-0.0391	(0.0417)
25-34 years	-0.0295	(0.0436)	0.0053	(0.0484)
35-44 years	0.1084**	(0.0446)	0.0180	(0.0561)
45-55 years	-0.0697*	0.0422	0.0158	0.0480
School leaving degree (Ref.: None)				
Lower sec. degree	-0.0483	(0.0461)	-0.0268	(0.0486)
Middle sec. degree	0.0568	(0.0496)	0.0214	(0.0580)
Upper sec. degree	0.0022	(0.0405)	0.0090	(0.0484)
Higher education (Ref.: None)				
Internal/external prof. training	-0.0414	(0.0428)	-0.0303	(0.0492)
University degree	0.0398	(0.0360)	0.0355	(0.0424)
German citizenship	-0.0061	(0.0225)	0.0422	(0.0431)
Migration background	-0.0243	(0.0352)	-0.0543	(0.0507)
Married (or cohabiting)	0.1028**	(0.0488)	0.0398	(0.0574)
Problems with childcare	0.0632	(0.0970)	-0.0342	(0.1360)
Partner is full-time employed	0.0011	(0.0211)	-0.0053	(0.0246)
Children in household				
Age 0-3 years	0.0038	(0.0307)	0.0057	(0.0330)
Age 4-6 years	0.0273	(0.0263)	0.0298	(0.0290)
Age 7-15 years	0.0605	(0.0381)	0.0249	(0.0464)
Age 16-18 years	-0.0027	(0.0279)	0.0062	(0.0299)
Searching for full-time employment	0.0943***	(0.0339)	0.0488	(0.0358)
Region				
West-Germany & UE rate 0-6%	0.0707	(0.0471)	-0.0380	(0.0575)
West-Germany & UE rate 6+%	-0.0350	(0.0478)	-0.0136	(0.0545)
East-Germany & UE rate 9-14%	0.0231	(0.0368)	0.0477	(0.0344)
East-Germany & UE rate 15+%	-0.0588*	(0.0346)	0.0038	(0.0362)
Entry into unemployment (Ref.: 2nd quarter 2007)				
3rd quarter 2007	0.0363	(0.0396)	-0.0057	(0.0471)
4th quarter 2007	-0.0091	(0.0449)	0.0381	(0.0476)
1st quarter 2008	-0.0583	(0.0444)	-0.0688	(0.0547)
2nd quarter 2008	0.0232	(0.0370)	0.0161	(0.0424)
Time to interview				
7 weeks	-0.0094	(0.0122)	0.0012	(0.0101)
8 weeks	-0.0253	(0.0432)	-0.0316	(0.0493)
9 weeks	0.0018	(0.0419)	0.0233	(0.0437)
10 weeks	-0.0248	(0.0377)	-0.0085	(0.0496)
11 weeks	0.0361	(0.0367)	0.0121	(0.0416)
12 weeks	-0.0214	(0.0271)	-0.0059	(0.0295)
13 weeks	0.0325*	(0.0176)	0.0070	(0.0259)
14 weeks	0.0105	(0.0235)	0.0024	(0.0232)
Unemployment benefit recipient	(0.0349)	0.0381	-0.0087	(0.0411)
Last daily income in €	-1.2772	(3.1967)	0.5645	(3.5257)
Employment status before unemployment (Ref.: Other)				
Regular employment	-0.0769*	(0.0440)	-0.0082	(0.0487)
Subsidized employment	0.0139	(0.0394)	-0.0076	(0.0425)
Last job was full-time employment	-0.0200	(0.0431)	0.0125	(0.0461)
Months in employment				
in last year	0.4743	(0.4612)	0.0690	(0.5090)
in last 5 years	2.0820	(1.8653)	-0.6831	(2.1805)
in last 10 years	3.8462	(3.5512)	1.3529	(4.1941)
Months in unemployment				
in last year	-0.1893	(0.1725)	-0.0746	(0.1862)
in last 5 years	-1.4042*	(0.7452)	0.3888	(0.8685)
in last 10 years	-1.7865	(1.5033)	0.9238	(1.5544)
Openness	0.0038	(0.0995)	-0.0266	(0.1143)
Conscientiousness	0.0925	(0.0932)	-0.0091	(0.0943)
Extraversion	0.1178	(0.0988)	-0.0271	(0.1098)
Neuroticism	0.0200	(0.0973)	0.0554	(0.1120)
Locus of Control	0.0650**	(0.0291)	0.0145	(0.0392)

Note: Depicted are differences-in-differences (DID) between participants in long-term training and short-term training with high, respectively low expected assignment probabilities π with respect to observed characteristics: 1) unconditional DID and 2) DID based on inverse probability weighting (IPW). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table 3: Balancing Test of DID with Respect to Expected Labor Market Outcomes

	Effect of expected assignment probability π-high v. π-low		
	Long-term training	Short-term training	Difference-in-Difference
Outcome variable	(1)	(2)	(3)
Expected reemployment probability within six months			
very low	-0.0409**	-0.0274**	-0.0135
	(0.0178)	(0.0111)	(0.0209)
low	-0.0334	-0.0593***	0.0259
	(0.0284)	(0.0178)	(0.0335)
high	0.0834*	0.0891***	-0.0057
	(0.0451)	(0.0288)	(0.0535)
very high	-0.0000	-0.0089	0.0089
	(0.0486)	(0.0297)	(0.0570)
Log expected monthly net income	-0.0286	-0.0206	-0.0080
	(0.0346)	(0.0228)	(0.0414)
Assumed influence of employment agency on job finding			
will improve reemployment prospects	0.1665***	0.1503***	0.0163
	(0.0418)	(0.0289)	(0.0508)
will worsen reemployment prospects	-0.0254	-0.0253*	-0.0001
	(0.0181)	(0.0148)	(0.0234)
No. of observations	707	1,457	2,164
Control variables			
Socio-demographic characteristics	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes

Note: Depicted are average treatment effects of the expected assignment probability π-high (relative to π-low) based on inverse probability weighting (IPW). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table 4: The Impact of Expectations on Labor Market Outcomes Separated by Realized Treatment Status

