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Are active labor market policies (cost-)effective in the long run? Evidence from the Netherlands

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Abstract

The long-run effects of active labor market policies can be quite different from their short-run effects. Negative short-run effects can be explained by the lock-in effect: During training, the job search efforts of unemployed individuals decrease or even seize, thereby causing an initial drop in the probability of employment for those attending training programs. We show that in the long run (4–7 years after the start of a program) all programs have a positive and long-lasting impact on the probability of employment. However, the cost-effectiveness over the period of 4–7 years depends crucially on the magnitude of the initial lock-in effect. For programs which *increase* the job search efforts of participants during the program, like placement services, no lock-in effect is observed. In the long run, only placement services and training courses are cost-effective.

Keywords ALMPs · Unemployment · Welfare recipients · Matching

JEL Classification C25 · J08 · J64

1 Introduction

Active labor market policies are an important tool to decrease (long-term) unemployment, especially during an economic downturn. On average, OECD countries spent 0.5% of their GDP on active labor market policies in 2015 (OECD 2017), with the aim of increasing employment prospects of the unemployed and decreasing the costs of benefits. It is therefore relevant to assess of short- and long-term (cost-)effectiveness of active labor market spending. Most existing studies focus only on short-run effects of ALMPs and therefore only provide a partial answer to

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this question. (Kluve 2010; Card et al. 2010, 2018 provide recent meta-analyses, and Heyma and van der Werff provide recent results for the Netherlands.) Moreover, few studies that do address long-term effectiveness usually concern only individuals on unemployment insurance (UI) and not those on welfare, and do not confront the monetary effects of the programs with their costs (Lechner et al. 2011 and the references therein). In the words of Martin (2014), not much is known on effective programs for benefit recipients who are 'not as close to the labor market as the typical recipient of UI benefits.' A notable exception is Couch (1992), who studies the long-term cost-effectiveness of subsidized unemployment for female welfare recipients in Great Britain.

We add to the literature by calculating the medium- and long-run (cost-)effectiveness of ALMP programs for both UI recipients and welfare recipients. We estimate effects on earnings from employment and confront these returns from ALMPs with their costs. Placement services for welfare recipients are cost-effective, both in the medium run (4 calendar years after inflow) and in the long run (7 calendar years after inflow). Training courses are cost-effective for UI recipients. Other programs do increase the probability of employment in the long run, but are not cost-effective.

We use a rich administrative dataset obtained from Statistics Netherlands, with which we are able to track individuals for up to 8 years after the start of a program. The data contain all major relevant characteristics that determine whether a program is offered, including personal characteristics, labor market and earnings history, information on the unemployment period such as the remaining potential benefit duration and regional indicators on the level of the municipality. Following Lechner et al. (2011), we apply a static approach to program evaluation using matching methods. We confirm that the results in Lechner et al. (2011) for Germany also hold for the Netherlands. In particular, we find that all programs have a positive and long-lasting impact on the probability of employment in the long run in the Netherlands (60–96 months after inflow into UI/welfare). Almost all programs are more effective for those without recent labor market history. The lower educated benefit more from training than the higher educated. This holds for both welfare recipients and UI recipients. In contrast, placement services are especially effective for higher educated welfare recipients and for welfare recipients with recent work experience.

The remainder of the paper is set up as follows. Section 2 gives an overview of active labor market policies in the Netherlands. Section 3 presents our dataset and some descriptive statistics. Section 4 discusses the matching techniques used before turning to the main results in Sect. 5. Section 6 concludes.

2 Active labor market policies

During the period 2003–2008, over € 2 billion per year or almost 0.5% of GDP was spent on active labor market policies in the Netherlands (Table 1). Municipalities, who are responsible for re-employment of welfare recipients, spent the largest share of this budget. Every year about 100,000 welfare recipients started a program. The Public employment service (PES) is responsible for re-employment of individuals receiving unemployment insurance (UI) or disability insurance (DI).

Table 1 Expenditures on active labor market policies 2003–2008

	2003	2004	2005	2006	2007	2008
Expenditures on active labor market policies in millions						
Municipalities	1844	1667	1636	1665	1647	1581
Public employment service (PES)	635	605	560	561	489	485
Other	235	257	131	61	9	
Total	2714	2529	2325	2287	2145	2066
Number of programs started (× 1000)						
Municipalities—welfare recipients	105	109	98	91	91	100
PES—unemployment insurance	30	53	53	37	39	41
PES—disability insurance	44	42	33	32	33	33

Source: Rijksbegroting 2007, CBS Statline, UWV Kwartaalverkenning 2009—III, letter from the minister of Social Affairs d.d. July 12, 2010

Every year between 30,000 and 55,000 UI recipients started a program in the period 2003–2008—see Table 1. Re-employment services are offered yearly to around 30,000–45,000 DI recipients who are partially disabled and have residual work capacities.

During the years 2003–2005, municipalities were legally obliged to buy training programs from private re-employment companies. Commonly bought programs include career counseling, placement services, training and 'social activation.' *Career counseling* usually consists of one or more career tests and/or personality assessments, accompanied by several conversations with a career counselor. *Placement services* directly aim to bring a welfare recipient under the attention of a network of employers. *Training* is a very diverse instrument, ranging from short courses to acquire job-specific skills (for example, to obtain a reach truck certificate) to more general classroom training courses providing an update of general knowledge such as computer skills or job acquiring skills. Not all training is aimed directly at finding a job. Training can also be meant to decrease the distance to the labor market or prepare for formal vocational education. *Social activation* programs are not directly aimed at finding a job. They are meant to help welfare recipients to develop a daily routine and participate in society. Individuals who participate in these programs are discarded from the analysis since social activation is not expected to enhance job prospects of participants.

The PES makes yearly arrangements with private re-employment companies about the type and number of programs that will be offered to UI recipients. In the data at hand, a distinction is made between regular programs, individual budgets and training. The regular programs and individual budgets consist of the following steps: (1) drafting the plan, (2) activities toward placement and (3) follow-up during placement. Activities toward placement can consist of career counseling, training, job search assistance, etc. It usually combines a job application training with job search assistance. Follow-up during placement is meant to increase the probability that the re-employed keep their job, for example by using a job coach. This part of the program is only available for those with a large distance from the labor market

Table 2 Content regular programs and individual budgets, 2006

	Regular program (%)	Individual budget (%)
Career choice tests	10	12
Job application training	62	25
Job search assistance	61	28
Short training (up to 3 months)	6	16
Vocational training (longer than 3 months)	5	18
Internship	7	10
Job coaching	7	8

Source: IWI (2007). Information is based on a survey. The figures do not add up to 100% since a program typically consists of multiple components. The separate components are not identifiable in the data

(distance 3 and 4, see Sect. 3). All programs usually have duration between 14 and 65 weeks, including the follow-up (UWV 2005).

