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Should the unemployed care for the elderly?

The effect of subsidized occupational and further training in elderly care

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Content

Abstract

Demographic change implies an increasing demand for elderly care and a lower labor force potential at the same time. Training unemployed workers in care occupations might mitigate this problem. This study analyzes the effectiveness of subsidized training in elderly care professions for the unemployed in Germany over 12 years. We find that subsidized further training and retraining in elderly care improves the employment chances of unemployed workers substantially in the long term. Moreover, a high share of these re-employed workers remain in the care sector. A high percentage of part-time work and conditional wage gains for only certain retraining participants indicate shortcomings in the quality of employment. However, subsidized training seems to be an adequate measure to re-employ unemployed workers in the elderly care sector and to narrow the gap between demand and supply in elderly care.

Zusammenfassung

Der demografische Wandel wirkt sich in doppelter Weise auf den Bedarf an Pflegepersonal aus. Während die Zahl der pflegebedürftigen Personen immer weiter ansteigt, sinkt das Erwerbspersonenpotenzial. Eine Möglichkeit, einem Fachkräftemangel in der Altenpflege entgegenzuwirken, ist die Qualifizierung Arbeitsloser in diesem Berufsfeld. In dieser Studie untersuchen wir die Effekte geförderter Weiterbildung in der Altenpflege für Arbeitslose in Deutschland über einen Zeitraum von 12 Jahren. Unsere Ergebnisse zeigen, dass geförderte Weiterbildung in der Altenpflege die Beschäftigungschancen von Arbeitslosen langfristig deutlich verbessert. Zugleich verbleibt ein hoher konstanter Anteil dieser wiederbeschäftigten Arbeitslosen langfristig im Pflegebereich. Auf ein Defizit bei der Arbeitsqualität deuten jedoch ein hoher Teilzeitanteil und nur partielle positive Lohneffekte für bestimmte Umschulungsteilnehmer hin. Generell scheinen Weiterbildungsmaßnahmen in der Altenpflege aber ein geeignetes Mittel um Arbeitslose langfristig in der Altenpflege zu beschäftigen, was einem Fachkräfteengpass in diesem Bereich entgegenwirken könnte.

JEL-Klassifikation: I11, J24, J68

Keywords: Training, elderly care, program evaluation, dynamic treatment effects, active labor market policy

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1 Introduction

In many countries, demographic change has increased the need for skilled labor in the field of elderly care. In OECD countries, for example, the share of the population aged 65 years and older is expected to double and amount to 27 percent by 2050. In Japan, Korea, and Spain, the share of older people will reach approximately 40 percent. In Germany, the share of people older than 65 in the population will also be above the OECD average, with 33 percent in 2050 (OECD 2015). Consequently, the number of older people in need of long-term care will increase, which will translate into an increasing demand for care workers, although improving the health of older people might mitigate this need.

Currently, informal caregivers, such as family members or friends, are the most important home care providers (Bettio and Verashchagina 2010). However, delayed childbearing; changes in family structures, i.e., decreasing family size; weaker family ties; family members living farther apart; and the increasing labor market participation of women (who perform the lion's share of informal care) may lead to a shift towards formal care (Lilly et al. 2010, van Houtven and Norton 2004). For many societies, these changes imply that the number of elderly people in need of formal long-term care is rising, while the total labor force is declining. Although some countries have projected positive labor force trends (e.g., the UK and France), for 20 of 28 EU countries, the projections of the European Commission predict a fall in labor supply (European Commission 2015).

Generally, given the tough working conditions and low wages, care professions are not popular among school leavers, and job turnover is high. Moreover, the elderly care workforce is rather old, but only a few workers stay in the sector until retirement (Colombo et al. 2011a). As a consequence, governments must choose among different strategies to address potential skill shortages in the care sector. Many countries recruit immigrants or unemployed people as caregivers (Colombo et al. 2011b). Legal immigrant workers are particularly important in countries such as the United States or Australia (Colombo et al. 2011a) and also in many southern European countries (Simonazzi 2009). By contrast, Germany critically supplements the insufficient number of care workers with unemployed workers (Bundesagentur für Arbeit 2015).

In this paper, we close a gap in the literature by analyzing the extent to which subsidized elderly care training for unemployed workers is successful in improving the employment prospects of participants., particularly in the care sector. We expect the training to be very effective, given the increasing demand for skilled labor in these occupations. Thus, subsidized training might improve an individual's prospects and help secure skilled labor in the care sector.

In health economics, previous studies on elderly care consider a number of different aspects. One strand of literature concentrates on informal care, its relationship to formal care (e.g., Bonsang 2009, van Houtven and Norton 2008) and its effects on patients' and caregivers' outcomes (e.g., well-being and health, labor force participation, hours of work, and wages). In the US, less costly informal care has become a substitute for more expensive formal care (van Houtven and Norton 2004). However, increasing retirement income has decreased the use of informal and increased the use of formal care (Tsai 2015). Barnay and Juin (2016) show that informal care reduces elderly dependent individuals' risk of depression, while formal care increases general mental health. By contrast, informal caregiving affects caregivers' mental health negatively, at least in the short term (Schmitz and Westphal 2015, van den Berg et al. 2014, Bobinac et al. 2010). However, caregiving does not affect physical health (Schmitz and Westphal 2015).

Moreover, there seems to be a two-way causality between employment status and caring responsibilities. On the one hand, workers with high opportunity costs, who are employed and earn high wages, are less likely to undertake care (Carmichael et al. 2010). On the other hand, caregiving affects labor force participation negatively (van Houtven et al. 2013). This is particularly true for intensive caregiving (Lilly et al. 2010) and for caregiving women, who are more likely than men to reduce their hours of weekly work and to experience wage losses (van Houtven et al. 2013). These adverse effects for informal caregivers might be mitigated by enhancing the availability of formal care, for example, through additional nursing staff.

Another important topic is the quality of care and its determinants. Collier and Harrington (2008) give an overview of studies on how staffing rates and staff turnover affect the quality of care. Lin (2014) shows that registered nurse staffing has a significant impact on the quality of care, which is not the case for nurse aide staffing. Finally, many studies (e.g., Utriainen and Kynga 2009, Di Tommaso et al. 2009) focus on the quality of jobs in the (elderly) care sector. Burns et al. (2016) show that financial cutbacks in British nursing homes reduce job quality and in many cases also the quality of care. Shields and Ward (2001) analyze the determinants of job satisfaction for British nurses and its importance for nurses' intentions to quit. By contrast, we focus on the recruitment potential of unemployed people who receive training in elderly care.

Many empirical studies analyze the effects of training for the unemployed. The majority of these studies find an initial lock-in period and positive impacts in the medium and long term (Card et al. 2010, 2015). The extensive literature on German programs shows very similar findings (see, e.g., early studies by Fitzenberger and Völter 2007, Fitzenberger et al. 2008, Lechner et al. 2007, 2011). In more recent studies, Biewen et al. (2014) find positive effects of long-term and short-term training, starting between 2000 and 2002, on employment and earnings in the medium run if participants have been unemployed for some time, while Doerr et al. (forthcoming) find strong lock-in effects but only modest positive effects after four years for unemployed workers who received a training voucher in 2003 and 2004.

Only a few studies explicitly zoom in on specific occupations. Osikominu (2013) estimates the effects of short-term and long-term training programs by occupational groups based on participants' occupations prior to unemployment. She finds that those previously working in low- and medium-skilled manual occupations (such as service workers) benefit with respect to earnings, whereas those previously working in medium-skilled analytic and interactive occupations benefit with respect to employment stability. Most similar to our study is a study by Kruppe and Lang (2014). They analyze vocational retraining for the unemployed by targeted occupation and show that its effectiveness depends strongly on participants' future occupational field. Health care occupations – which includes elderly care nurses – are among those professions that yield the highest retraining employment effects.

Our study differs in various aspects. First, we focus on training for the unemployed in one specific health care sector, i.e., elderly care. Second, the particular focus on elderly care retraining allows us to estimate the supply-side effect of subsidized training for the unemployed. For many years, the demand for skilled labor in the elderly care sector has been high, and participants are therefore very likely to be absorbed by the labor market after completing their courses. Third, we consider not only retraining that aims at a vocational degree for unemployed workers (costly training with a duration of up to three years), but also further training (shorter and less costly). On the one hand, including further training measures makes our results more comparable to those from the previous literature. On the other hand, analyzing retraining as well as further training allows us to directly compare the relative effectiveness of long and costly versus short and cheap training. Fourth, we exploit extremely rich data and present results for all unemployed workers who have been trained over more than a decade. Thus, with an observation period of up to 11.5 years, we can identify long-term effects and analyze whether employment after training is sustainable, thereby advancing the literature.

We use German administrative data on training participants in the field of elderly care who started a training course between 2003 and 2015. The German case is interesting for two reasons: first, elderly caregiving, with almost 15 percent of all retraining courses in 2015, is the most important target occupation for subsidized retraining in Germany. Among further training participants, nearly one of 20 receives training in the field of elderly care (Statistik der Bundesagentur für Arbeit). Second, Germany had the second-highest share in the OECD of people older than 80 years by 2015 (OECD 2013). Thus, ranking second after Japan, it is a country that is particularly strongly affected by demographic change. Studying the German case might provide important insights for other countries faced with aging societies that so far have predominantly relied on immigration to meet the demand for elderly caregiving.

Applying propensity score matching, we compare participants with similar non-participants and find that training in elderly care strongly increases participants' employment prospects. We estimate the effects separately for unemployed workers in the unemployment insurance system (UI), who are closely attached to the labor market, as well as for workers receiving welfare benefits, who are generally rather hard to place. We find that women in the UI profit most from training in the field of elderly care and that subsidized training predominantly increases employment rates rather than wages.

2 Institutional background on elderly care and data

2.1 Institutional background

In 2013, approximately 55 percent of the elderly care workforce in Germany was qualified nurses, and 45 percent worked as care helpers. The fact that there are 37 unemployed nurses for the elderly per 100 posted vacancies underlines a shortage of skilled labor in the elderly care sector. For elderly care helpers, the picture is different, as the number of unemployed helpers exceeds the number of vacancies. For every 100 vacancies, there were 715 unemployed elderly care helpers in 2013. This illustrates the demand for skilled caregivers. The employment agencies have reacted by shifting resources to training for skilled nurses instead of helpers in recent years. In fact, in the school year 2013/14, one of four trained elderly care workers was a retrained unemployed worker (Bundesagentur für Arbeit 2015).