	A. Effect of expected assignment probability π-high v. π-low			
	Participants		Non-participants	
	Uncond.	IPW	Uncond.	IPW
Outcome variable	(1)	(2)	(3)	(4)
Regular employed in month				
$t+12$	0.1337***	0.1211***	0.0277*	0.0239
	(0.0390)	(0.0413)	(0.0152)	(0.0158)
$t+30$	0.1316***	0.1033**	0.0165	0.0169
	(0.0405)	(0.0476)	(0.0151)	(0.0157)
Average monthly earnings in €	-152.85	-29.27	-28.62	-22.11
	(152.98)	(158.69)	(29.88)	(31.73)
No. of observations	707	707	4,301	4,301
	B. Effect of expected treatment effect δ-high v. δ-low			
	Participants		Non-participants	
	Uncond.	IPW	Uncond.	IPW
Outcome variable	(1)	(2)	(3)	(4)
Regular employed in month				
$t+12$	0.0328	0.0091	0.0210	0.0239
	(0.0358)	(0.0378)	(0.0173)	(0.0182)
$t+30$	0.0101	0.0088	-0.0106	-0.0092
	(0.0372)	(0.0394)	(0.0171)	(0.0181)
Average monthly earnings in €	-176.22	-153.47	7.25	45.60
	(139.42)	(144.73)	(33.95)	(38.70)
No. of observations	707	707	4,301	4,301
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 of the expected assignment probability π-high (relative to π-low) and the expected treatment effect δ-high (relative to δ-low): 1) as unconditional differences in mean outcomes (column 1 and 3) and 2) based on inverse probability weighting (IPW) (column 2 and 4). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table 5: Difference-in-Difference Model: The Impact of the Expected Assignment Probability for Different ALMP Programs

	Effect of expected assignment probability π-high v. π-low				
	Long-term training	Short-term training	Difference-in-Difference[a]		
	IPW	IPW	DID	DDD_{t-2}	DDD_{t-5}
	(1)	(2)	(3)	(4)	(5)
Regular employed in month					
$t+12$	0.1211***	-0.0682**	0.1893***	0.2210***	0.1997***
	(0.0413)	(0.0300)	(0.0510)	(0.0651)	(0.0635)
$t+30$	0.1033**	0.0005	0.1028*	0.1345**	0.1131*
	(0.0476)	(0.0299)	(0.0562)	(0.0611)	(0.0584)
Average monthly earnings in €	-29.27	-54.26	24.99	19.54	
	(158.69)	(66.67)	(172.06)	(172.66)	
No. of observations	707	1,457	2,164	2,164	2,164
Control variables					
Socio-demographic characteristics	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes	Yes	Yes

Note: Depicted are average treatment effects of the expected assignment probability π-high (relative to π-low) based on inverse probability weighting (IPW). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

[a] The difference-in-difference model (column 3-5) shows the impact of π-high on participants in long-term training relative to the impact of π-high on participants in short-term training. DDD_{t-2}/DDD_{t-5} refers to the conditional difference-in-difference-in-difference model, where the reference level is given by the average employment rate within the last two/five years before the entry into unemployment. For average earnings the reference level of the conditional difference-in-difference-in-difference model is given by the last income before becoming unemployed.

Table 6: Observed Differences with respect to Potential Mechanisms

	Effect of expected assignment probability π-high v. π-low
A. Job search strategies	
Average weekly number of own applications	-0.5004 (0.4608)
Expected effort adjustment when ALMP program is imminent (1=yes)	0.0785* (0.0473)
B. Actual and expected program characteristics	
Months between entry into UE and program start	-1.4964*** (0.3000)
Program duration in months	0.1127 (0.3101)
Expected treatment effect δ-high	0.2203*** (0.0498)
C. Related expectation measures and contact to caseworker	
Information treatment received	0.2222*** (0.0420)
Utilizing caseworker as search channel	0.1047** (0.0433)
Average weekly number of offers by employment agency	0.0580 (0.0383)
No. of observations	707
Control variables	
Socio-demographic characteristics	Yes
Household characteristics	Yes
Labor market histories	Yes
Regional and seasonal information	Yes
Personality traits	Yes

Note: Depicted are average treatment effects of the expected assignment probability π-high (relative to π-low) and the expected treatment effect δ-high (relative to δ-low) based on inverse probability weighting (IPW) for participants in long-term training. Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table 7: Subgroup Analysis of Participants with respect to Potential Effect Mechanisms

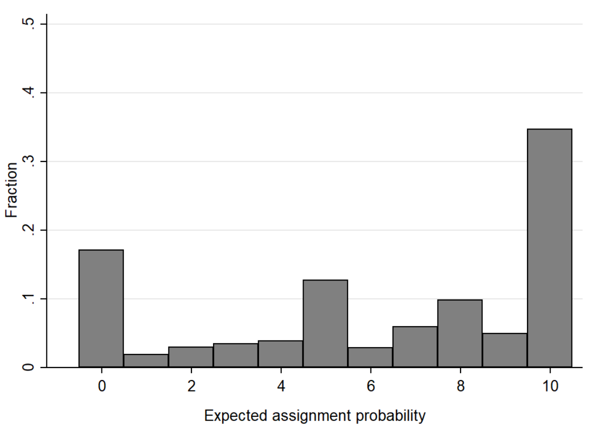
	Effect of expected assignment probability π-high v. π-low					
	A. Job search strategies and related traits					
	No. of own job applications		Expected effort adjustment		Locus of control	
	$\leq$ median (1)	$>$ median (2)	No (3)	Yes (4)	External (5)	Internal (6)
Regular employed in month $t+30$	0.0979	0.0998	0.1521***	-0.0676	0.2158***	0.0112
	(0.0682)	(0.0676)	(0.0541)	(0.0840)	(0.0648)	(0.0644)
Mean π-low	0.4632	0.5225	0.4551	0.6200	0.4300	0.5566
No. of observations	347	360	485	222	346	361
	B. Actual and expected program characteristics					
	Month of treatment start		Program duration $\geq$ 5 months		Expected treatment effect	
	1-4 (7)	5-12 (8)	No (9)	Yes (10)	$\delta-$low (11)	$\delta-$high (12)
Regular employed in month $t+30$	-0.0015	0.1281*	0.1454**	0.0279	0.1771***	-0.0300
	(0.0711)	(0.0655)	(0.0602)	(0.0783)	(0.0566)	(0.0893)
Mean π-low	0.6377	0.4234	0.5169	0.4659	0.4702	0.5636
No. of observations	350	357	412	295	382	325
	C. Contact between job seeker and caseworker					
	Information treatment		Caseworker as search channel		No. of job offers by agency	
	No (13)	Yes (14)	No (15)	Yes (16)	$\leq$ median (17)	$>$ median (18)
Regular employed in month $t+30$	0.1314**	-0.0047	0.1674**	0.0565	0.1337**	0.0384
	(0.0591)	(0.0863)	(0.0850)	(0.0564)	(0.0574)	(0.0795)
Mean π-low	0.4625	0.6087	0.4559	0.5145	0.4351	0.6000
No. of observations	428	279	172	535	407	300
Control variables						
Socio-demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes	Yes	Yes	Yes