The key feature of a *regular program* is that the PES has made preset arrangements with the private re-employment companies. Private re-employment companies for regular programs are chosen by a tender procedure. The PES assesses quotations on price of a complete program, experience, predicted results and proposed methods to get the unemployed back to work. Companies offer a fixed price for a complete program and are paid on a no cure–no pay or no cure–less pay basis. Because the regular programs could not be tailored to the individual wishes of the unemployed, the possibility of an *individual budget* was introduced. With an individual budget of €5,000 at maximum, a client can approach the re-employment company himself and negotiate an individually tailored program. Table 2 reveals that there is a large difference in the composition of regular UI programs and individual budgets. A regular program contains mainly job application training and job search assistance. Individual budgets are more often than regular programs spent on short training and vocational training and far less on job application training and job search assistance.

From 2006 onwards, training could be assigned as a separate module. These training modules were often short term and diverse. Typical training programs include a course in computer skills or administrative skills, or a training to become a (taxi or personal) driver (Groenewoud and Slotboom 2009). However, most training modules (78%) were still part of a complete program (*regular* or *individual budget*, Slotboom et al. 2007).

3 Data and descriptives

3.1 Data

We make use of high-quality administrative data obtained from Statistics Netherlands. A file with data from municipalities, tax authorities and social insurance administrations is used as a basis for estimation. For every individual in the Netherlands, and for every month in the period 2001–2011, this file contains dummy variables indicating whether an individual receives any social insurance or social security benefit, the type of benefit (welfare/unemployment benefits/disability benefits), an indicator whether an active labor market program has started, variables for being in paid employment in that month and information on gender and age.

This information on benefit receipt and jobs is merged with information on active labor market instruments for welfare recipients in 2003 and 2004 (obtained from municipalities) and for unemployment insurance recipients in 2006/2007 (obtained from the unemployment office). Various other administrative data are merged, containing the education of the individual, the type of household, nationality, number and age of children, the sector of previous employment, yearly wage payments, a variable containing a subjective assessment of the caseworker regarding the distance to the labor market (with individuals in 'distance' 1 being the most employable and individuals in 'distance' 4 being the least employable) and various variables on the level of the municipality such as labor force participation, number of inhabitants, unemployment rate, percentage of low-income households and location. We also include variables for the maximum potential benefit duration for UI recipients, which are based on age and labor market history in the 2–5 years before inflow in UI. The merged dataset thus presents us with all background variables that are of major importance in the correct identification of treatment effects of active labor market programs (Dolton and Smith 2011; Lechner and Wunsch 2013; Caliendo et al. 2017).

3.2 Selection of treatment and control groups

We select two groups of individuals for analysis: (1) all individuals who start to receive welfare benefits in 2003 and (2) all individuals who start to receive UI benefits in 2006. The welfare inflow in 2003 has been selected such that there remain 2 years of labor market history (2001 and 2002) which we can use as background information in the matching procedure described in Sect. 4, while retaining a period of 8 years after inflow to study long-term effects.[1] We select UI inflow in 2006, since from that year onwards training programs are separately identifiable in the data, such that we can also evaluate the effects of individual training modules.

A number of selections on these groups have been carried out. First, for those on welfare benefits (group 1), we select only individuals for those municipalities that delivered data on their use of ALMPs—about 60 of the largest municipalities in the Netherlands. Second, in both groups we select only individuals aged 25–55 so that results are not influenced by any early retirement decisions. Third, we select only individuals that are fully unemployed at the moment that they flow into welfare/UI. Finally, for the UI inflow we discard any individual who worked as a civil servant before inflow. As from July 1, 2005, governmental organizations are fully

[1] Short-term labor market history variables are important determinants of both selection into training and subsequent labor market outcomes (e.g., Dolton and Smith 2011; Lechner and Wunsch 2013).

responsible for re-employment of their former employees, including offering active labor market programs. Programs offered by a governmental organization are not observable in the data.

3.3 Descriptive statistics and selection of programs for analysis

Tables 8 and 9 in "Appendix 2" show selected background characteristics for the two samples of participants. For individuals flowing into UI, background characteristics of participants and non-participants are comparable, although those on a regular program have a slightly lower education, whereas those on an individual budget have a slightly higher education. For individuals flowing into welfare, participants of placement services have some characteristics that increase their probability of employment: They have the strongest attachment to the labor market (distance 1) and are higher educated. They also worked a larger number of months preceding their inflow in welfare, and those who worked had a higher wage. Moreover, they were less likely to receive any kind of social insurance benefit in the 24 months before inflow. Non-participants are the worst risks: They received an average of 5.7 months of welfare in the 24 months before inflow, against 2.4–2.5 months for participants.

The differences in employment probabilities between participants and non-participants are confirmed in Fig. 2. This figure shows the fraction of individuals working in the months before and after inflow. For UI inflow, the fraction of working participants and the fraction of working non-participants are similar. For welfare inflow, there is a relatively high fraction of working individuals before inflow among those receiving placement services, as opposed to non-participants. Note that in case of welfare recipients, those who are working right before inflow do not necessarily have a high probability to find a job: Individuals with a long labor market history will first receive UI benefits before flowing into welfare.

From Fig. 2, the lock-in effect for UI recipients participating in a program seems prevalent: The fraction of working non-participants increases strongly in the first 12 months of UI, whereas the fraction of working participants stays behind. The difference in employment probabilities between participants and non-participants 6 months after inflow is about 40 percentage points. However, in the descriptives this apparent 'lock-in' effect can also be caused by the fact that the non-participants are just not attending any program because they already found a job before a program could be offered (Fredriksson and Johansson 2003, 2008). The next section elaborates on the estimation procedure and explains the way in which we correct for this selection bias.

4 Identification and estimation

4.1 Matching

Let $Y_t(1)$ be the value of some outcome (e.g., the probability of employment) at time t since inflow in UI/welfare when participating in training program P. Likewise, let $Y_t(0)$ be the value of the same outcome at time t since inflow in UI/welfare when not participating in training program P. This paper aims to estimate the average treatment effect on the treated (ATET) of participating in training program P:

$$\text{ATET}_P = E\left(Y_t(1) - Y_t(0)|P = 1\right) = E\left(Y_t(1)|P = 1\right) - E\left(Y_t(0)|P = 1\right)$$

The counterfactual outcome $E\left(Y_t(0)|P = 1\right)$ is not observed and therefore needs to be constructed from the outcome of non-participants. The ATET can be identified under two assumptions:

1. Conditional independence assumption (CIA): Given a set of observable characteristics X which are not affected by treatment status, the potential outcome in case of no treatment $Y_t(0)$ is independent of treatment status P.
2. Common support: Given a set of observable characteristics X which are not affected by treatment status, the probability of treatment is between 0 and 1: $0 < P(P = 1|X) < 1$. This condition ensures that treatment status P is not perfectly predictable conditional on X.

We use propensity score matching (Rosenbaum and Rubin 1985) to estimate the ATET. The matching procedure followed is developed by Lechner et al. (2011) and implemented in STATA by Huber et al. (2012). This estimator combines propensity score radius matching with bias adjustment for possible mismatches. Importantly, this estimator is superior in terms of the root mean square error (RMSE) in a study by Huber et al. (2013) who test the finite sample performance of various estimators in estimating the effects of active labor market policies. The estimators tested include inverse probability weighting, various types of matching estimators as well as different parametric methods.