The German Federal Employment Agency (FEA) finances the direct costs of training programs in care professions for eligible job-seekers. Generally, workers qualify for training if it is necessary to equip them with any vocational qualification to prevent impending unemployment and to reintegrate them into the labor market. Still, the caseworker ultimately decides whether an eligible worker can participate in a training program after he identifies, together with the worker, which training course fits best, e.g., in terms of the occupation. If the caseworker grants subsidized training, the worker receives a training voucher that indicates the objective and duration of training. With this voucher, the worker can choose an adequate course within a defined period (at most three months, most frequently one month). Once the voucher is redeemed, participation is compulsory and non-attendance can entail sanctions (Doerr et al. forthcoming).

In this paper, we analyze two different types of training programs that are most important for the elderly care sector: retraining (Umschulungen) and further training (berufsbezogene und berufsübergreifende Weiterbildungen).[1]

First, retraining covers training courses in occupations in which vocational training commonly lasts at least two years, combining classroom and on-the-job periods. Retraining entails a (new) vocational degree upon completion. Job-seekers are eligible for retraining if they either have never completed any vocational training (with a duration of two years or longer) or have not worked in their original occupation for more

[1] Another important type of training in German active labor market policy is short-term training, which lasts on average about four weeks (Biewen et al. 2014). This kind of training is not relevant in this setting, as its main purpose is to improve the job search process and to examine a worker's labor market possibilities and willingness to work rather than to extend occupational skills.

than four years. Retraining in care occupations normally takes three years and eventually qualifies participants as specialized nurses for the elderly. Workers already holding a vocational degree in another care occupation are able to reduce the duration of retraining for elderly care nurse, in most cases by one year. Since 2013 such a reduction is also possible for workers without such a degree but with sufficient work experience in the field of care professions.

Second, further training programs, which usually aim to improve and extend existing skills, typically take weeks or months. Further training provides both general knowledge – e.g., handling computer software – and occupation-specific skills – e.g., care methods for dementia patients. In our setting, this implies that further training targets people both with and without work experience in the field of elderly care. This has two implications: first, further training that updates existing skills could be particularly useful for the long-term unemployed who need to adjust to vocational requirements that have changed over time. Second, special further training, which takes up to one year, is fit to qualify workers as care helpers. Such a care helper degree again enables workers to participate in retraining with a reduced duration and to become a specialized elderly care nurse.

Between 2003 and 2005, major labor market reforms (Hartz reforms) concerning the organization of unemployment benefits occurred. In 2005, policy makers reformed the unemployment benefit and welfare systems. Since then, the law has distinguished between two types of unemployed workers: workers in the unemployment insurance system, i.e., unemployed for up to 12 months (older workers for up to 24 months) and entitled to unemployment insurance benefits (unemployment benefit I), and long-term unemployed (i.e., > 12-24 months) workers in the social welfare system who have exhausted their unemployment insurance benefits and are entitled to welfare benefits (unemployment benefit II). The latter group also comprises workers who are not eligible for unemployment insurance benefits. As welfare recipients have worse employment prospects and thus differ from workers receiving unemployment insurance, we expect differences regarding the workers' characteristics and the effectiveness of training. Thus, we distinguish between these two types of workers below.

2.2 Data

2.2.1 Sample restriction

The empirical analysis exploits administrative records provided by the Institute for Employment Research of the German FEA. These data, called the Integrated Employment Biographies (IEB), comprise information on all unemployed workers who register at least once with the FEA for benefit receipt, job search, and participation in active labor market policy programs. Furthermore, the data contain information on the employment careers of all individuals liable to social security contributions. As all this information is process-generated, it is exceptionally precise (start and end dates of the different spells have daily precision) and highly reliable (for more information, see Jacobebbinghaus and Seth 2007, or Dorner et al. 2010).

For the analysis, we identify individuals registering as unemployed and job-seeking for at least one day. The group of participants – treated workers – consists of workers who, within the unemployment spell, enter one of the two types of subsidized training in the occupational field of elderly care. We focus only on the first participation in subsidized elderly care training within the randomly chosen unemployment spell.

The group of non-participants – potential comparison workers – consists of workers who do not enter retraining or further training in elderly care until the moment of potential treatment. If potential comparison workers have more than one unemployment spell that corresponds to our definition, we choose one spell randomly. We restrict the sample of potential comparison workers to those who are openly unemployed at the moment of potential treatment. That is, we allow that a worker has already participated in another kind of short labor market program during the unemployment spell but is unemployed and not involved in any kind of program activity at the moment of potential participation.

Regarding the sample of workers entering unemployment, we do not condition on transitions from employment to unemployment, thus allowing for transitions from outside the labor market to unemployment. This kind of transition is potentially frequent among women, especially those who are recently divorced or returning from maternity leave (Biewen et al. 2014). However, to not be restricted to one very specific group of workers participating in elderly care training, we decided not to condition on transitions from employment to unemployment. This seems problematic at first, because women outside the labor force might register as unemployed with the intention to receive elderly care training. One might claim that for these women, we might not observe the corresponding comparison workers who are still out of the labor force and potentially not interested in taking up employment. However, as we focus only on training participation within one occupation, i.e., the field of elderly care, we observe potential comparison workers among women coming from non-participation in the labor market who register as unemployed because they plan to participate in training for another occupation. Controlling for labor market status immediately before unemployment registration should prevent us from comparing workers with different employment intentions. Moreover, excluding workers coming from non-participation who register as unemployed in a robustness check yields very similar qualitative and quantitative results.[2]

We restrict the sample to workers who became unemployed between January 2003 and December 2015. Among the group of participants, we further restrict the analyses to workers who entered subsidized training between January 2003 and December 2015. We further straighten the sample by dropping workers not 20 to 60 years old

[2] The results are available from the authors upon request.

and for whom information is lacking on the type of vocational degree, schooling, and marital status.

The outcomes of interest comprise employment liable to social security contributions and the corresponding daily wage (deflated to 2010 Euros and imputed according to Gartner (2005)), which we measure every 30 days after the moment of potential treatment.[3] In the Appendix (Table A.1 and A.2), we list sample statistics and information on the independent variables that we include in the propensity score estimations.

2.2.2 Treatment characteristics

As described above, the German system distinguishes between unemployed workers receiving UI and welfare. In the following section, we estimate the program effects separately for the two groups. Moreover, we distinguish between the program effects on men and women.

Relative to other occupations, care occupations make up an important percentage of subsidized training (Kruppe and Lang, 2014). Table 1 presents participation numbers for the different subgroups. The sample contains approximately 58,000 participants for the whole observation period. Approximately 28,000 participants (48 percent) are in UI, and approximately 30,000 participants (52 percent) are in welfare. Not surprisingly, the majority of participants (78 percent) are female. Workers are more likely to participate in further training (74 percent) than retraining (26 percent). However, retraining is more likely among unemployed participants in UI, with approximately 36 percent of all cases. By contrast, welfare workers receive retraining in approximately 16 percent of all cases.[4]

[Table 1 about here.]

Figure 1 presents the number of participants by the year they started program participation. On average, participants in UI (welfare) started training 101 (114) days after the beginning of the unemployment spell (see Tables A.3 and A.4 in the Appendix). Institutional changes and the global economic crises of 2008 and 2009 affected participation numbers over time. Retraining in 2003 and 2004 was particularly important for workers in UI (welfare was introduced in 2005). In 2005, as part of the Hartz reforms, resources were re-allocated to shorter training programs. This re-allocation entailed a sharp decline of UI retraining participants to the lowest level in 2005, which

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[3] Furthermore, we look into unemployment. However, the informative value of the unemployment effects is similar to that of employment. Therefore, we provide these results only on request.

[4] The next paragraph shows that the high number of people starting retraining before 2005 causes the higher share of retraining participants in UI.

lasted until 2008. In 2009 and 2010, the participation numbers rose again. The number of participants in further training strongly increased especially between 2007 and 2009, with very similar participation numbers in welfare and UI.

[Figure 1 about here.]

Enrollment in retraining lasts almost half a year longer for workers in UI than for workers in welfare (see Tables A.3 and A.4 in the Appendix). It lasts approximately 872 (815) days for women (men) in UI and 721 (711) days for women (men) in welfare. Higher dropout rates among the often hard-to-place unemployed workers in the welfare regime explain this difference. The percentage of participants who successfully complete the retraining course is approximately 8 points (11 points) higher for women (men) in UI. For further training, dropout rates are generally lower and enrollment length is shorter. Moreover, differences in dropout rates (8 to 12 percent) and enrollment length (191 to 226 days) between men and women and participants in welfare and UI are less pronounced.

3 Empirical approach

3.1 Multiple treatments in a dynamic setting

To identify the causal impacts of training in the elderly care sector, we choose the potential outcome approach (Roy 1951, Rubin 1974) and rely on propensity score matching (Rosenbaum and Rubin 1983). Like Biewen et al. (2014), we distinguish between a non-treatment state and two different kinds of treatment: further training and retraining in the occupational field of elderly care. Thus, we denote the potential outcome of participating in further training (FT) as YFT and in retraining (R) as YR, while Y0 represents the outcome without any participation in an elderly care program. Per unemployed worker, we observe one of these three outcomes. We focus on the first treatment in elderly care within a given unemployment spell. We estimate two different sets of average treatment effect on the treated (ATT):

The effect of treatment versus searching. This is the ATT of receiving treatment a = FT, R against nonparticipation b = 0. As Biewen et al. (2014) note, this setting reflects the decision-making process of caseworkers and unemployed workers of waiting if a job search is successful or starting participation in a program.

The differential effect of further training and retraining. This is the ATT of receiving treatment a against treatment b, with a ≠ b ≠ 0. This approach analyzes whether participants in one or the other program would have performed differently had they chosen the alternative kind of training in the same month, conditional on previous unemployment duration.