Note: Depicted are average treatment effects of the expected assignment probability π-high (relative to π-low) based on inverse probability weighting (IPW) for various subgroups. Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

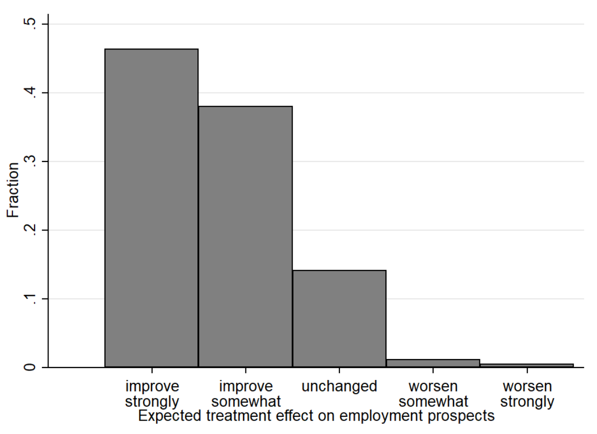
Figure 1: Distribution of Expectations by Realized Treatment Status

Participants

Expected assignment probability:[a] π

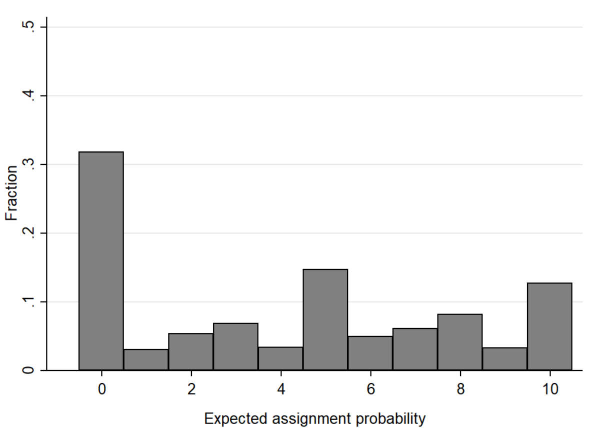


Expected treatment effect:[b] δ

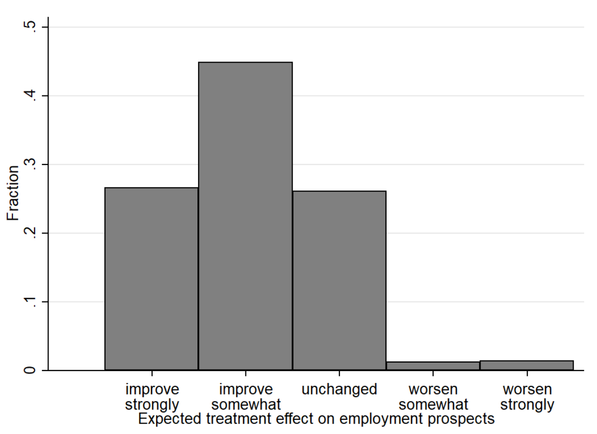


Non-participants

Expected assignment probability:[a] π

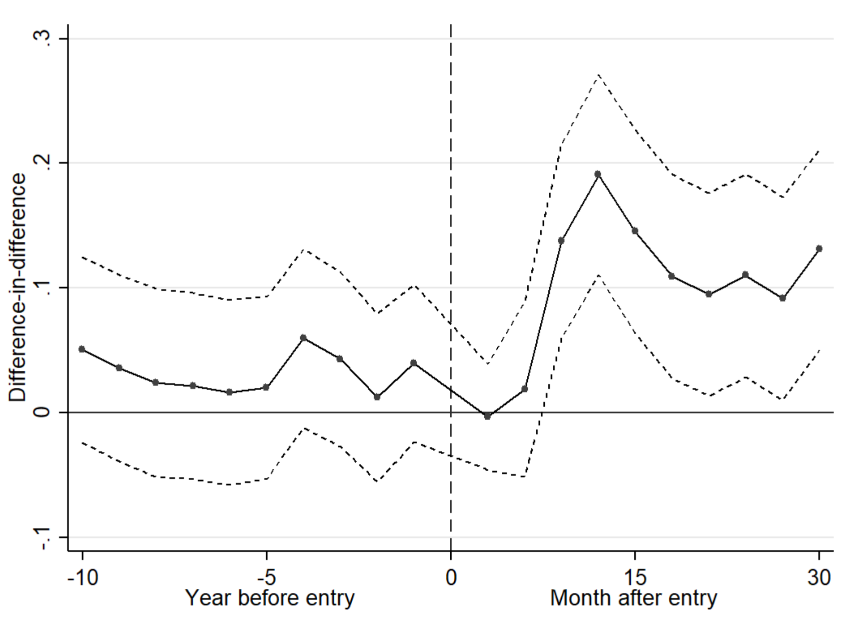


Expected treatment effect:[b] δ



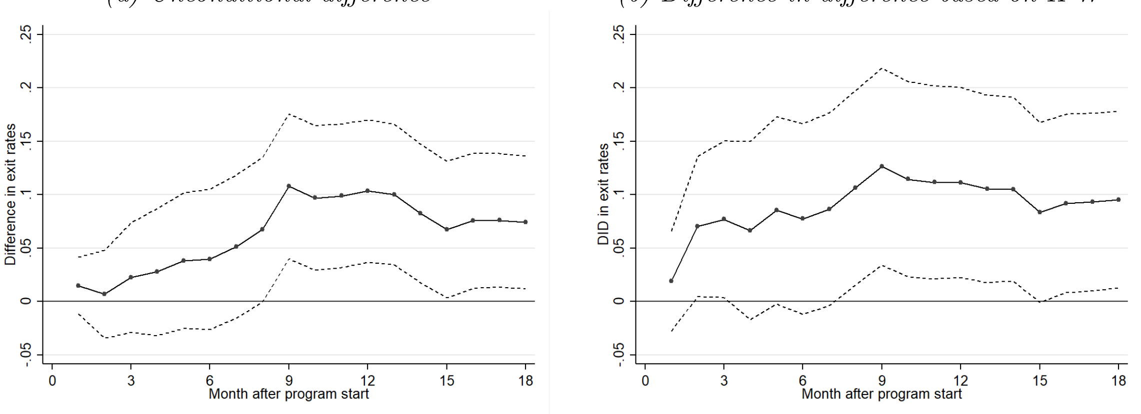
[a] Depicted are answers to the question: *"Assuming that you are still unemployed during the next 3 months. What is the probability that you will participate in a training scheme?"* 0 = very unlikely; 10 = very likely.
[b] Depicted are answers to the question: *"In your opinion, to what extent would 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 2: Unconditional Difference-in-Differences Over Time



Note: Depicted are unconditional differences-in-differences (DID) referring to the impact of π-high on participants in long-term training relative to the impact of π-high on participants in short-term training 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.

Figure 3: Impact of the Expected Assignment Probability π Relative to Program Start



Note: Depicted are differences in cumulated monthly exit rates from unemployment to regular employment relative to beginning of the program.