4.2 Conditional independence

In order for the CIA to be satisfied, we should be able to control for all major factors that jointly determine selection into the program and the estimated outcome (e.g., probability of employment). Therefore, it is important to know which factors determine selection into program participation.

In the Netherlands, policy in the period 1997–2007 stated that every unemployed should be offered a program within the first 12 months of unemployment (UI or welfare). In practice, not every individual was offered a program: Around 75% of individuals who were unemployed for 12 months were not offered a program in the first 12 months (Kok et al. 2004). However, there was no well-defined targeting of programs during this period (Heyma and van der Werff 2014). The only official selection criterion for the timing of participation in an active labor market program was the so-called distance of the individual: a subjective assessment of the employment prospects of an individual by the caseworker. Individuals in ‘distance’ 1 were considered to be able to find work within 6 months without any training program and for this reason were not offered a training program within the first 6 months of UI/welfare. The data include a variable indicating the ‘distance’ for individuals flowing into welfare (but not for those flowing into UI). A variable that reflects a subjective assessment of the caseworker can be of importance since the judgment of the caseworker may include some factors that are not observable to us (Sianesi 2004, 2008; Lechner and Wiehler 2013).

Both selection by the caseworker and selection by the individual is likely similar between the Netherlands and Germany. In both countries, caseworkers select their program participants on the basis of their employment prospects (including local labor market conditions and qualification needs: Lechner and Wunsch 2013). In both countries, self-selection of individuals into ALMPs is driven by the fear of a benefit sanction at the moment they refuse to participate in a program. We can therefore use previous results on simultaneous selection into programs and employment for Germany (Lechner and Wunsch 2013; Caliendo et al. 2017) to the case of the Netherlands.

Based on a simulation study, Lechner and Wunsch (2013) compose a list of the major characteristics that should be included in the match. These characteristics are personal characteristics, unemployment period, regional indicators and short-term labor market and earnings history. We can control for all major characteristics and some of the less important characteristics mentioned by Lechner and Wunsch (2013), such as the part-time factor of the last job, number of months receiving disability insurance (as a crude indicator of health), searching for a full-time or part-time job and regional information on the level of the municipality. All conditioning variables are measured from the beginning of unemployment, such that they are not affected by treatment status or anticipation effects. “Appendix 1” contains full estimation results for several of the estimated probit models for the probability of treatment.

A recent paper by Caliendo et al. (2017) shows that characteristics such as personality traits, attitudes, expectations and job search behavior play a significant role in selection into active labor market programs, but hardly change estimated treatment effects of active labor market programs with propensity score matching estimators, if detailed labor market histories of the individual are included in the matching procedure.[2] They argue that unobserved characteristics, especially those that are constant over time, are captured by prior labor market performance. Any remaining variation in selection into the program which is driven by unobserved personality traits is therefore unlikely to drive our results. Moreover, our estimated effects on the probability of employment are very much in line with results presented by Heyma and van der Werff (2014). They estimated the effect of active labor market programs in the Netherlands on the probability to regain employment for UI recipients after 18 months of unemployment with a multivariate mixed proportional hazard duration

[2] The treatment effects estimated by Caliendo et al. (2017) are the probability of employment at 12 and 30 months, the number of months employed within 30 months and cumulated earnings within 30 months.

model, correcting for unobserved heterogeneity in their specification. Altogether we are confident that the CIA is satisfied for all programs studied in this paper.

4.3 Static evaluation and program start dates

We follow the static evaluation method outlined in Lechner et al. (2011) and consider those who start a particular program within the first 12 months of their UI/welfare spell as participants and those who do not start any program in this period as non-participants. Participants are divided in subgroups based on the *first program* they participated in within the first 12 month of their unemployment spell.

There are two main potential biases associated with static evaluation approaches in the literature, which both result in the underestimation of the treatment effect. First, the underestimation of the treatment may occur because non-participants are a positively selected control group: Some non-participants are not attending any program just because they quickly found a job (Fredriksson and Johansson 2003, 2008). Sianesi (2004, 2008) therefore takes a different approach and estimates treatment effects for 1-month windows. She therefore estimates the effect of starting a different program this month, versus postponing program start. Biewen et al. (2014) compare the Sianesi approach and the Lechner approach and indeed find that the Lechner approach leads to lower estimated treatment effects.

Second, the underestimation of the treatment effect may occur since employment outcomes of those who are treated *now* are compared to employment outcomes of those who are *potentially* treated later on, such that part of the control group also receives treatment. Fredriksson and Johansson (2008) therefore develop a matching estimator which compares outcomes of those who are treated in a particular month with those that are not (yet) treated, and non-treated are used as controls only during the time that they remain non-treated. Crépon et al. (2009) use a similar estimator and compare it to a static matching approach. They show that the bias resulting from future treatment is small (less than 0.5% points) when around 5% of non-treated individuals are treated afterward. In our case, only 2% of the UI non-participants are treated after the 12-month time window such that this contamination bias is probably small (Table 3). For welfare inflow, the bias may be larger since over 20% of non-participants are treated later on.

In our case, since participants are divided in subgroups based on the *first program* they start during the first 12 months of unemployment, the effect of any single program participation could also be overestimated when treated individuals participate in multiple programs. Again, this bias is expected to be small for UI recipients. For UI recipients, only 10–12% of participants start a second program after participating in the first program (Table 3). This is a direct consequence of the policy of the PES, which states that a UI recipient can participate in a maximum of one active labor market program during a single UI spell. An exception is those who start with a separate training program; here, almost 30% starts another program later on. For welfare recipients, around half of the program participants do not take place in a single program, but in a sequence of programs. However, subsequent participation usually consists of participation in the same type of

Table 3 Future program participation by group and treatment status

Future program participation in same UI/welfare spell	First program within 12 months after inflow			
	UI inflow 2006			
	Non-participant (%)	Regular (%)	Individual budget (%)	Training (%)
No future program	**98**	88	89	71
Future program, of which:	2	12	11	29
Regular	0.8	**1.9**	0.6	5.6
Individual budget	0.7	2.2	**0.8**	16.1
Training	0.1	3.8	6.5	**2.9**
Other	0.0	0.3	0.3	0.9
Unknown	0.9	3.5	2.7	3.9
	Welfare inflow 2003			
	Non-participant (%)	Career counseling (%)	Training (%)	Placement services (%)
No future program	**79**	40	48	53
Future program, of which:	21	60	52	47
Career counseling	2.4	**16.9**	8.7	9.3
Training	0.4	9.3	**15.9**	2.6
Placement services	0.5	11.9	7.4	**18.4**
Other	0.0	3.3	3.5	2.4
Unknown	17.4	19.0	16.9	14.6

Bold here just means they are on the diagonal

The type of program is unknown for programs started from 2008 (2005) for UI inflow (welfare inflow)

program or career counseling. Since results in Sect. 5 show that career counseling has a relatively small impact on the probability of employment, estimates for welfare recipients are also close to the pure effect of the first type of program.