In our setting, workers register as unemployed and job-seeking. Treatment D is observed only if the counterfactual unemployment duration if not treated, T0, is longer than the duration until the start of treatment S: $D = I(T^0 > S)$. Fredriksson and Johannson (2008) note that this data-generating process implies by construction that T0 is longer for treated than for potential comparison workers. In other words, workers with a long T0 are more likely to receive treatment than workers who leave unemployment quickly, for example to return to employment.

A static pre-determined definition of treatment and potential comparison observations — comparing treated workers with those who are never treated — is therefore biased, because it conditions on the future outcome (shorter conditional unemployment durations) of workers in the potential comparison group. By contrast, a dynamic framework that incorporates equal unemployment durations up to the potential moment of treatment accounts for this kind of bias (Sianesi 2004, 2008).[5] Conditioning on the duration already spent in unemployment, s, yields T0, which is independent of the treatment status. Thus, $T^0 \perp D(s)$.

Estimating treatment effects conditional on a specific starting date within the unemployment spell and applying propensity score matching, we follow the approach suggested by Sianesi (2004, 2008). For this purpose, we divide the unemployment spell into monthly strata. As most workers receive treatment during the first months of unemployment, we focus on the first treatment spell within the first 12 months of unemployment. Unemployed workers not participating in treatment in month t can start treatment anytime later, as long as they are still unemployed.

Let t = 1,…,12 denote the month of unemployment in which an individual starts treatment a with a = FT, R. τ = 0,…,108 denotes the months since the beginning of potential treatment a, such that Ya(t, τ) is the potential outcome at moment (t + τ) for treatment a starting in month t. The potential outcome for alternative treatment b (with b = 0, FT, R) starting in month t can be written as Yb (t, τ).

The ATT of treatment a (with $a \in \{FT, R\}$) against alternative treatment b (with $b \in \{0, FT, R\}$ and $a \neq b$) is therefore

$$\mathrm{ATT_t}(a, b, \tau) = E\left(Y_t^a(t+\tau) - Y_t^b(t+\tau)\middle|\, T^0 = t, D_t = a\right)$$

T0 is random time spent in untreated unemployment, and $D_t \in \{0, FT, R\}$ is the treatment status in month t. Thus, for treatment a starting in period t, we require that potential comparison individuals receiving treatment b have spent the same amount of time in unemployment as of period t and receive treatment in the same month as the treated individual. For b = 0, the potential comparison group comprises all workers whose unemployment spells last at least t periods and who do not participate in any elderly care program in month t. For b=FT or b=R, the potential comparison group comprises all workers whose unemployment spells last at least t periods and who do

[5] The resulting estimator is unbiased in the absence of treatment effects. In the case of positive or negative treatment effects and if the effects have the same sign for all unemployment durations, there is attenuation bias.

participate in the alternative kind of elderly care program in month t. Thus, we compare participation in one program to participation in another program within the same month of unemployment duration.

As outlined above, we conduct separate matching regressions for the first 12 months of elapsed unemployment duration. We do not consider later program starts. We chose nearest-neighbor matching with replacement and 20 neighbors and a caliper bandwidth of 0.01 using the Stata module psmatch2 (Leuven and Sianesi, 2015). We report the estimates as averages over all 12 subsamples.

Standard errors are taken from weighted OLS regressions using weights obtained with psmatch2. This estimated variance of the treatment effect does not include the variance resulting from the estimation of the propensity score, which again creates additional variation beyond the normal sampling variation (Heckman et al. 1998, Smith 2000). Therefore, the unadjusted standard errors of the nearest neighbor matching approach might be underestimated when taking the matched observations as given (Smith 2000). To solve this problem of biased standard errors, bootstrapping is a common approach in the literature. However, there is no formal justification for the validity of bootstrapped standard errors (Abadie and Imbens 2008). Other variance approximations are subject to strong parametric assumptions (e.g., Abadie and Imbens 2008, Lechner 2001).

Therefore, we accept the potentially biased standard errors but are convinced that this bias is very unlikely to impact the significance of our results importantly, as the following example shows: the positive effect of program participation in further training on employment after ten years for workers in UI is 19.66 percentage points; the potentially biased standard error is 1.56 percentage points. Thus, this effect is highly significant at the 1 percent significance level. This significance would still hold if the standard error was 4.9 times larger than estimated (19.66/2.576 (Student t-value for more than 500 degrees of freedom) = 7.63 →7.63/1.56 = 4.9).

3.2 Assumptions

There are three important assumptions to identify the estimates: a dynamic version of the conditional mean independence assumption (DCIA), a no-anticipation assumption, and a stable unit treatment value assumption (SUTVA).

First, the DCIA implies that conditional on previous unemployment T0 and observable characteristics X, the incidence and timing of treatment leave the potential outcome unaffected:

$$E\left(Y_t^b(t+\tau)\middle|\, T^0=t, D_t=a, X\right)= E\left(Y_t^b(t+\tau)\middle|\, T^0=t, D_t=b, X\right)$$

Applying propensity score matching, we replace the vector of observable characteristics X by the probability of treatment P(X). If we consider all determinants of X that affect the treatment status and the potential outcomes for the estimation of the propensity scores, treatment in a given month of unemployment is as good as random, and the treatment estimates are valid. The rich data enable us to include a vast quantity of variables that determine both treatment status and outcomes (for more details, see Tables A.1 to A.2 in the Appendix). In addition to individual characteristics, we include detailed information on the last job and employer and on the labor market career prior to unemployment (up to five years prior to the start date of the unemployment spell). Controlling extensively for labor market history should also capture usually unobserved personality traits (Caliendo et al. 2016, Caliendo et al. 2014). Moreover, we use variables for the unemployment rate at the county level, dummy variables for the 176 local employment offices, and 156 dummies for the year and month when unemployment starts.

Second, the no-anticipation assumption demands that anticipation of treatment does not affect the job search. Future participation must not affect a job-seeker's behavior. In our setting, the no-anticipation assumption holds because caseworkers can award training vouchers for job-seekers anytime during the unemployment spell. Further training courses start constantly throughout the year, and caseworkers award the vouchers at short notice. There is usually very little time between the notification date, i.e., the moment when the participant receives the training voucher, and the start date of the further training course. As outlined earlier, the voucher is valid for only three months, and once it is redeemed, participation is compulsory, and caseworkers can sanction non-attendance. Moreover, the incidence and timing of training participation depend on the supply of training programs by external training providers. Thus, workers cannot perfectly anticipate whether and when training will occur.

The situation differs somewhat for retraining participants. Retraining usually starts on specific dates, i.e., on the first of March or September. Thus, there might be a period of anticipated treatment between the notification of retraining and the start of the program. However, for most workers, the period between unemployment and the treatment start is relatively short. More than 50 percent of the eventually treated workers in our sample begin treatment in the first three months after the start of unemployment. Within such a short period, it is difficult to find a well-matched job (or any job to avoid treatment) and leave unemployment; thus, the risk of anticipation is small. Even though anticipation is less likely to occur at the beginning of an unemployment spell than after several months, a robustness check shows that the long-term effects of retraining for UI workers do not differ between participants who start treatment within three months of unemployment and participants who start treatment after being unemployed for at least three months (Figure A.1). Therefore, a decreased job search in anticipation of treatment should not create the huge effects that we find for matched treated and control workers and that prevail over a period of 11.5 years.

Third, we imply the common assumptions that potential outcomes are independent across individuals (SUTVA) and that there are no general equilibrium effects.

4 Causal estimates of training impacts

4.1 Baseline estimates

4.1.1 Unemployed workers in UI

Figure 2 shows the employment rates for participants and their matched non-participants in retraining and further training and the average treatment effect on the treated (ATT).[6] The horizontal axis indicates time before and after the treatment start in months. As our observation period starts in 2003 and ends in 2015, we can follow participants in UI, i.e., closely attached to the labor market, for 11.5 years.[7]

[Figure 2 about here.]

Figure 2a presents employment rates and ATTs for *retraining* participants and their matched controls. We find that retraining entails strong lock-in effects. One year after the program start, participants have over 28 percentage points lower employment rates than similar non-participants. Correspondingly, the ATTs stay negative during the first three years – the common duration for elderly care retraining – after the treatment start. After the lock-in period, participants' employment rates increase sharply, and we find strong effects of up to 32 percentage points. Eleven years after the treatment start, the ATT still amounts to approximately 23 percentage points.

Figure 2b presents employment rates and ATTs for *further training* participants and their matched controls. In addition to overall lower ATTs, the most striking difference to the results for retraining is a much shorter and weaker lock-in effect. Only during the first four months after the treatment start do participants in further training have slightly lower employment rates than their matched non-participants. After the lock-in period, the treatment effects add up to 23 percentage points and remain at approximately 20 percentage points until 11.5 years after the treatment start.

As the employment rate in the control group is lower in the case of further training in the longer term, relative gains are more pronounced for further training than for retraining. Ten years after the treatment start, the employment stability increases by 54 percent for retraining participants and by 63 percent for further training participants.

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6 To check the matching quality, we conduct t-tests for equal mean values of all covariates between the treated and control group after matching. The results show that only in very rare cases do significant differences remain between the treatment group and the matched control group. Moreover, balancing tests show that in most cases, we achieve a substantial reduction of the mean standardized bias. The results are available from the authors upon request.

7 To check for differences in the results across years, we also conducted more detailed analyses by the year of treatment start (2003-2005, 2006-2008, 2009-2012, and 2013-2015) for UI workers. These results are available on request. The overall patterns for retraining and further training remain stable over time, but employment and wage effects are slightly larger for early participants in the years 2003-2005. This might be attributable to a changing composition of participants.

Figure 3 shows that approximately 70 (50) percent of UI workers in retraining (further training) are employed in a care profession in the long term. The remaining participants end up in employment in other occupational fields. Thus, even though both kinds of training have strong positive effects, retraining brings more unemployed workers into caregiving.

[Figure 3 about here.]

Figure 2 also illustrates the corresponding wage effects of retraining and further training. Wages are measured unconditionally on employment. This implies that we assume wages of 0 if workers are non-employed. We find that the estimated effects on daily wages appear similar to those on employment. After a pronounced lock-in period, retraining participants realize higher daily wages of up to 21 Euros than their matched controls. Further training participants realize wage gains of up to 14 Euros per day. Expressed as relative gains, due to a weaker control group for further training, the unconditional wage effects of retraining and further training are 76 percent and 72 percent more similar.