(a) Unconditional differences between participants in long-term training with high expected assignment probabilities (π-high) and low expected assignment probabilities (π-low).
(b) Differences-in-differences between participants in long-term training and short-term training with high, respectively low expected assignment probabilities π based on inverse probability weighting (IPW). *Control variables:* socio-demographic characteristics, household characteristics, labor market histories, regional/seasonal information and personality traits.

Supplementary Appendix:

The Power of Expectations: Anticipation Effects and the Effectiveness of Active Labor Market Policies

December 13, 2018

The supplementary appendix provides additional information to the reviewer and is not intended to be published but will be made available online.

Section A provides additional Tables and Figures.

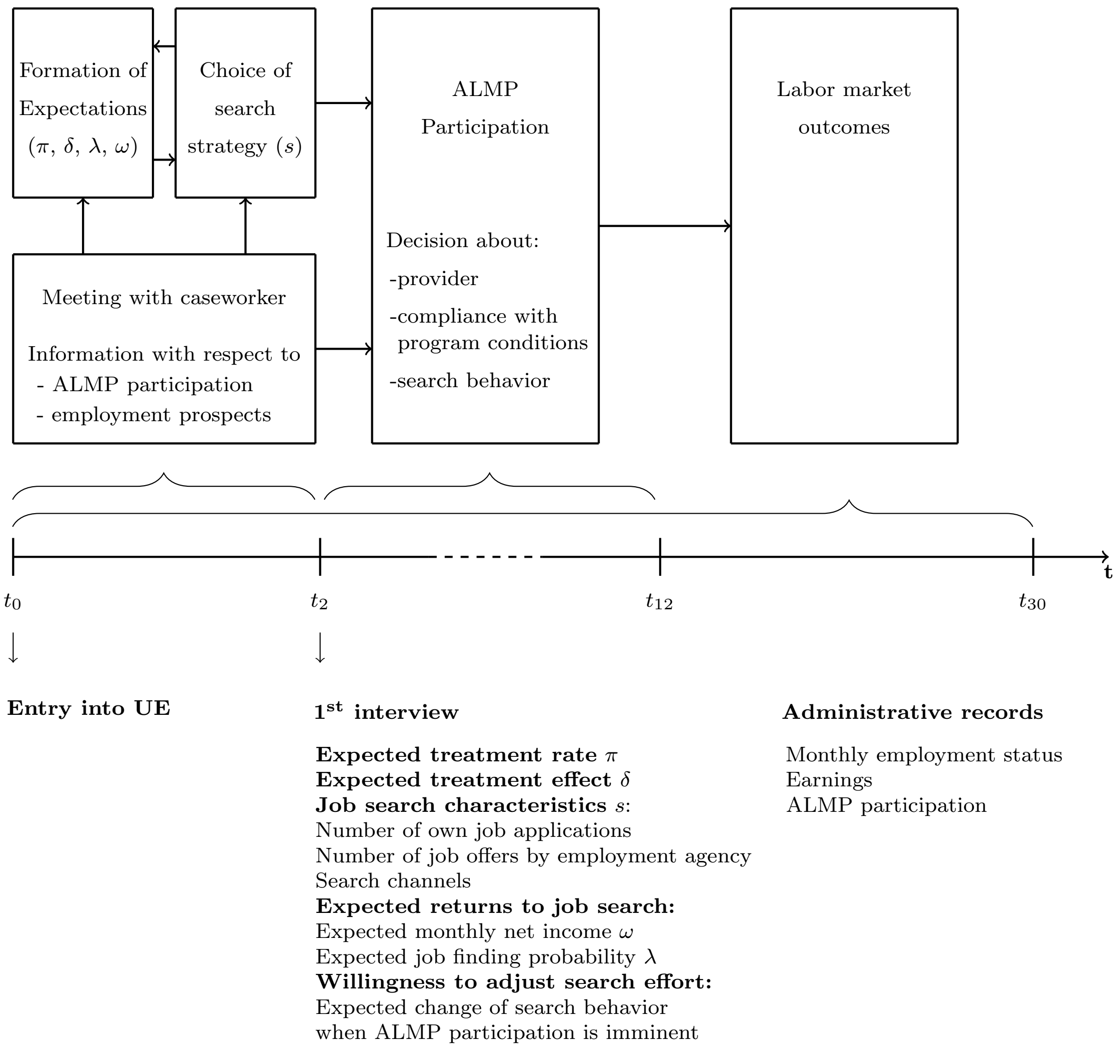
Section B provides details on the job search model discussed in Section 2.

A Supplementary Tables and Figures

A.1 Data and Empirical Setting

Figure A.1 shows the empirical setting of the study. In particular, it shows the timing of the individual choices and the corresponding observations in the dataset.

Figure A.1: Empirical Setting and Economic Framework



A.2 Baseline Results

Table A.1 presents supplementary estimates of the baseline results presented in Table 3 using ordinary least squares (OLS) regression instead of inverse probability weighting (IPW).