The matching method of Lechner et al. (2011) ideally corrects for the first bias by additionally matching participants and non-participants according to their (hypothetical) program start dates, estimated using a log-linear model. Non-participants who flow out of UI/welfare before their (hypothetical) program start are removed from the matching procedure. They are not eligible for program participation at the moment of their hypothetical program start and therefore cannot serve as a proper control group.

We estimate (hypothetical) start dates of a program for non-participants using a logit model. The logit model predicts the cumulative probability of starting a program after 1, 2, 3, …, 12 months for each individual. Subsequently, this predicted probability distribution is confronted with a random probability between 0 and 1 to determine the start date of the non-participant. For example, suppose an individual has a 10% chance to start a program in month 1 and a 20% chance to start a program in month 2. When the random draw is smaller than 0.1, the individual is assigned month 1 as starting date. When the random draw is between 0.1

and (0.1 + 0.2 =)0.3, month 2 will be his simulated starting date. The advantage of using a logit model instead of a log-linear model as in Lechner et al. (2011) is that all simulated program dates are between 0 and 12, such that we do not need to remove any non-participants with simulated starting dates exceeding 12 months. The distribution of simulated starting dates for non-participants mirrors the observed distribution of starting dates for participants closely.[3]

5 Estimation results

5.1 Treatment effects on the treated

5.1.1 Impact on probability of employment

Figure 1 shows the probability of employment for the various programs on a monthly basis, taking the matched group of non-participants as a baseline. The lines indicate the effect estimate, and the symbols indicate significance on the 5% level. Starting at the left-hand side, each figure shows that (a) before inflow into unemployment, there are no persistent significant differences in the probability of unemployment between the participants and the matched group of non-participants, which is a sign of a good match,[4] (b) in the first 12–24 months after inflow into unemployment, participants experience a negative *lock-in effect* while participating in the program[5] and (c) after the initial lock-in effect, all programs show a positive effect on the probability of employment. For most programs, this effect sustains for the full follow-up period of 8 years. Apparently, individuals who are able to find a job as a result of participation in active labor market policies are either able to keep that job or having a job that makes them more attractive on the labor market such that it is easier to find another job in case they get unemployed (again).

For UI recipients, individual budgets and specific training measures are more effective than the more general regular programs. Individual budgets more often contain training (see Table 2), which might explain why they are more effective than regular programs. For welfare recipients, placement services seem especially effective in increasing employment probability. The increase in the probability of employment is about 3–10% points after eight years for all programs, which is substantially lower than the 10–20% point increase in employment

[3] Results from the logit models and simulated starting dates of non-participants are available from the authors on request.

[4] This is also the case for the UI inflow, for which the subjective caseworker assessment is not available. This indicates that, given all other background characteristics, inclusion of a subjective caseworker assessment is not pivotal. For individual budgets, there are a few marginally significant pre-inflow deviations in employment history. These are significant at the 5% level but not at the 1% level. Effects for individuals with an individual budget *are* significant at the 1% level (t-values > 5 for both the lock-in and the long-term positive effect).

[5] The average duration of a program is 8 months for UI recipients (Tempelman et al., 2010). We examine programs starting up to 12 months after inflow in UI, and the major share of programs of UI recipients in our sample will therefore run up to 20 months after inflow in UI.

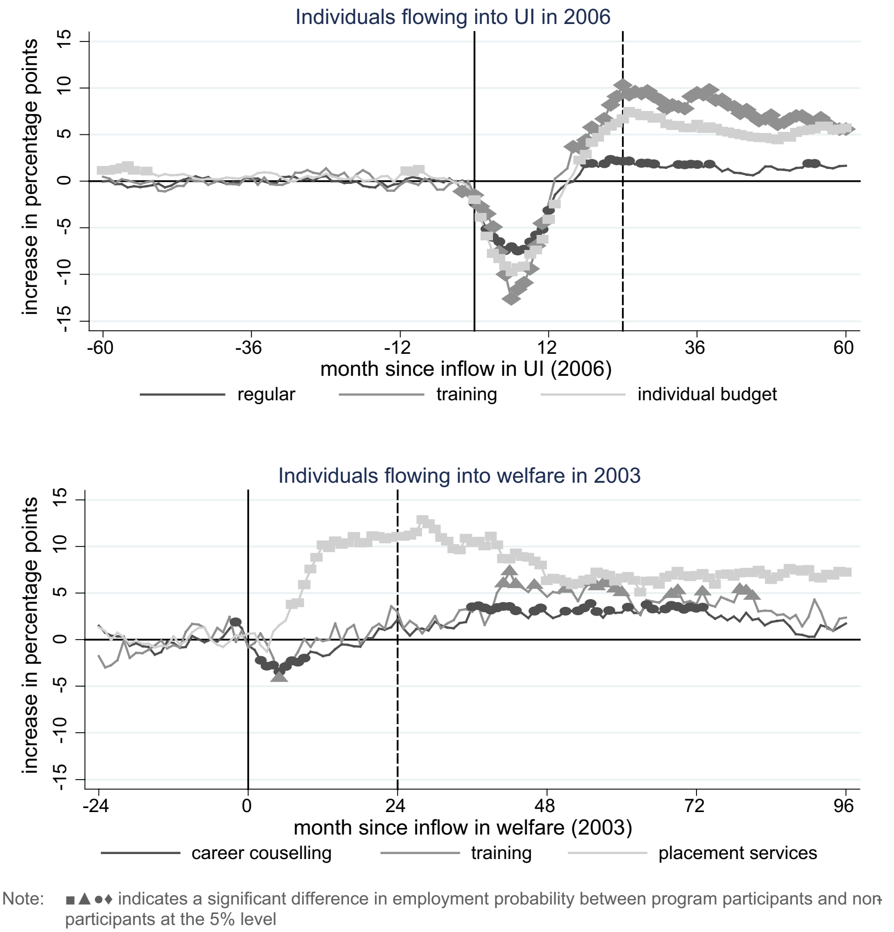

Fig. 1 Probability of employment: percentage point difference between participants and non-participants

found in Lechner et al. (2011). However, our results are in line with the effects found in Heyma and van der Werff (2014), who study the employment probabilities of Dutch UI recipients 18 months after inflow in UI during the years 2008–2011, using a multivariate mixed proportional hazard model. They show that regular programs decrease the probability of employment with about 3% points 18 months after inflow in UI, whereas individual budgets increase employment probability with 1.4% points.