Two channels of training can drive unconditional wages. First, as we already showed, training participation can impact the probability of finding a job. Second, training participation can also impact the quality of a job. To unravel whether training also affects job quality, Table 2 presents the ATTs on conditional daily wages as well as unconditional daily wages. When analyzing conditional wage effects, we must take into account that, in addition to selection into treatment, there is also selection into employment. Wages are observed only for people who actually take a job, and employment itself is affected by treatment. In such a case, several authors propose estimating bounds for the treatment effects for specific subgroups of the population (e.g., Zhang et al. 2008, Lee 2009, Lechner and Melly 2010, Blanco et al. 2013).

Flores and Flores-Lagunes (2009) suggest estimating a net average treatment effect for a subpopulation for which the treatment does not affect the mechanism variable (in our case employment). Given very similar propensity scores and the same employment status, we can assume that adequately matched treated workers would also have been employed without the treatment. We compare the wages of treated and matched controls who are both employed at a given point in time. For retraining, we find positive effects of up to 11 Euros on conditional wages for the subpopulation of people who take up employment and whose employment probability is not affected by training, compared to up to 21 Euros on unconditional wages. This proves that treatment indeed affects both the probability of finding a job and job quality up to twelve years after the treatment. By contrast, participants in further training do not find better-paid jobs than non-participants – although they are more likely to find a job–in the long term.

[Table 2 about here.]

4.1.2 Unemployed workers in welfare

For training participants in the welfare benefits system, who are often long-term unemployed, hard to place, and overall loosely attached to the labor market, the observation period starts in 2005.

[Figure 4 about here.]

For retraining participants, the lock-in effects are much smaller than for participants in the UI system due to a weaker comparison group with lower employment rates before and after the treatment start (Figure 4a). Therefore, the ATTs already become positive two years after the treatment start and reach a maximum of almost 37 percentage points after 51 months. After nine years, the effect still amounts to 22 percentage points.

Figure 4b shows that participants in the welfare system also benefit from further training—less in absolute terms but even more so relative to control workers' baseline employment rates. As for workers in UI, the treatment effects are positive and significant until the end of the observation period, with a maximum of almost 13 percentage points after four years that slowly drops to 11 percentage points by the end of the observation period. Ten years after the treatment start, the relative employment effect of further training is 53 percent, compared to 47 percent for retraining. Like workers in UI, approximately 70 (50) percent of workers in welfare find jobs in elderly care in the long term, as Figure 3 shows.

Regarding the unconditional wages of workers in retraining and further training (Figures 4a and 4b), ATTs for workers in welfare are generally lower than those for workers in UI. For retraining, ATTs reach a maximum of 23 Euros per day 51 months after the treatment start and become somewhat lower in the long term, similar to employment. For further training, unconditional wage effects vary between approximately 3 and 7 Euros. Again, in relative terms, the difference between retraining and further training is less pronounced. After ten years, the unconditional wages of retraining participants increase by 65 percent and the wages of further training participants by 45 percent. As we showed above for further training participants in UI, unconditional wage improvements reflect not necessarily higher daily wages for employed participants but higher employment shares for the treated. Table 2 reveals that this is also true for participants in welfare. Again, there are no conditional wage gains for further training participants. In contrast to retraining participants in UI, retraining participants in welfare also do not find better-paid jobs than comparable non-participants in the longer term.

A thorough interpretation must take into account, however, that the data provide information about daily wages, not hourly wages. As part-time employees work fewer hours per day, their daily wages are by construction lower than those of full-time workers. Thus, differing percentages in part-time and full-time employment between the treatment and control groups potentially explain the lack of wage improvements. To explore this, we focus on the roles of part-time and full-time employment in the next section.

4.2 Part-time and full-time work

Part-time employment in the elderly care sector is common in many OECD countries (Colombo et al. 2011a). This is true for Germany, where more than half of all elderly care workers work part-time (Bundesagentur für Arbeit 2015). In this section, we split employment into part-time and full-time employment and estimate the corresponding effects.

Table 3 and 4 show that unemployed workers treated in elderly care re-enter employment in about half of all cases through part-time work. We attribute almost two-thirds of UI workers' total treatment effects for retraining and further training to part-time employment. For unemployed workers in welfare, part-time employment explains 50 percent of the ATT for retraining and 75 percent for further training. Figure A.2 in the Appendix reveals, furthermore, that employment rates and ATTs in part-time and full-time work remain relatively stable over time for unemployed workers in UI. There is no indication that the employment effects are initially driven by increased part-time work and later by increased full-time work. Only for further training do the full-time effects slightly increase and the part-time effects slightly decrease after seven years. Thus, for further training, there might be a small long-term stepping-stone effect into full-time employment. By contrast, for retraining, we can rule out part-time work in the elderly care sector serving as a stepping-stone into full-time employment for unemployed workers.[8]

[Table 3 and Table 4 about here.]

What we do not know is whether part-time work is voluntary – e.g., due to preferences for flexible working hours – or involuntary. If people preferred full-time jobs to part-time jobs, we could interpret part-time work as another indicator of adverse working conditions in the elderly care sector, in addition to low hourly wages (Statistisches Bundesamt 2016).

Figure 5 presents the full-time unconditional wage results for participants in the UI and welfare regime.[9] The results closely resemble the combined wage effects shown in Table 2, where the effects are stronger for retraining participants.

[Figure 5 about here.]

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[8] Results for welfare workers are qualitatively similar (yet there is no indication that there is a stepping-stone effect for further retraining) and are available upon request.

[9] As we do not have any information on the exact number of working hours, and as part-time working hours vary much more than full-time working hours, we concentrate on daily wages for full-time employment. Moreover, due to the relatively small sample size, we do not report conditional wage results for full-time employment.

4.3 Heterogeneity by gender

Constituting 87 percent of this industry's workforce in 2013, women dominate elderly care work in Germany (Bundesagentur für Arbeit 2015). This is comparable to other OECD countries (Colombo et al., 2011a). Thus, at approximately 18 percent of elderly care training participants, men are overrepresented in our sample. While many studies on the effects of subsidized training have reported clear differences by gender (e.g., Biewen et al. 2014, Bergemann and van den Berg 2008), other studies have found differing returns to work for men and women depending on whether the occupation is more "male" or "female" (e.g., Blau et al 2012, Busch and Holst 2011, Hegewisch and Hartmann 2014). To contribute to these strands of literature, we discuss ATT differences between men and women in this section.

In both the UI and the welfare system, women benefit more from retraining than men. In both cases, female participants have an employment rate of up to 34 to 38 percentage points, whereas the maximum for male participants is approximately 27 to 32 percentage points (see Figures 6 and 7). Ten years after the treatment start, the ATTs for employment are 21 percentage points for women and 18 percentage points for men in UI. For welfare recipients, the effects are lower, with 15 percentage points for women and 10 percentage points for men. For further training, the employment effects for UI workers are in the long term quite similar to those for retraining, albeit with larger gains for men. Further training effects for workers in the welfare system are substantially smaller than for retraining but are relatively similar for men and women.

[Figure 6 and Figure 7 about here.]

Estimates of the wage effects by gender (Figures 8 and 9) show similar patterns: in the UI and welfare system, women in retraining realize higher wage gains and profit significantly more than men. The effects for UI men and women in further training differ more: in the first seven years, women profit more than men, but in the long term, the wage effects are larger for men than for women. For welfare participants, the long-term effects of further training are overall very similar for men and women.

[Figure 8 and Figure 9 about here.]

In sum, as in other studies on training, we find statistically significant gender differences in the effectiveness of retraining and further training in elderly care occupations. Generally, women profit more than men, except for UI participants in further training, among whom men have higher long-term effects on employment and wages than women. Our analyses also show that in the absence of occupational segregation, gender differences exist in the effectiveness of subsidized training programs. This is insightful, as some studies argue that gender differences regarding the choice of occupation are particularly likely to cause differences in the training effectiveness (Lechner et al. 2007, Osikominu 2013). As we restrict our analysis to one occupational group, i.e., elderly care, we rule out this driver.

4.4 The differential effects of further training and retraining

Our results suggest that participation in retraining is more beneficial than participation in further training. However, retraining participants and further training participants differ with respect to their characteristics (see Table A.5). Further training participants are, e.g., on average older and have lower levels of educational attainment, which indicate different selection mechanisms. Therefore, it is not necessarily true that people attending further training would have better employment prospects if they had participated in retraining. Accordingly, it must not be true that retraining participants would have worse employment prospects if they had participated in further training instead. Bearing in mind that retraining lasts at least 1 to 2 years longer and is more expensive than further training, a direct comparison of participants' outcomes in both types of training can provide additional important insights. Therefore, we now analyze whether participants in one or the other program would have performed differently had they chosen the alternative kind of training in the same month, conditional on previous unemployment duration.

Figure 10 shows the effects for participating in elderly care retraining instead of further training for retraining participants in the UI and welfare system. As retraining lasts on average almost three years and further training about six months, there are strong lock-in effects during the first three years after the program start. Afterwards, retraining participants in the UI regime benefit only a little in employment rates (and in the long term statistically insignificantly) compared to those in further training. Retraining participants in the welfare system, however, have a significantly higher employment probability after the lock-in period. Regarding unconditional wages, retraining participants earn significantly more than if they had participated in further training. Thus, compared to further training, participants in retraining in the UI system seem to profit in increased wages rather than increased employment stability, while retraining participants in welfare profit in both regards.

[Figure 10 about here.]

Figure 11 presents the results of the opposite scenario, the effect of further training instead of potential retraining participation for further training participants. During the first three years, further training generates more beneficial effects than retraining due to the lock-in period. Afterwards, however, further training participants would profit more had they participated in retraining. The negative employment effects of further training versus retraining become temporarily insignificant after six years, but the negative wage effects persist. Thus, participants in further training would have been better off had they been assigned to a retraining course.

[Figure 11 about here.]

To sum up, from a worker's perspective, retraining seems more beneficial than further training. For an overall assessment, however, it is important to keep in mind that the costs of retraining are much higher and that retraining participants are re-employed much later.