Table A.1: Comparing Baseline Results for IPW and OLS

	A.Effect of expected assignment probability π-high v. π-low					
	Participants			Non-participants		
	Uncond.	IPW	OLS	Uncond.	IPW	OLS
Outcome variable	(1)	(2)	(3)	(4)	(5)	(6)
Regular employed in month						
$t+12$	0.1337***	0.1211***	0.1222***	0.0277*	0.0239	0.0232
	(0.0390)	(0.0413)	(0.0404)	(0.0152)	(0.0158)	(0.0151)
$t+30$	0.1316***	0.1033**	0.1037**	0.0165	0.0169	0.0162
	(0.0405)	(0.0476)	(0.0418)	(0.0151)	(0.0157)	(0.0150)
Average monthly earnings in €	-152.85	-29.27	-70.73	-27.62	-22.11	-26.40
	(152.98)	(158.69)	(158.85)	(29.88)	(31.73)	(28.58)
No. of observations	707	707	707	4,301	4,301	4,301
	B. Effect of expected treatment effect δ-high v. δ-low					
	Participants			Non-participants		
	Uncond.	IPW	OLS	Uncond.	IPW	OLS
Outcome variable	(1)	(2)	(3)	(4)	(5)	(6)
Regular employed in month						
$t+12$	0.0328	0.0091	0.0102	0.0210	0.0239	0.0244
	(0.0358)	(0.0378)	(0.0369)	(0.0173)	(0.0182)	(0.0169)
$t+30$	0.0101	0.0088	0.0042	-0.0106	-0.0092	-0.0072
	(0.0372)	(0.0394)	(0.0381)	(0.0171)	(0.0181)	(0.0168)
Average monthly earnings in €	-176.22	-153.47	-178.34	7.25	45.60	39.66
	(139.42)	(144.73)	(143.99)	(33.95)	(38.70)	(31.97)
No. of observations	707	707	707	4,301	4,301	4,301
Control variables						
Socio-demographic characteristics	No	Yes	Yes	No	Yes	Yes
Household characteristics	No	Yes	Yes	No	Yes	Yes
Labor market histories	No	Yes	Yes	No	Yes	Yes
Regional and seasonal information	No	Yes	Yes	No	Yes	Yes
Personality traits	No	Yes	Yes	No	Yes	Yes

Note: Depicted are average treatment effects of the expected assignment probability π-high (relative to π-low) and the expected treatment effect δ-high (relative to δ-low): 1) as unconditional differences in mean outcomes (column 1 and 4), 2) based on inverse probability weighting (IPW) (column 2 and 5) and 3) based on OLS estimation (column 3 and 6). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

A.3 Difference-in-difference Model

Table A.2 shows the balance test for the DID model with respect to expect labor market outcomes for the expected treatment effect δ (corresponding to the balance test for the expected assignment probability presented in Table 2).

Table A.3 shows the difference-in-difference estimates with respect to the expected treatment effect δ (corresponding to the difference-in-difference estimates or the expected assignment probability presented in Table 4).

Figure A.2 shows the distribution of the expected labor market outcomes, i.e. the expected reemployment prospects, the expected earnings and the expected impact of the caseworker on the chances of finding a job, which are exploited for the balancing test presented in Table 2, respectively A.3.

Figure A.3 shows the unconditional differences-in-differences over time with respect to the expected treatment effect δ (corresponding to the difference-in-difference over time for the expected assignment probability presented in Figure 4).

Table A.2: Balance Test of DID with Respect to Expected Labor Market Outcomes for δ

	Effect of expected treatment effect δ-high v. δ-low		
Outcome variable	Long-term training (1)	Short-term training (2)	Difference-in-Difference (3)
Expected reemployment probability within six months			
very low	0.0264*	0.0049	0.0214
	(0.0149)	(0.0086)	(0.0172)
low	-0.0041	0.0046	-0.0087
	(0.0275)	(0.0148)	(0.0312)
high	0.0238	0.0314	-0.0076
	(0.0417)	(0.0269)	(0.0496)
very high	-0.0427	-0.0435	0.0008
	(0.0399)	(0.0275)	(0.0484)
Log expected monthly net income	0.0324	-0.0148	0.0472
	(0.0330)	(0.0211)	(0.0392)
Assumed influence of employment agency on job finding			
will improve reemployment prospects	-0.0687*	-0.0296	-0.0391
	(0.0417)	(0.0275)	(0.0499)
will worsen reemployment prospects	-0.0185	-0.0019	-0.0166
	(0.0145)	(0.0122)	(0.0189)
No. of observations	707	1,457	2,164
Control variables			
Socio-demographic characteristics	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes

Note: Depicted are average treatment effects of the expected treatment effect δ-high (relative to δ-low) based on inverse probability weighting (IPW). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table A.3: Difference-in-Difference Model: The Impact of the Expected Treatment Effect for Different ALMP Programs

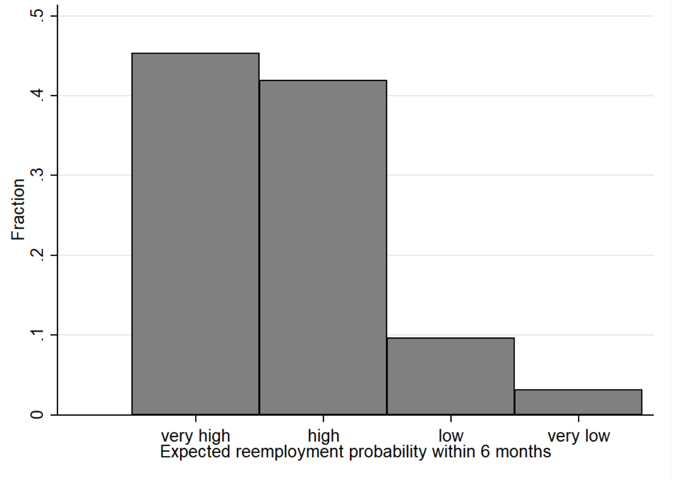
	Effect of expected treatment effect δ-high v. δ-low				
	Long-term training	Short-term training	Difference-in-Difference$^{(a)}$		
	IPW	IPW	DID	DDD_{t-2}	DDD_{t-5}
	(1)	(2)	(3)	(4)	(5)
Regular employed in month					
$t+12$	-0.0091	-0.0039	-0.0052	-0.0117	0.0050
	(0.0378)	(0.0296)	(0.0480)	(0.0568)	(0.0555)
$t+30$	-0.0088	0.0679	-0.0767	-0.0832	-0.0665
	(0.0394)	(0.0293)	(0.0491)	(0.0558)	(0.0549)
Average monthly earnings in €	-153.47	-50.08	-103.39	-116.34	
	(144.73)	(62.78)	(157.70)	(157.27)	
No. of observations	707	1,457	2,164	2,164	2,164
Control variables					
Socio-demographic characteristics	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes
Labor market histories	Yes	Yes	Yes	Yes	Yes
Regional and seasonal information	Yes	Yes	Yes	Yes	Yes
Personality traits	Yes	Yes	Yes	Yes	Yes