Figure 1 shows that the lock-in effect is much smaller for the programs offered to welfare recipients as compared to the programs offered to UI recipients. For placement services in particular, the lock-in effect seems to be nonexistent. The literature on ALMPs identifies three situations in which lock-in effects can be more severe: (1) 'positive' characteristics of the unemployed that enable them to find a job without participating in a program, (2) an economic boom and/or (3) long program duration. Both the first and the last can be an explanation for the virtual absence of lock-in effects for welfare recipients. First, non-participants flowing into welfare in 2003 only had a 21% probability to find a job within 2 years, as opposed to 50% for non-participants flowing into UI in 2006. Second, programs for UI recipients typically last 14–65 weeks, whereas placement services and career counseling are usually short term. Moreover, placement service directly aims at increasing job search efforts of participants, whereas other programs initially decrease job search effort. A difference in regulations can also play a role. In the Netherlands, UI recipients are *automatically exempted* from any job search efforts when they participate in a training course which is believed to be necessary for reintegration on the labor market. Welfare recipients *can* be exempted from their job search requirements when attending any reintegration program.

5.1.2 Impact on probability of benefit receipt and number of months on benefits

Although (almost) all programs increase the probability of employment in the long run, the probability of benefit receipt does not decline. In the long term, the number of months of benefit receipt is actually higher for UI recipients who follow a program as compared to non-participation (see Table 4). This finding confirms previous results from Germany: Fitzenberger and Völter (2007) and Lechner et al. (2011) conclude that ALMPs for UI recipients do not lead to a significant decline in the probability to receive UI benefits.

Why does benefit dependency not decline for those who receive a program, while the employment probability increases? The most likely explanation is that when a UI recipient starts a job after following a training program, he will become eligible for renewed UI benefits after 26 weeks of work, meaning that he can start a new UI spell at the moment he loses (part of) his job. On the other hand, when he does not start a training program and therefore does not find a job, his eligibility for UI benefits expires after 6 months to 7.5 years (depending on working history and age). When eligibility for UI expires, the only option left is to apply for welfare, which is tested against the household's savings and income of the spouse. Some former UI recipients will not be eligible for welfare benefits and will stop receiving benefits altogether. For welfare recipients, this process cannot explain the remaining benefit dependency, since they can receive welfare benefits for an indefinite period of time when they stay unemployed. Potentially part of the welfare recipients who find work do not earn enough to support their family and therefore still receive (partial) welfare payments.

5.1.3 Impact on earnings from employment

Table 4 summarizes the average treatment effects on the treated populations in terms of employment, (any) benefit receipt and earnings from employment. All programs have a positive impact on the cumulative number of months employed in the long run (96 months after inflow into UI or welfare). Cumulated earnings from employment mirror the increase in cumulated number of months employed: Large (small) positive increases in cumulated earnings signal large (small) positive increases in cumulated number of months employed. The results on earnings from employment are input for the cost–benefit analysis in the next section.

Table 4 Average treatment effect on the treated: employment, benefit receipt and earnings

	UI inflow 2006			Welfare inflow 2003		
	Regular	Training	Individual budget	Career counseling	Training	Placement services
P (employment) 60 months	1.6	5.6*	5.7*	2.9	5.1*	6.6*
P (employment) 96 months				1.7	2.4	7.2*
Months employed within 60 months	− 0.1	2.4*	1.4*	0.6	1.4	4.9*
Months employed within 96 months				1.5	2.7	7.3*
P (benefit) 60 months[a]	3.5*	− 3.2	0.5	− 2.7	− 0.7	− 4.2*
P (benefit) 96 months				− 1.2	− 2.0	− 4.9*
Months benefit within 60 months	1.4*	0.6*	0.8*	0.2	0.1	− 2.9*
Months benefit within 96 months				− 0.4	− 0.6	− 4.2*
Cumulated wage earnings 4 calendar years (€)[b]	− 1,807	4,195*	1,465*	60	1,236	7,351*
Cumulated wage earnings 7 calendar years (€)				1,381	3,877	13,226*
N	6,819	1,152	7,370	2,118	680	1,598

*Indicates a significant difference in number of months employed between program participants and non-participants at the 5% level

[a]Benefit receipt indicates any benefits: UI, welfare or disability benefits

[b]Information on gross earnings is available up to the year 2010 such that individual's wage income can be tracked for a maximum of 7 (4) calendar years after inflow into unemployment

5.2 Cost–benefit analysis

In order to assess the cost-effectiveness of active labor market policies form a societal point of view, we compare the costs of these programs with the benefits.

Costs of programs have been calculated based on results in Tempelman et al. (2010). Tempelman et al. (2010) calculate costs per program by dividing total program costs by the number of started programs in 2008. We deflate these costs with the increase in hourly labor costs in the sector business services in the period 2003–2008 (14.1 for welfare inflow 2003) or 2006–2008 (6.5 for UI inflow in 2006, www.statline.nl). We add 25% costs of taxation and perform sensitivity analyses with 0% and 35% costs of taxation; also see the discussion below. Costs of programs for welfare recipients include costs of future programs as these may have contributed to the effect (see Table 3).

Productivity increases are the main benefit of active labor market policies (Heckman et al. 1999; Jespersen et al. 2008). An increase in production leads to a higher gross national product. Programs may also lead to lower benefit dependency and higher tax contributions by the formerly unemployed. These benefits are transfers: They are costs for the taxpayer and benefits for the unemployed who receive them. However, lower benefit dependency and higher tax payments lead to lower tax rates and thus reduce the burden of taxation. This stimulates the economy and thus induces a welfare gain. There are also immaterial benefits in terms of greater happiness of those who find work, better health and less crime (see, for example, Schuring et al. 2010; Lin 2008). On the other hand, leisure time of those who find work decreases, which is a welfare loss. Furthermore, welfare losses occur if those re-employed by the programs displace non-participants (Jespersen et al. 2008).

In the baseline calculations, we only take the productivity increase and the welfare effect of a change in tax rates into account. We do not take the effects on health and crime into account since there is no robust evidence on the size of these effects. Leisure time is not taken into account in the baseline calculations because there are no empirical estimates on the value of leisure time. In theory, the value of leisure time is equal to the hourly net wage rate. However, this is only valid for marginal changes and only if there is free choice of the number of hours worked. These conditions are obviously not met for involuntary unemployed who return to work. The value of leisure will therefore be much lower than 100% of the net wage increase for them. In a sensitivity analysis, we assume that the value of leisure time is 70% of the net income increase (wage earnings minus lost benefits). Displacement effects are not taken into account because Dahlberg and Forslund (2005) only find evidence of displacement effects of programs whose main mechanism is to provide wage subsidies. The programs in our study do not involve wage subsidies, but aim at increasing labor supply (training) or improve the working of the labor market (placement services, career counseling).

Productivity of employees is proxied by total labor costs: gross wage plus 30% employer's costs (like contributions for pensions and UI contributions). The net present value of productivity gains in 2003 and 2006 is calculated by using a discount factor of 5.5%, consisting of a risk-free discount rate of 2.5% and a risk premium of 3%, as prescribed by the Dutch Ministry of Finance (2009). For these reasons, productivity changes in Table 5 differ from the effects on earnings in Table 4: Adding employers' costs has an upward effect, while discounting has a downward effect.

Moreover, the effect of discounting depends on the timing of the effects over the years, which differs between treatments.