5 Conclusion

Due to aging societies, governments face challenges that are twofold. On the one hand, in future decades, the demand for formal care will increase. On the other hand, predictions suggest that labor force participation, and thus eventually the supply of elderly caregivers, will decrease. Previous evidence suggests that investments in the extension of formal care will potentially increase social welfare. A sufficient number of well-trained elderly caregivers improves the quality of formal care, mentally relieves caregiving relatives, and keeps informal caregivers attached to the labor force. Effectively training unemployed workers in elderly care increases the supply of qualified caregivers and reduces unemployment. In this paper, we therefore evaluate whether subsidized elderly care training puts unemployed workers into long-term elderly care employment.

We analyze data for Germany, where the elderly care professions are among the most important target occupations of publicly sponsored training. Germany is particularly strongly affected by demographic change, as it had the second-highest share of people older than 80 years in the OECD by 2015 (OECD 2013). Studying how Germany tries to meet the challenge through subsidized elderly care therefore provides important insights for countries that so far have predominantly relied on immigration to meet the demand for elderly caregiving.

Using rich administrative data, we analyze unemployed workers who enter subsidized retraining or subsidized further training in elderly care between 2003 and 2015. Unlike the majority of studies in the evaluation literature, we observe treatment effects over a long period (up to 11.5 years) and focus on an occupation in which the labor demand for skilled work is high and open positions cannot be filled (Bundesagentur für Arbeit 2016). This allows us to identify the pure supply-side effect of subsidized retraining, i.e., the extent to which the subsidy improves a worker's employability given that the labor demand absorbs all the supply.

In sum, both retraining and further training in elderly care are beneficial. Further training, which typically lasts only weeks or months, positively impacts participants' employment in the very short term. By contrast, retraining, which yields a vocational degree as a nurse for the elderly and lasts up to three years, entails a lock-in period of up to three years but leads to substantial long-lasting employment and wage effects afterwards. However, for the group of employed workers, we find only clear long-term wage gains – and thus an improvement in job quality – for retraining participants in UI. Distinguishing between full-time and part-time employment, we show, furthermore, that most workers leave unemployment for part-time employment, where they are likely to remain throughout the observation period. These results suggest that compared to remaining unemployed, participation in subsidized training increases the probability of becoming employed but does not necessarily improve the quality of employment. Furthermore, except for UI participants in further training, we find that women profit more from training in elderly care than men. Women realize higher effects absolutely and relatively.

Except for wages conditional on employment, we find, furthermore, that both kinds of training are relatively more effective for workers in UI: ten years after the treatment start, employment stability for retraining (further training) increases by 54 percent (63 percent) and unconditional wages by 76 percent (71 percent). For workers in welfare, these effects are smaller, with employment effects of approximately 47 percent (53 percent) for retraining (further training) and unconditional wage effects of approximately 65 percent (45 percent).

Finally, we directly compare the two types of training programs to evaluate whether participants in one program would have fared better in the other program and vice versa. First, we estimate the effect of retraining versus further training for retraining participants. Second, we estimate the effect of further training versus retraining for further training participants. We find that retraining participants are better off with their choice than with further training. By contrast, further training participants would more likely be employed and achieve higher wages if they had chosen retraining. Retraining brings about three-quarters and further training brings about half of all participants into elderly care employment, Thus, although retraining entails stronger and longer-lasting lock-in effects, the positive employment and wage effects in the long term exceed those of further training and make retraining more effective from a worker's point of view. From the government's perspective, retraining is more effective, as it brings a higher share of workers into elderly care employment and thus helps to close the gap in meeting the demand for formal caregivers.

In sum, we find that publicly sponsored training successfully integrates unemployed workers into the labor market and contributes to securing skilled labor in the German care sector. The positive employment effects are long-lasting, irrespective of the type of training and the trained group. Therefore, we conclude that the analyzed programs are one way to narrow the increasing gap in care demand and supply.

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Tables

Table 1
Number of training participants

	Women	Men	Further training	Retraining	Total
Welfare	31,860	7,827	33,485	6,202	39,687
UI	37,196	7,290	30,187	14,299	44,486
Total	69,056	15,117	63,672	20,501	84,173

Note: *Welfare* indicates unemployed workers in welfare and *UI* indicates unemployed workers in unemployment insurance.

Source: IEB V12.01.00 – 160927. Own calculations.

Table 2
Unconditional and conditional wage effects

Months after treatment start	ATT unconditional daily wages		ATT conditional daily wages	
	UI	Welfare	UI	Welfare
Retraining				
12	-14.52*	-3.81*	-9.15*	-14.58*
24	-14.54*	-3.29*	-8.41*	-11.35*
36	-9.31*	0.65*	-8.14*	-11.58*
48	18.94*	22.26*	3.50*	7.93*
60	19.85*	22.50*	4.87*	8.10*
72	19.81*	20.31*	5.32*	9.79*
84	20.54*	18.61*	7.68*	12.24*
96	20.79*	16.85*	8.64*	10.37
108	20.35*	16.58*	9.25*	-6.51
120	20.16*	11.86*	10.63*	-5.70
132	19.52*		11.61*	
144	15.22*		10.63*	
Further training				
12	4.57*	2.22*	-5.60*	-2.19
24	7.18*	4.38*	-5.38*	-0.62
36	6.81*	4.45*	-5.23*	-1.54
48	7.22*	5.02*	-5.77*	-2.09
60	7.16*	5.23*	-4.77*	-2.20
72	7.35*	5.21*	-5.99*	-0.86
84	7.63*	5.01*	4.01	0.77
96	10.95*	6.88*	-1.86	
108	10.78*	6.76*	-4.61	
120	11.82*	5.02*	-2.26	
132	12.87*		-6.40	
144	10.48*			

Note: * indicates significance at the 1% level. Because of small sample sizes we do not report results of further training on conditional wages for workers in UI in month 144 and workers in welfare in months 96, 108 and 120.

Source: IEB V12.01.00 – 160927. Own calculations.

Table 3
Employment shares and ATTs ten years after treatment start – unemployed workers in UI

	Employment shares	Treated	Controls	ATT
Retraining	**Total**	0.699	0.454	0.245*
	Of which are:			
	Part-time	0.354	0.207	0.147*
	≙ in percent of total employment	*50.6%*	*45.6%*	*60.0%*
	Fulltime	0.345	0.247	0.098*
	≙ in percent of total employment	*49.4%*	*54.4%*	*40.0%*
Further training	**Total**	0.511	0.314	0.197*
	Of which are:			
	Part-time	0.300	0.174	0.126*
	≙ in percent of total employment	*58.7%*	*55.4%*	*64.0%*
	Fulltime	0.211	0.141	0.070*
	≙ in percent of total employment	*41.3%*	*44.6%*	*36.0%*

Note: * indicates significance at the 1% level
Source: IEB V12.01.00 – 160927. Own calculations.

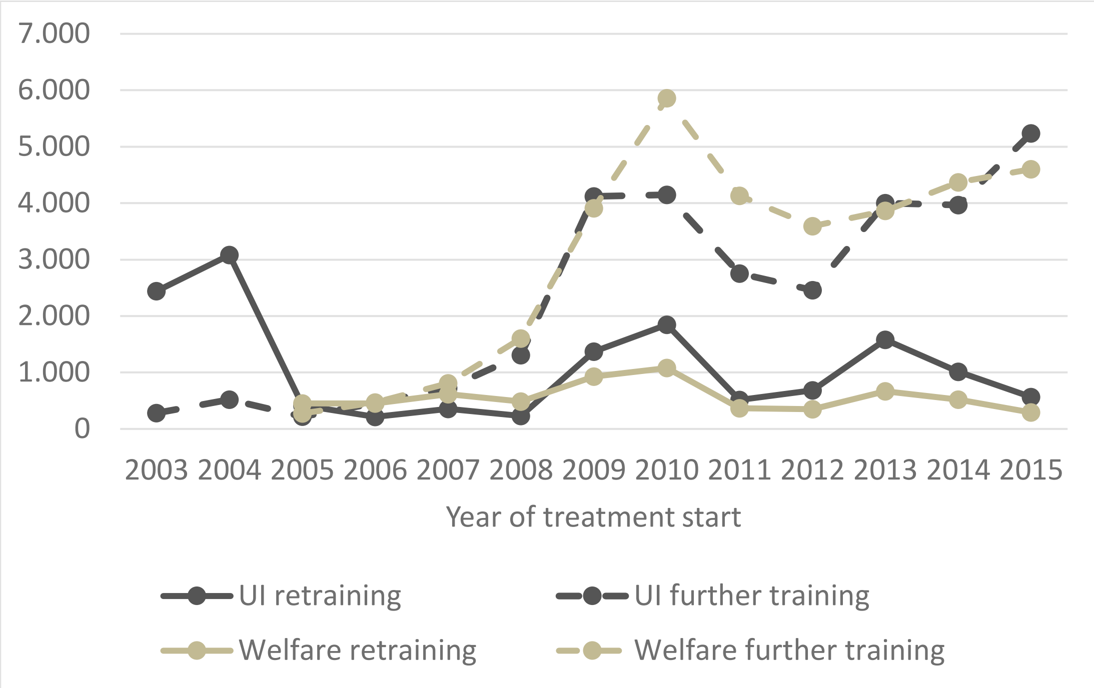
Table 4
Employment shares and ATTs ten years after treatment start – unemployed workers in welfare

	Employment shares	Treated	Controls	ATT
Retraining	**Total**	0.476	0.325	0.151*
	Of which are:			
	Part-time	0.238	0.160	0.078*
	≙ in percent of total employment	*50.0%*	*49.2%*	*51.7%*
	Fulltime	0.238	0.165	0.074*
	≙ in percent of total employment	*50.0%*	*51.8%*	*49.0%*
Further training	**Total**	0.320	0.209	0.111*
	Of which are:			
	Part-time	0.197	0.113	0.084*
	≙ in percent of total employment	*61.6%*	*54.1%*	*75.7%*
	Fulltime	0.122	0.095	0.027
	≙ in percent of total employment	*38.1%*	*45.5%*	*24.3%*

Note: * indicates significance at the 1% level. Source: IEB V12.01.00 – 160927. Own calculations.
Source: IEB V12.01.00 – 160927. Own calculations.