Note: Depicted are average treatment effects of the expected treatment effect δ-high (relative to δ-low) based on inverse probability weighting (IPW). Standard errors are shown in parenthesis. */**/*** indicates statistical significance at the 10%/5%/1%-level.

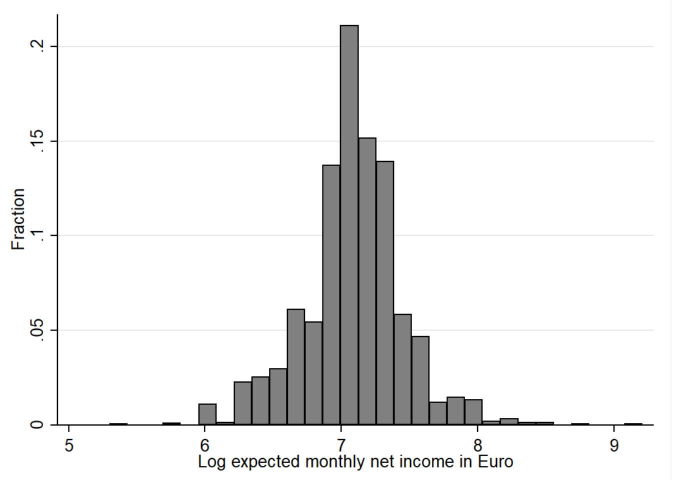
[(a)] The difference-in-difference model (column 3-5) shows the impact of π-high on participants in long-term training relative to the impact of π-high on participants in short-term training. DDD_{t-2}/DDD_{t-5} refers to the conditional difference-in-difference-in-difference model, where the reference level is given by the average employment rate within the last two/five years before the entry into unemployment. For average earnings the reference level of the conditional difference-in-difference-in-difference model is given by the last income before becoming unemployed.

Figure A.2: Distribution of Expected Labor Market Outcomes

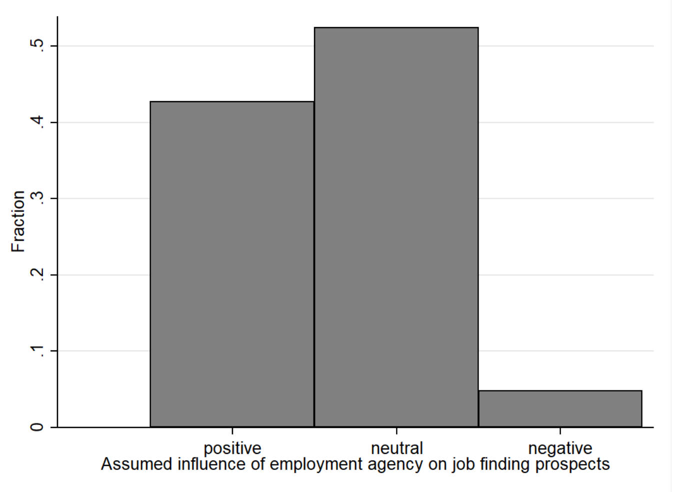
(a) Expected reemployment prospects



(b) Expected income

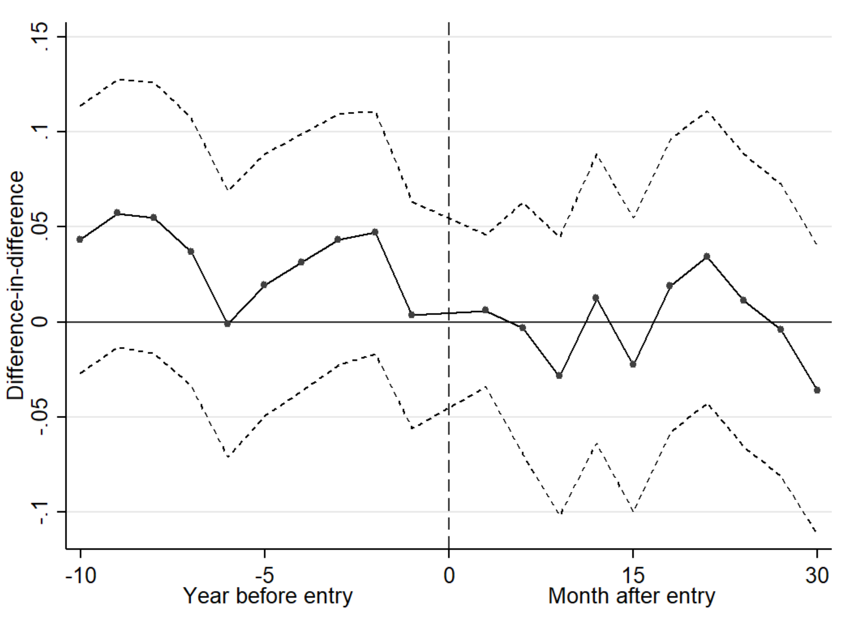


(c) Assumed influence of employment agency on job finding



Note: Depicted is the distribution of the expected reemployment probability within the next six months, the log expected income and the assumed influence of the employment agency on fob finding measured at the first interview after the entry into unemployment for participants (in long- and short-term training).

Figure A.3: Unconditional Difference-in-Differences Over Time



Note: Depicted are unconditional differences-in-differences (DID) referring to the impact of δ-high on participants in long-term training relative to the impact of δ-high on participants in short-term training 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.4 Effect Mechanisms

Figure A.4 shows the distribution of the expected willingness to adjust the job search behavior for different levels of expected treatment effects $\delta-$low and $\delta-$high.