The welfare gain of reduced tax rates is assumed to be 25% of the reduction in public expenses.[6] Empirical estimates on the relative size of the welfare gain as a result of a reduction in public expenses vary substantially. Ruggeri (1999) gives an overview of estimates in seven studies varying from 0 to 81% of the reduction in public expenses. Kleven and Kreiner (2006) present estimates up to 251%. Some argue that the marginal excess burden of distortionary taxes is by definition zero, because it equals the marginal distributional gain at the optimal tax system (Sandmo 1998; Jacobs 2018). We therefore use a low figure in the baseline calculations (25%) and conduct a sensitivity analysis with 0% and 35% costs of taxation. The effect on public expenses consists of the effects on benefit transfers and tax transfers. The effect on benefit transfers is calculated by multiplying the effect on the number of months on benefit by the average monthly benefit amount. The effect on tax transfers is estimated by multiplying the average tax rate in the Netherlands (20%) by the net present value of the gross wage increase.

Table 5 shows the results. For the unemployed on UI benefits, only training is (marginally) cost-effective. Training for those on UI benefits is often short-term trainings, like courses in computer skills or administrative skills, or trainings to become a taxi driver. The result that training is cost-effective is thus consistent with the results of Osikominu (2013) for Germany. For welfare recipients, placement services are highly cost-effective, already after 4 years and even more so after 7 years. This is probably because this program does not have a lock-in effect. Training does not seem to be cost-efficient for welfare recipients. This might be because trainings for those on welfare range from short courses aimed directly at finding a job to more general classroom training directed at decreasing the distance to the labor market or preparing for returning to formal vocational education.

As a sensitivity analysis, we incorporate the loss of leisure time at 70% of the net income gain as an extra cost of resuming work. A tentative analysis on our data shows hourly wage rates are hardly affected by the programs, so all net income gain is due to a change in working hours. The net benefit of placement services for welfare recipients then stays positive at € 10,070 after 7 years. However, the net result for training for UI recipients becomes negative at -€ 680 after 4 years.

Assuming the costs of taxation are zero instead of 25% does not change the results qualitatively. Assuming costs of taxation are 35% instead of 25%, the net benefits of placement services for welfare recipients increase since placement benefits reduce benefit dependency substantially. However, the net benefits of training for UI recipients decrease and become negative, since benefit dependency does not decline from training, whereas the costs of training (and other programs) are raised through distortionary taxation.

The net benefits of placement services for welfare recipients are thus robustly positive, while the (marginally) positive result for training for UI recipients is sensitive to assumptions about the costs of taxation and the loss of leisure time.

[6] In the short to medium term, benefit dependency increases due to the lock-in effect, resulting in extra costs of taxation. These are also taken into account.

Table 5 Cost-effectiveness of programs per participant (in €)

	UI inflow 2006			Welfare inflow 2003		
	Regular	Training	Individual budget	Career counseling	Training	Placement services
Costs program	– €4,270	– €4,180	– €3,930	– €3,340	– €4,860	– €2,950
Production change after 4 years	– €2,130	€4,530	€1,430	– €10	€1,270	€8,310
Costs taxation transfers	– €500	– €230	– €180	– €50	€20	€1,040
Net benefit after 4 years	– €6,900	€120	– €2,680	– €3,400	– €3,570	€6,400
Production change after 7 years				€1,250	€3,770	€13,820
Costs taxation transfers				€150	€290	€1,580
Net benefit after 7 years				– €1,940	– €800	€12,450

Costs are estimated based on Tempelman et al. (2010)

5.3 Impact heterogeneity

To test whether treatment effects differ across groups of individuals with different observable characteristics, we stratify the sample and perform matching on the resulting subsamples:

- Males versus females
- Low educated versus high educated
- Young (25–45 years) versus middle-aged (45–55 years)
- Recent labor market history versus no recent labor market history
- Singles versus couples

Some interesting results stand out (see Table 6). Almost all programs are more effective for those without recent labor market history. An exception is placement services, which seems slightly more effective for those who worked in the period just prior to inflow in welfare. These results are in line with results previously found in the literature on active labor market policies. Lechner et al. (2011) find that UI recipients with an a priori low probability of a job offer benefit more from ALMPs in comparison with individuals with an a priori high probability of a job offer.

The lower educated benefit more from training than the higher educated. This holds for both welfare recipients and UI recipients. In contrast, placement services are especially effective for higher educated welfare recipients. A job hunter might experience less difficulty in 'selling' a highly educated individual to employers. There are no large or systematic differences in effectiveness between gender, age and household composition.

6 Conclusion

We show that in the long run, 4–7 years after the start of the program, active labor market programs have a positive and persistent effect on the probability of employment. In the short run, active labor market programs show only modest results. The difference between short-run and long-run effects can be explained by the lock-in effect: During the program, participants do not seek a job, which lowers their probability of finding a job compared to non-participants. Only after this initial lock-in effect, the employment probability of those who took place in an active labor market program increases. The productivity gains in the long run are therefore larger than in the short run.

However, also in the long run only the productivity gains of placement services for welfare recipients and training courses for UI recipients outweigh the costs. Placement services have no lock-in effect because the nature of the program is that the unemployed are assisted in searching a job. Search effort therefore immediately increases from the start of the program. Training courses for UI recipients do have a lock-in effect, but also show large positive effects on the probability of employment in the long run.

For other programs, it takes more than 7 years before the financial costs and productivity losses during the initial lock-in phase are fully compensated by the long-run

Table 6 Heterogeneous treatment effect on the treated: effect on number of months worked until 8 years after inflow (5 years for UI inflow 2006)

	UI inflow 2006			Welfare inflow 2003		
	Regular	Training	Individual budget	Career counseling	Training	Placement services
Gender						
Male	0.7	2.6*	2.0*	1.4	3.1	7.6*
Female	− 0.1	0.8	0.8	2.6*	1.8	8.6*
Education						
Low (primary or low level of secondary school)	− 0.1	5.4*	2.2*	− 0.7	4.9*	5.1*
High (high level of secondary school up to university degree)	0.3	1.0*	− 0.1	1.6	2.1	8.5*
Age						
25–45 years	0.3	2.0*	0.8	0.5	2.7	5.5*
45–55 years	− 1.0	3.1*	1.2*	0.4	0.8	7.2*
Recent labor market history						
Did not work in 24 months before inflow in welfare	1.4*	4.3*	3.8*	4.2*	7.2*	5.8*
Worked at least one day in 24 months before inflow	− 1.3*	1.2	− 0.5	0.2	1.6	6.6*
Household composition						
Single/single parent	− 2.3*	1.4	1.3	− 0.5	X[a]	5.4*
Married/cohabiting	0.5	2.2*	1.1*	1.5	3.5*	7.3*

*Indicates a significant difference in number of months employed between program participants and non-participants at the 5% level

[a]Results for groups of less than 100 participants were not calculated and are indicated with an x

productivity gains. Career counseling and training for welfare recipients is not cost-effective, and neither are full programs for UI recipients (regular programs and individual budgets). Full programs are usually a combination of job application training and job search assistance. These programs typically last for about 9 months to a year, during which job search effort is reduced. Moreover, these programs are less effective than separate training modules in raising the long-run employability of UI recipients.