Figures

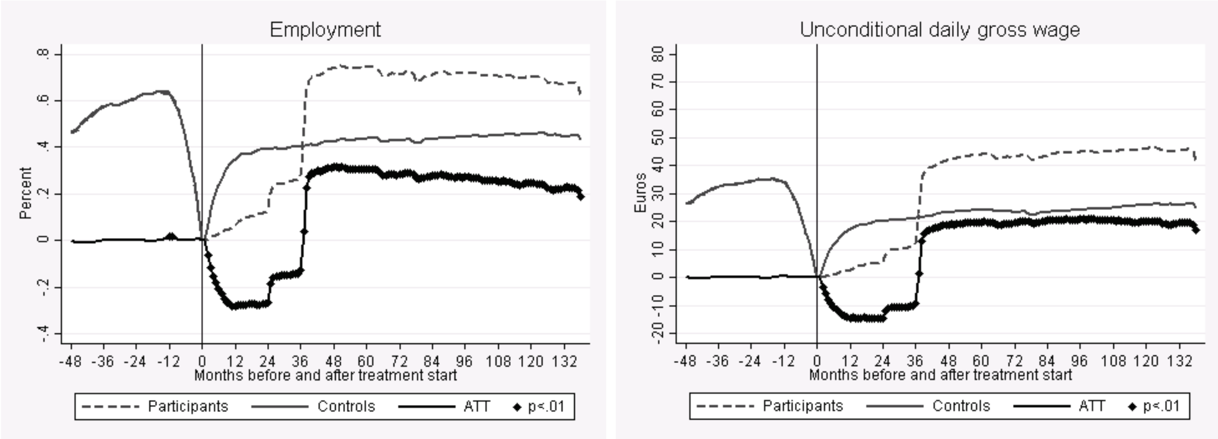
Figure 1
Inflow to subsidized elderly care training and further training by year of treatment start



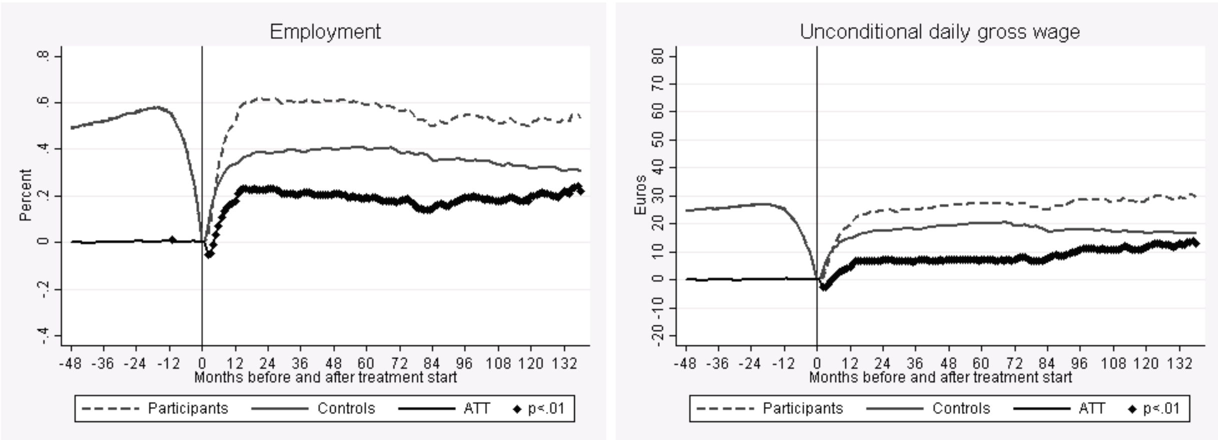
Source: IEB V12.01.00 – 160927. Own calculations.

Figure 2
Employment and wage effects of retraining and further training for workers in UI

a: Retraining



b: Further training

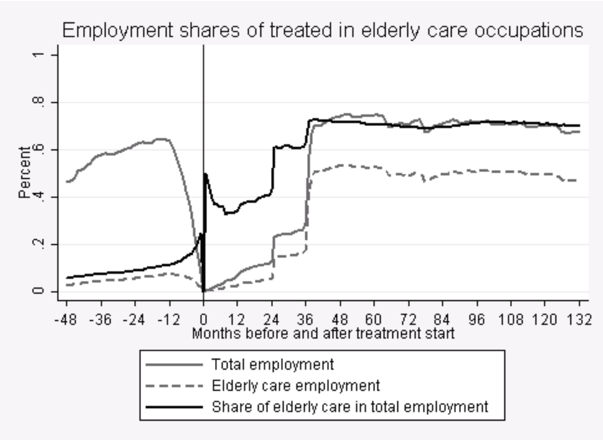


Source: IEB V12.01.00 – 160927. Own calculations.

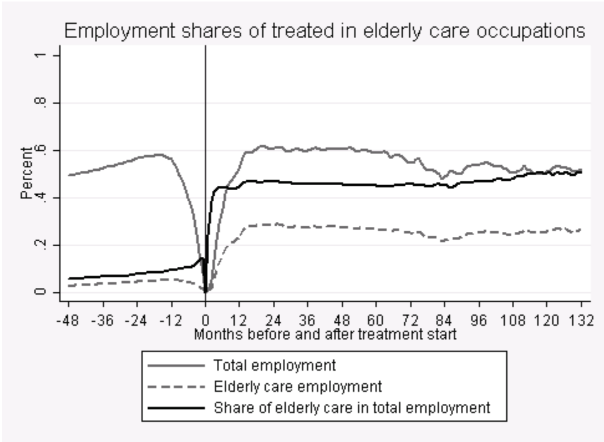
Figure 3
Employment shares of program participants in care occupations for unemployed workers in UI and welfare

UI workers

a: Retraining

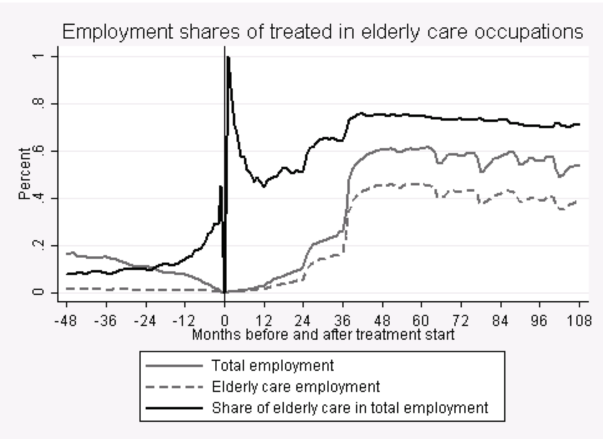


b: Further training

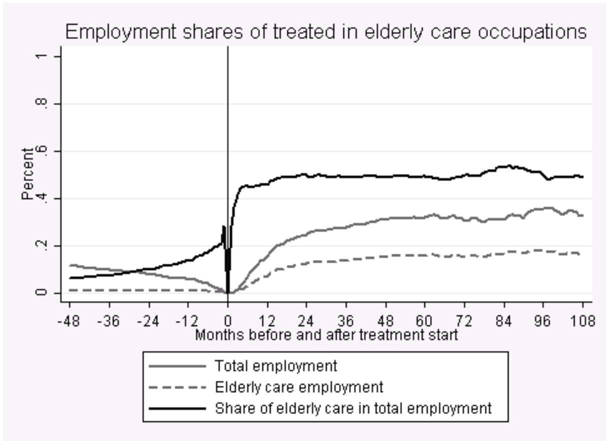


Welfare workers

c: Retraining



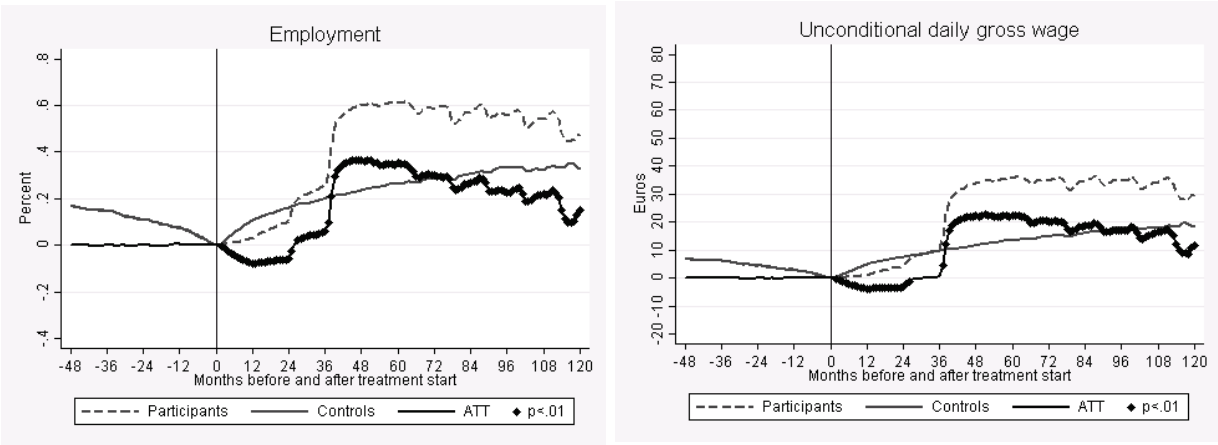
d: Further training



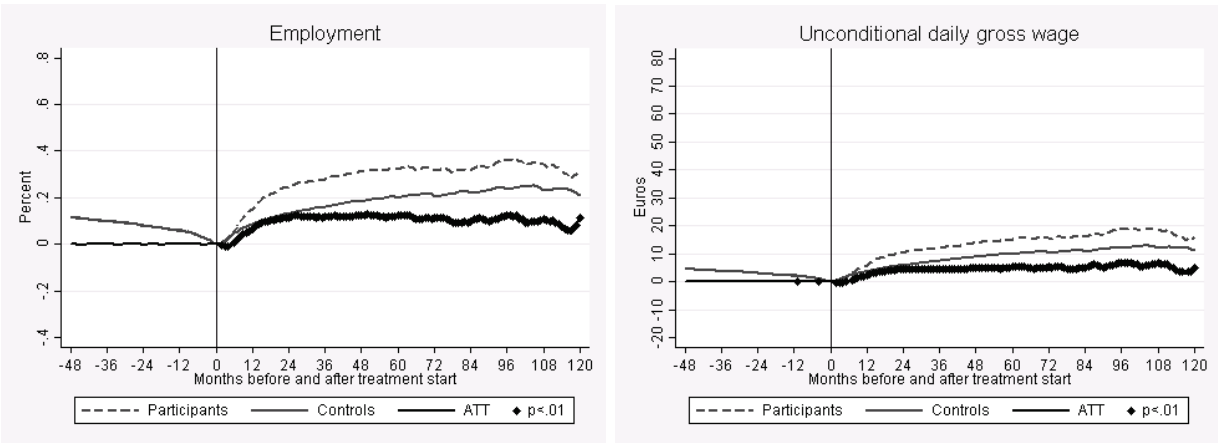
Source: IEB V12.01.00 – 160927. Own calculations.