Table A.4: Willingness to Adjust Search Effort and Expected Treatment Effects

Expected treatment effect	$\delta-$low	$\delta-$high	$P-$value
A. Non-participants			
No. of observations	3,171	1,130	
Expected adjustment of search behavior			
will increase search effort	0.27	0.41	0.00
will keep search effort constant	0.69	0.54	0.00
will decrease search effort	0.03	0.04	0.23
B. Participants			
No. of observations	382	325	
Expected adjustment of search behavior			
will increase search effort	0.22	0.34	0.00
will keep search effort constant	0.75	0.59	0.00
will decrease search effort	0.03	0.06	0.08

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

B Details on Theoretical Framework

The following section provides additional calculations with respect to the theoretical framework discussed in Section 2. Section B.1 shows the properties of the optimal job search behavior of individuals who have not yet been treated, while Section B.2 discusses implications for the search behavior for those who already entered the program. Section B.3, respectively Section B.4 show the corresponding results for the optimal effort invested into the choice of an appropriate program provider, respectively the bargaining with the caseworker.

B.1 Search strategy of not-yet treated job seeker

The optimal behavior of net-yet treated job seekers is characterized by the first-order condition:

$$\begin{aligned}\frac{1}{\rho}\sum_{j\in\{s,z,b\}}\frac{\partial c(s_t,z_t,b_t)}{\partial j_t} &= \frac{\partial\lambda(s_t|\eta)}{\partial s_t}\Big\{\omega-(1-\pi(b_t|\eta))V^u_{t+1}-\pi(b_t|\eta)V^p_{t+1}\Big\}\\ &+(1-\lambda(s_t|\eta))\Big\{\rho\pi(b_t|\eta)\frac{\partial\lambda^p(s_{t+1},z_t|\eta)}{\partial z_t}(\omega-V^p_{t+2})+\frac{\partial\pi(b_t|\eta)}{\partial b_t}(V^p_{t+1}-V^u_{t+1})\Big\}\end{aligned} \tag{B.1}$$

This implies that the relationship between the job seekers expectations about π, respectively δ, and the search strategy is given:

$$\frac{\partial s_t}{\partial\pi}=\frac{\frac{\partial\lambda}{\partial s_t}\delta+(1-\lambda)\frac{\partial\lambda^p}{\partial z_t}(\omega-V^p_{t+2})}{-\frac{1}{\rho}\sum_j\frac{\partial^2c}{\partial j_ts_t}+\frac{\partial^2\lambda}{\partial s_t^2}(\omega-V_{t+1}-\pi\delta)-\frac{\partial\lambda}{\partial s_t}(\rho\pi\frac{\partial\lambda^p}{\partial z_t}(\omega-V^p_{t+2})+\frac{\partial\pi}{\partial b_t}\delta)} \tag{B.2}$$

$$\frac{\partial s_t}{\partial\delta}=\frac{\frac{\partial\lambda}{\partial s_t}\pi+(1-\lambda)\frac{\partial\pi}{\partial b_t}}{-\frac{1}{\rho}\sum_j\frac{\partial^2c}{\partial j_ts_t}+\frac{\partial^2\lambda}{\partial s_t^2}(\omega-V_{t+1}-\pi\delta)-\frac{\partial\lambda}{\partial s_t}(\rho\pi\frac{\partial\lambda^p}{\partial z_t}(\omega-V^p_{t+2})+\frac{\partial\pi}{\partial b_t}\delta)} \tag{B.3}$$

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 $\partial^2c(s_t)/\partial s_t^2>0$, this implies

$$\frac{\partial s_t}{\partial\pi}\begin{cases}>0 \text{ if } \delta<-(1-\lambda)(w-V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t}\\ <0 \text{ if } \delta>-(1-\lambda)(w-V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t}\end{cases} \quad\text{and} \tag{B.4}$$

$$\frac{\partial s_t}{\partial\delta}\begin{cases}<0 \text{ if } \frac{\pi}{(1-\lambda)}>-\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t}\\ >0 \text{ if } \frac{\pi}{(1-\lambda)}<-\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t}\end{cases}. \tag{B.5}$$

Equation B.4 shows that job seekers increase their search effort with an increasing assignment probability π if the expected treatment effect δ is sufficiently low, while the cutoff $\delta \gtreqless -(1-\lambda)(w-V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t}$ implies that job seekers do not only take into account the initial expectation about the treatment effect δ, but also the possibility of increasing the program efficiency by spending effort into the provider choice z_t. Equation B.5 implies that a more positive expectation about the treatment effect δ leads to lower levels of search effort if the participation probability is sufficiently high relatively to the likelihood of remaining unemployed. However, if the marginal returns to the job search effort are sufficiently high and δ is negative, job seekers would invest less effort into bargaining with caseworker if δ increases, which in turn would increase the participation probability and it could be therefore optimal to increase also the level of search effort.

B.2 Search strategy of treated job seeker

The optimal behavior of an individual after entering the program is characterized by the first order condition:

$$\frac{\partial c^p(s_t, g(\pi(b_t|\eta), \delta))}{\partial s_t} = \rho\frac{\partial\lambda^p(s_t|\eta)}{\partial s_t}(\omega - V^p_{t+1}). \tag{B.6}$$

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

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

$$\frac{\partial s_t}{\partial \delta} = \frac{\rho\frac{\partial^2 c^p(s_t, g(\pi,\delta))}{\partial s_t s_{t-1}}\frac{\partial g(\pi,\delta)}{\partial\delta}}{-\frac{\partial^2 c^p(s_t)}{\partial s_t^2} + \frac{\partial^2\rho\lambda^p(s_t)}{\partial s_t^2}(\omega - V^p_{t+1})}, \tag{B.8}$$

$s_{t-1} = g(\pi, \delta)$ is characterized by equation B.1 with properties defined in equation B.4 and B.5. Assuming that $\partial^2 c^p(s_t, s_{t-1})/\partial s_t \partial s_{t-1} > 0$, this implies the following relationship between the job seekers expectations and the search behavior after the beginning of the program:

$$\frac{\partial s_{t+1}}{\partial \pi}\begin{cases} < 0 \text{ if } \delta < -(1-\lambda)(w - V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t} \\ > 0 \text{ if } \delta > -(1-\lambda)(w - V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t} \end{cases} \quad \text{and} \tag{B.9}$$

$$\frac{\partial s_{t+1}}{\partial \delta}\begin{cases} > 0 \text{ if } \frac{\pi}{(1-\lambda)} > -\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t} \\ < 0 \text{ if } \frac{\pi}{(1-\lambda)} < -\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t} \end{cases} . \tag{B.10}$$

and vice versa if $\partial^2 c^p(s_t, s_{t-1})/\partial s_t \partial s_{t-1} < 0$.