Almost all active labor market programs are more effective for those with a relatively *low* probability to find work. These are the lower educated and those without recent work experience. The program does not 'lock them in,' since they are unable to find a job without any assistance. Programs that immediately increase search effort such as placement services are more effective for individuals with a *high* probability to find work. These programs do not suffer from a lock-in effect, and the effect of the program on job chances is higher for individuals that are easier to employ.

To ensure positive welfare effects of active labor market policies, the unemployed with a low probability to find a job should be offered a program which increases their probability to find a job in the long run, such as training courses. The unemployed with a high probability to find a job can be offered programs which immediately increase search effort such as placement services or training programs which do have a lock-in effect, but substantially increase employment probabilities afterward.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Appendix 1: Estimating the probability of program participation

See Table 7.

Table 7 Probits for the probability of program participation, various programs

	UI inflow 2006 Regular	Welfare inflow 2003 Placement service
Male	0.00	0.21***
Age 30–34 (ref = age 25–29)	0.24***	– 0.01
Age 35–39	0.32***	0.03
Age 40–44	0.35***	– 0.00
Age 45–49	0.34***	0.02
Age 50–55	0.35***	0.01
Distance 2/3 (ref = distance 1)		– 0.04
Distance 4		– 0.18***
Distance unknown		0.05
High school 1 (ref = primary school)	– 0.06**	0.15***
High school 2/low vocational	– 0.17***	0.18***
Higher vocational degree	– 0.42***	0.28***
University degree	– 0.50***	0.37***
Education unknown	– 0.14***	– 0.10
No Dutch citizenship	0.18***	– 0.07**
Single parent (ref = single household)	– 0.08	– 0.02
Married	– 0.06**	– 0.26***
Cohabiting	– 0.06*	– 0.13
Other household	– 0.02	– 0.17***
Child in household	0.06**	0.13*
Child in household < 5	0.01	– 0.06
Single parent with child < 5	0.25**	– 0.37*
Number of months employed 6 months before inflow	– 0.05***	– 0.00
Number of months employed 24 months before inflow	0.00	– 0.00
Number of months employed 60 months before inflow	0.00	
Times employed 24 months before inflow	0.03	0.04
Times employed 60 months before inflow	– 0.02	
Number of months since last job (max 24 months before inflow)	0.00	– 0.01
Number of months since last job (max 60 months before inflow)	0.00**	
Not employed in 24 months before inflow	0.21**	– 0.24**
Duration last job	0.00	0.00
Employed 6 months before inflow (y/n)		0.12**
Employed 18 months before inflow (y/n)		– 0.02
Number of months until program start	0.09***	– 0.01
Inflow month April–June (ref = Jan–March)	– 0.02	– 0.00
Inflow month July–Sept	– 0.05**	0.05
Inflow month Oct–Dec	– 0.09***	– 0.02
Looking for a job for 12–25 h a week (ref ≤ 12 h)		0.07
Looking for a job for 25–32 h a week		0.33**
Looking for a job for ≥ 32 h a week		0.19*
Wage 1 (calendar) year before inflow	0.00***	0.00

Table 7 (continued)

	UI inflow 2006 Regular	Welfare inflow 2003 Placement service
Employed 1 (calendar) year before inflow (y/n)	0.02	0.03
Wage 2 (calendar) years before inflow	0.00**	0.00
Employed 2 (calendar) years before inflow (y/n)	– 0.05	– 0.08
Wage 3 (calendar) years before inflow	0.00***	0.00
Employed 3 (calendar) years before inflow (y/n)	– 0.03	0.11*
Wage 4 (calendar) years before inflow	0.00	0.00
Employed 4 (calendar) years before inflow (y/n)	0.01	0.07
Wage 5 (calendar) years before inflow	0.00**	
Employed 5 (calendar) years before inflow (y/n)	0.14*	
Wage 6 (calendar) years before inflow	0.00	
Employed 6 (calendar) years before inflow (y/n)	– 0.05	
Wage 7 (calendar) years before inflow	0.00	
Employed 7 (calendar) years before inflow (y/n)	0.00	
Part-time factor 1 (calendar) year before inflow	0.16***	0.01
Part-time factor 2 (calendar) years before inflow	0.13**	0.06
Part-time factor 3 (calendar) years before inflow	0.10**	
Part-time factor 4 (calendar) years before inflow	0.09*	
Part-time factor 5 (calendar) years before inflow	0.03	
Number of working days 1 (calendar) year before inflow	0.00	0.00
Number of working days 2 (calendar) years before inflow	0.00	0.00
Number of working days 3 (calendar) years before inflow	0.00**	0.00
Number of working days 4 (calendar) years before inflow	0.00	0.00
Number of working days 5 (calendar) years before inflow	0.00	
Number of working days 6 (calendar) years before inflow	0.00	
Number of working days 7 (calendar) years before inflow	0.00	
Number of months UI 6 months before inflow	– 0.08***	0.01
Number of months UI 24 months before inflow	– 0.03***	0.01
Number of months UI 60 months before inflow	0.00	
Times UI 24 months before inflow	0.03	0.09
Times UI 60 months before inflow	– 0.01	
Number of months since last UI spell (max 24 months before inflow)	0.01***	– 0.01
Number of months since last UI spell (max 60 months before inflow)	0.00	
No UI in 24 months before inflow	0.36***	0.04
Number of months welfare 6 months before inflow	– 0.01	– 0.07*
Number of months welfare 24 months before inflow	0.00	– 0.01
Number of months welfare 60 months before inflow	0.00	
Times welfare 24 months before inflow	0.14	– 0.14*
Times welfare 60 months before inflow	– 0.09*	
Number of months since last welfare spell (max 24 months before inflow)	– 0.01	0.00

Table 7 (continued)