Figure 4
Employment and wage effects of retraining and further training for workers in welfare

a: Retraining



b: Further training

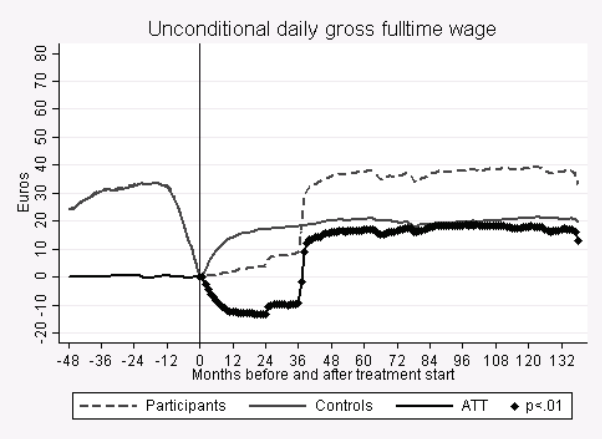


Source: IEB V12.01.00 – 160927. Own calculations

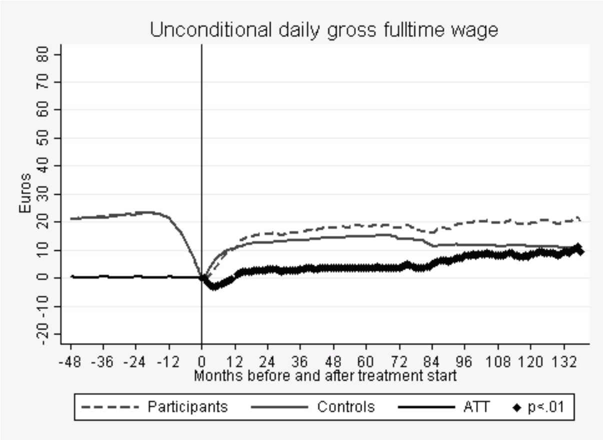
Figure 5
Unconditional wage effects for UI and welfare workers in fulltime employment

UI workers

a: UI retraining

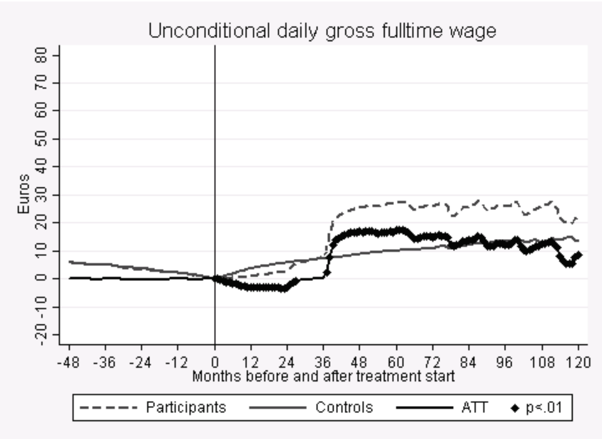


b: UI further training

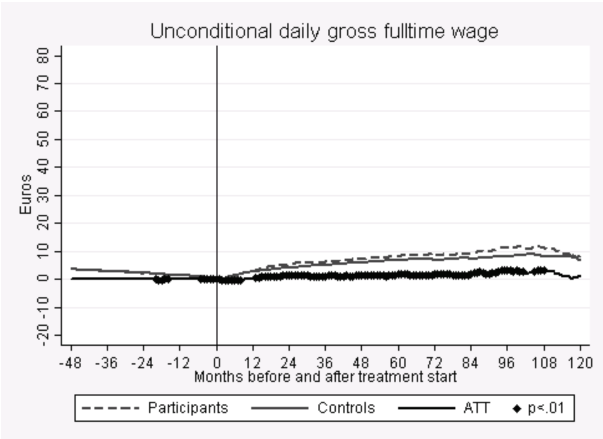


Welfare workers

c: Welfare retraining



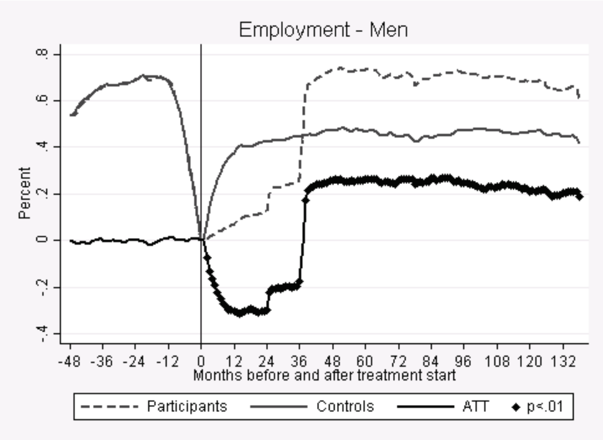
d: Welfare further training



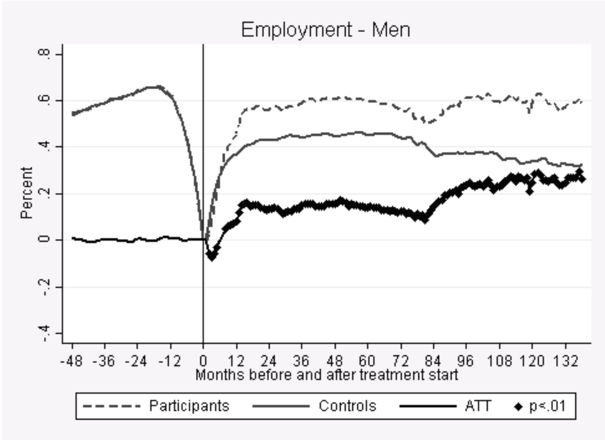
Source: IEB V12.01.00 – 160927. Own calculations.

Figure 6
Employment effects of retraining and further training by gender for UI workers

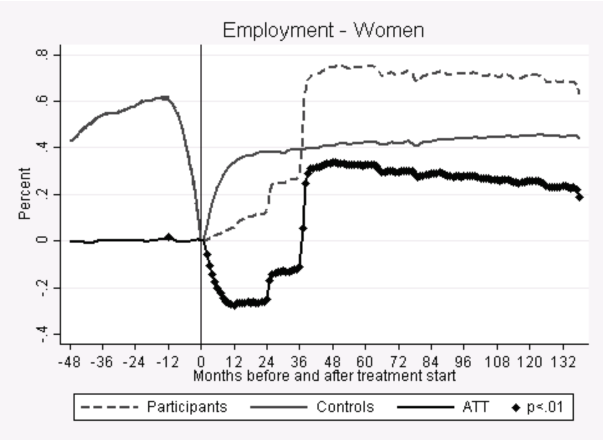
a: Retraining



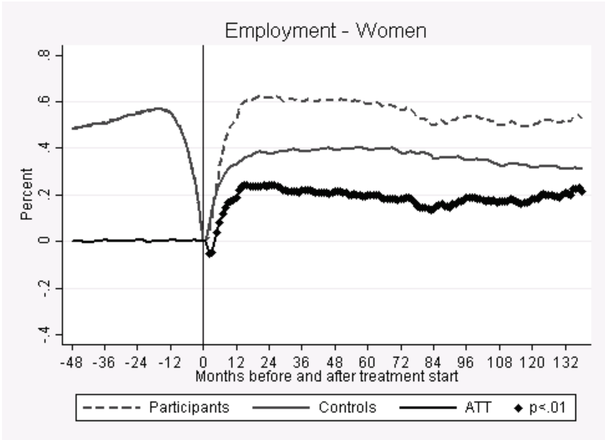
b: Further training



c: Retraining



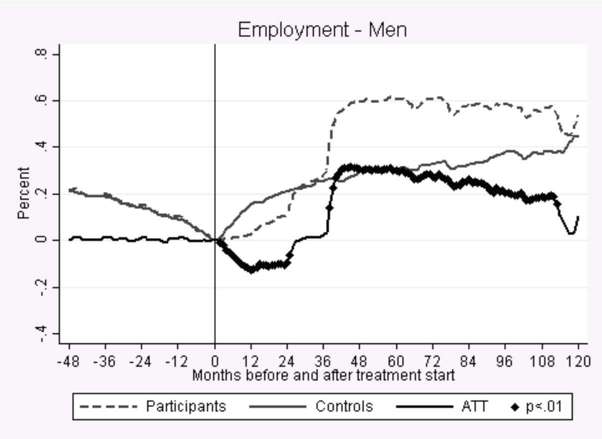
d: Further training



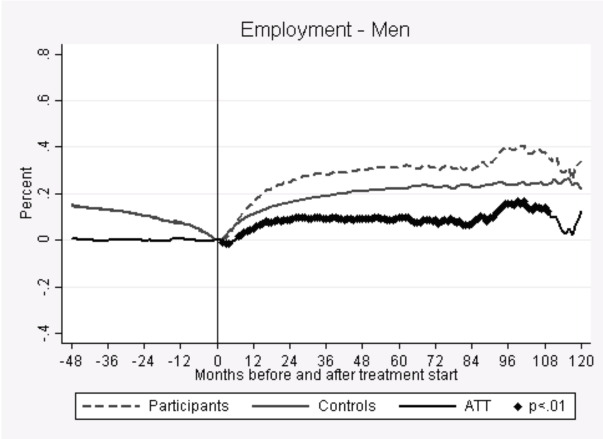
Source: IEB V12.01.00 – 160927. Own calculations

Figure 7
Employment effects of retraining and further training by gender for welfare workers