B.3 Choice of program provider:

The impact of the expected assignment probability on the effort spent into the provider choice is given as:

$$\frac{\partial z_t}{\partial \pi} = \frac{\frac{\partial\lambda}{\partial s_t}\delta + (1-\lambda)\frac{\partial\lambda^p}{\partial z_t}(\omega - V^p_{t+2})}{-\frac{1}{\rho}\sum_j \frac{\partial^2 c}{\partial j_t z_t} + \frac{\partial\lambda}{\partial s_t}\frac{\partial\delta}{\partial z_t} + (1-\lambda)\left[\rho\pi\frac{\partial^2\lambda^p}{\partial z_t^2}(\omega - V^p_{t+2}) - \rho\pi\left(\frac{\partial\lambda^p}{\partial z_t}\right)^2 + \frac{\partial\pi}{\partial b_t}\frac{\partial\delta}{\partial z_t}\right]} \tag{B.11}$$

$$\frac{\partial z_t}{\partial \delta} = \frac{\frac{\partial\lambda}{\partial s_t}\pi + (1-\lambda)\frac{\partial\pi}{\partial b_t}}{-\frac{1}{\rho}\sum_j \frac{\partial^2 c}{\partial j_t z_t} + \frac{\partial\lambda}{\partial s_t}\frac{\partial\delta}{\partial z_t} + (1-\lambda)\left[\rho\pi\frac{\partial^2\lambda^p}{\partial z_t^2}(\omega - V^p_{t+2}) - \rho\pi\left(\frac{\partial\lambda^p}{\partial z_t}\right)^2 + \frac{\partial\pi}{\partial b_t}\frac{\partial\delta}{\partial z_t}\right]} \tag{B.12}$$

where the change of the expected treatment effect with respect to the effort spent into the provider choice is given as:

$$\frac{\partial\delta}{\partial z_t} = \frac{\rho}{1-\rho(1-\lambda^p)}\frac{\partial\lambda^p}{\partial z_t}(w - V^p_{t+1}) - \frac{\partial c}{\partial z_t} \tag{B.13}$$

Assumed that the marginal effect on the increased provider efficiency exceeds the marginal costs of effort provision $\frac{\partial\delta}{\partial z_t} > 0$, i.e. searching for an appropriate provider increases the job seekers utility, this implies:

$$\frac{\partial z_t}{\partial \pi}\begin{cases} > 0 \text{ if } \delta < -(1-\lambda)(w - V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t} \\ < 0 \text{ if } \delta > -(1-\lambda)(w - V^p_{t+2})\frac{\partial\lambda_p/\partial z_t}{\partial\lambda/\partial s_t} \end{cases} \quad \text{and} \tag{B.14}$$

$$\frac{\partial z_t}{\partial \delta}\begin{cases} < 0 \text{ if } \frac{\pi}{(1-\lambda)} > -\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t} \\ > 0 \text{ if } \frac{\pi}{(1-\lambda)} < -\frac{\partial\pi/\partial b_t}{\partial\lambda/\partial s_t} \end{cases} . \tag{B.15}$$

B.4 Bargaining with the caseworker

The relationship the expected treatment effect and job seekers effort investment into bargaining with the caseworker is given as:

$$\frac{\partial b_t}{\partial \pi} = \frac{\frac{\partial \lambda}{\partial s_t}\delta + (1-\lambda)\frac{\partial \lambda^p}{\partial z_t}(\omega - V^p_{t+2})}{-\frac{1}{\rho}\sum_j \frac{\partial^2 c}{\partial j_t b_t} + \frac{\partial \lambda}{\partial s_t}\frac{\partial \pi}{\partial b_t}\delta + \frac{\partial \pi}{\partial b_t}(1-\lambda)\rho\frac{\partial \lambda^p}{\partial z_t}(\omega - V^p_{t+2})} \tag{B.16}$$

$$\frac{\partial b_t}{\partial \delta} = \frac{\frac{\partial \lambda}{\partial s_t}\pi + (1-\lambda)\frac{\partial \pi}{\partial b_t}}{-\frac{1}{\rho}\sum_j \frac{\partial^2 c}{\partial j_t b_t} + \frac{\partial \lambda}{\partial s_t}\frac{\partial \pi}{\partial b_t}\delta + \frac{\partial \pi}{\partial b_t}(1-\lambda)\rho\frac{\partial \lambda^p}{\partial z_t}(\omega - V^p_{t+2})} \tag{B.17}$$

Hence, when $\frac{1}{\rho}\sum_j \frac{\partial^2 c}{\partial j_t b_t} < \frac{\partial \lambda}{\partial s_t}\frac{\partial \pi}{\partial b_t}\delta + \frac{\partial \pi}{\partial b_t}(1-\lambda)\rho\frac{\partial \lambda^p}{\partial z_t}(\omega - V^p_{t+2})$, it implies:

$$\frac{\partial b_t}{\partial \pi}\begin{cases} > 0 \text{ if } \delta > -(1-\lambda)(w - V^p_{t+2})\frac{\partial \lambda_p/\partial z_t}{\partial \lambda/\partial s_t} \\ < 0 \text{ if } \delta < -(1-\lambda)(w - V^p_{t+2})\frac{\partial \lambda_p/\partial z_t}{\partial \lambda/\partial s_t} \end{cases}. \tag{B.18}$$

$$\frac{\partial b_t}{\partial \delta}\begin{cases} > 0 \text{ if } \frac{\pi}{(1-\lambda)} > -\frac{\partial \pi/\partial b_t}{\partial \lambda/\partial s_t} \\ < 0 \text{ if } \frac{\pi}{(1-\lambda)} < -\frac{\partial \pi/\partial b_t}{\partial \lambda/\partial s_t} \end{cases}. \tag{B.19}$$

and vice versa.