	UI inflow 2006 Regular	Welfare inflow 2003 Placement service
Number of months since last welfare spell (max 60 months before inflow)	0.00**	
No welfare in 24 months before inflow	0.04	– 0.10
Welfare 6 months before inflow (y/n)		– 0.26**
Welfare 12 months before inflow (y/n)		– 0.01
Welfare 18 months before inflow (y/n)		– 0.01
Welfare 24 months before inflow (y/n)		0.14
Number of months DI 6 months before inflow	0.06***	– 0.06
Number of months DI 24 months before inflow	0.00	0.02**
Number of months DI 60 months before inflow	0.00	
Times DI 24 months before inflow	0.12	– 0.40
Times DI 60 months before inflow	– 0.13**	
Number of months since last DI spell (max 24 months before inflow)	– 0.02**	0.02
Number of months since last DI spell (max 60 months before inflow)	0.00*	
No DI in 24 months before inflow	0.17	0.25
Employment rate	– 0.15	– 6.16
Municipality with 50,000–100,000 inhabitants (ref = 20,000–50,000)	– 0.15**	0.19***
Municipality with 100,000–150,000 inhabitants	– 0.05	0.51***
Municipality with 150,000–250,000 inhabitants	– 0.04*	0.74***
Municipality with 250,000 + inhabitants	0.02	0.46***
High number of inhabitants per km^2 (ref = very high)	– 0.05**	0.03
Low number of inhabitants per km^2	– 0.09***	0.03
Very low number of inhabitants per km^2	– 0.08***	– 0.16
Unemployment rate	0.00	– 0.06***
% of low-income households in municipality	0.01	0.03**
% of high-income households in municipality	– 0.01	0.02
East Netherlands (ref = north Netherlands)	– 0.27***	
Southeast Netherlands	– 0.22***	
Southwest Netherlands	– 0.29***	
Midwest Netherlands	– 0.14***	
Northwest Netherlands	– 0.23***	
Maximum potential UI benefit duration	0.01**	
Short-term UI eligibility	0.21**	
Long-term UI eligibility	– 0.01	
Constant	– 1.94***	0.14

Probits for the probability of an individual budget and training for UI inflow have the same specification as the probit for the probability of a regular program. Probits for the probability of training and probability of placement services for welfare inflow have the same specification as the probit for the probability of career counseling. All estimation results are available from the authors on request

Appendix 2: Descriptive statistics

See Tables 8, 9 and Fig. 2.

Table 8 Inflow in UI 2006—participants and non-participants comparable background characteristics

	Non-participant	Regular	Individual budget	Training
Male	50%	45%	49%	54%
Age	39	42	43	41
Primary school	5%	9%	3%	6%
High school 1	19%	25%	17%	22%
High school 2/low vocational	40%	38%	41%	45%
Higher vocational degree	14%	8%	19%	11%
University degree	6%	2%	8%	5%
Education unknown	16%	19%	12%	11%
No Dutch citizenship	29%	37%	23%	31%
Single household	20%	18%	21%	22%
Number of months employed in 24 months before inflow	17	15	16	16
Wage of those employed 1 year before inflow	€22,167	€20,460	€26,188	€23,165
Part-time factor of those employed 1 year before inflow	0.80	0.81	0.83	0.83
Number of working days 1 year before inflow	191	201	201	208
Number of months UI in 24 months before inflow	2.7	1.3	1.5	1.4
Number of months on welfare in 24 months before inflow	0.7	0.7	0.4	0.6
Number of months DI in 24 months before inflow	2.6	5.2	4.8	3.3
Number of months out of labor force in 24 months before inflow	3.2	3.7	3.5	3.8
Potential UI benefit duration in months	17	20	21	20
Number of observations	112,565	6819	7370	1152

Table 9 Welfare inflow 2003—participants more favorable background characteristics

	Non-participant	Career counseling	Train-ing	Placement services
Male	54%	60%	57%	69%
Age	37	37	37	36
Distance 1	24%	29%	25%	41%
Distance 2/3	37%	42%	51%	40%
Distance 4	19%	21%	14%	11%
Distance unknown	19%	9%	10%	8%
Primary school	15%	14%	15%	11%
High school 1	28%	30%	30%	28%
High school 2/low vocational	24%	31%	26%	32%
Higher vocational degree	7%	9%	11%	12%
University degree	5%	6%	6%	10%
Education unknown	21%	9%	11%	8%
No Dutch citizenship	57%	58%	67%	63%
Single household	34%	39%	32%	42%
Number of months employed in 24 months before inflow	6.9	9.1	7.2	10.8
Wage of those employed 1 year before inflow	€10,240	€11,566	€10,033	€11,900
Part-time factor of those employed 1 year before inflow	0.68	0.73	0.71	0.73
Number of working days 1 year before inflow	135	151	133	148
Number of months UI in 24 months before inflow	1.1	1.9	1.6	1.9
Number of months on welfare in 24 months before inflow	5.7	2.4	2.5	2.5
Number of months DI in 24 months before inflow	1.2	0.6	0.4	0.4
Number of months out of labor force in 24 months before inflow	10.4	11.0	13.3	9.5
Potential UI benefit duration in months	5	7	5	9
Number of observations	31,424	2118	680	1598

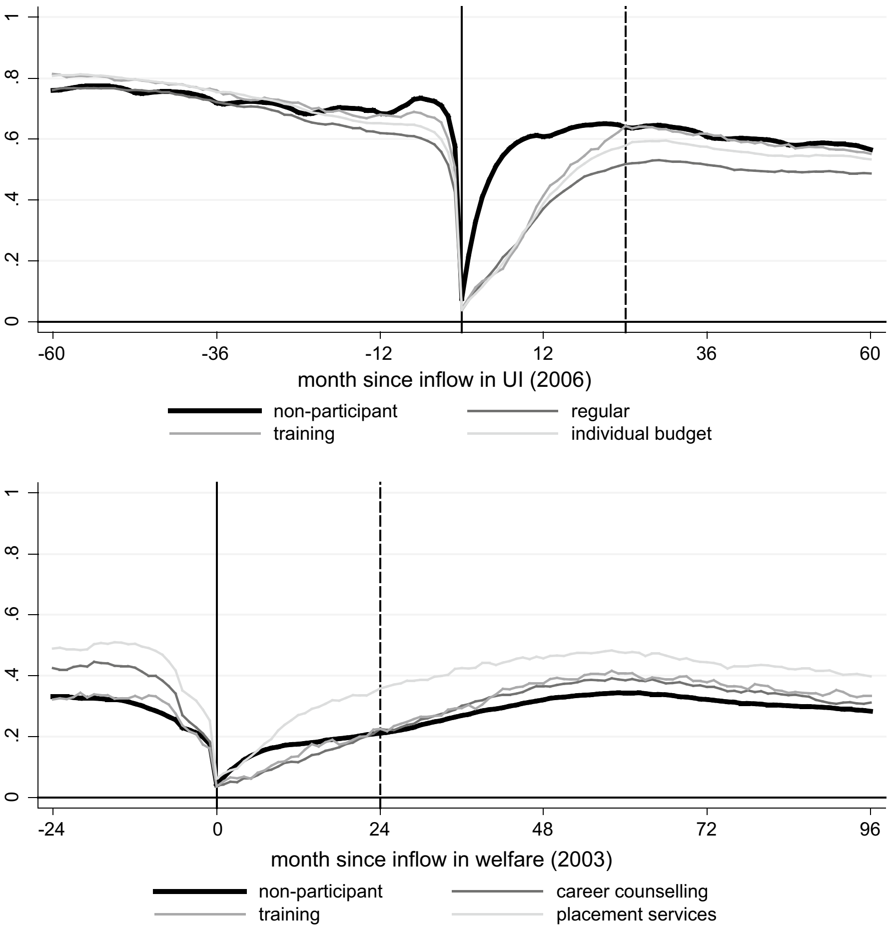

Fig. 2 Fraction of individuals working—UI inflow (2006), welfare inflow (2003)

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