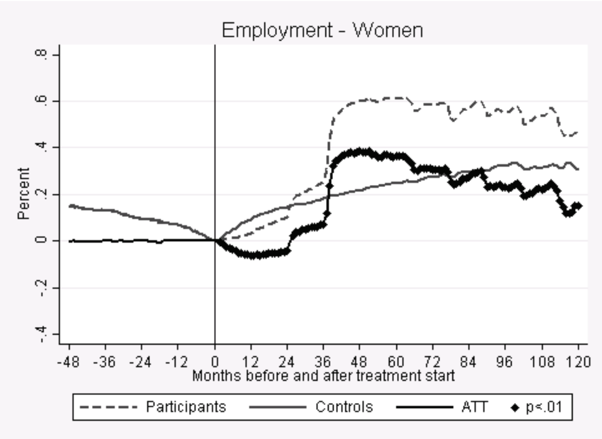
a: Retraining



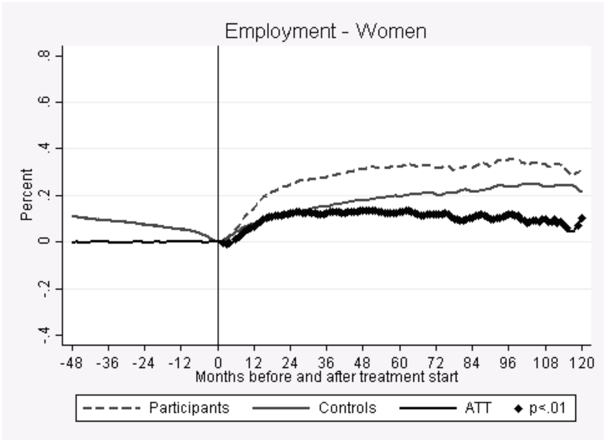
b: Further training



c: Retraining



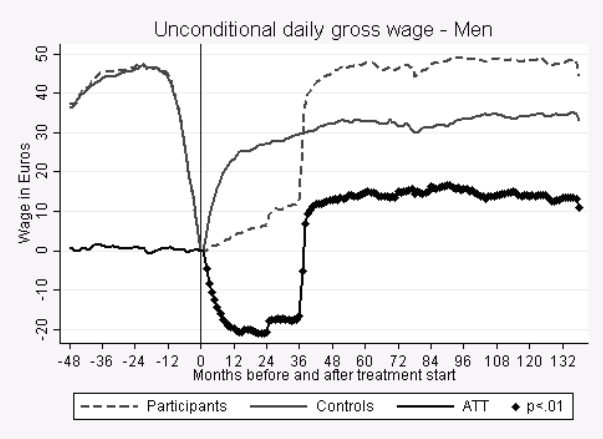
d: Further training



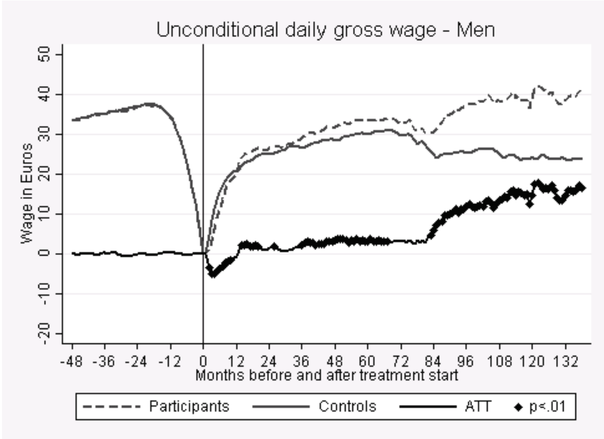
Source: IEB V12.01.00 – 160927. Own calculations.

Figure 8
Effects of retraining and further training on unconditional wages by gender for UI workers

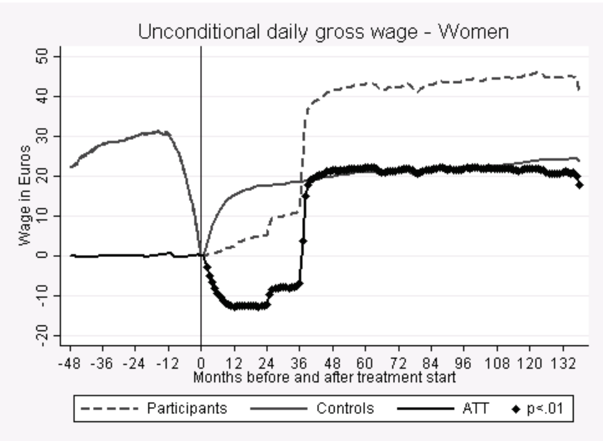
a: Retraining



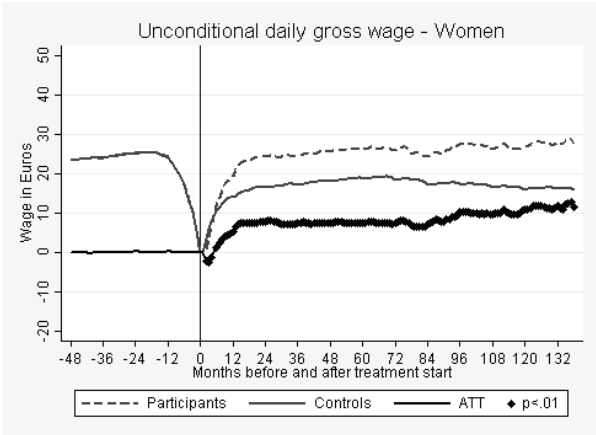
b: Further training



c: Retraining



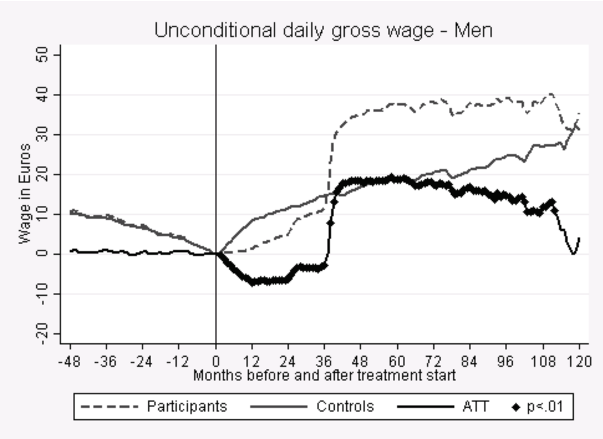
d: Further training



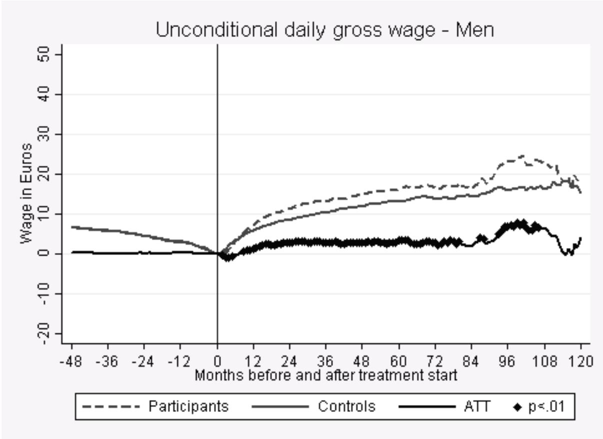
Source: IEB V12.01.00 – 160927. Own calculations.

Figure 9
Effects of retraining and further training on unconditional wages by gender for welfare workers

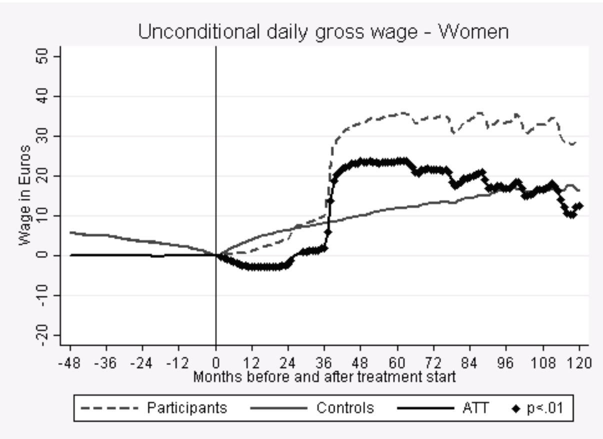
a: Retraining



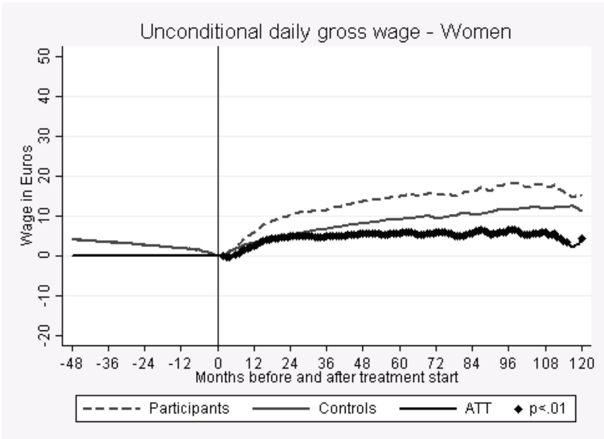
b: Further training



c: Retraining



d: Further training

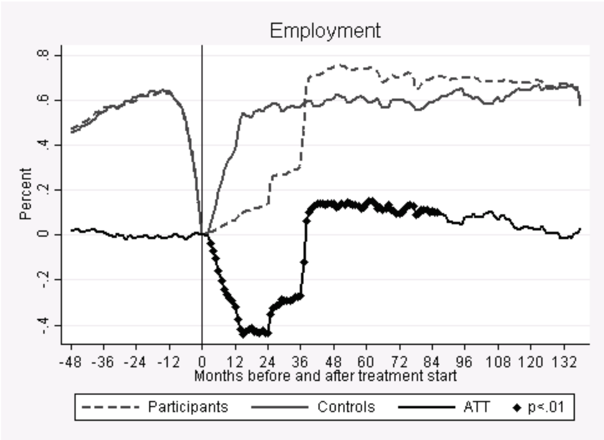


Source: IEB V12.01.00 – 160927. Own calculations.

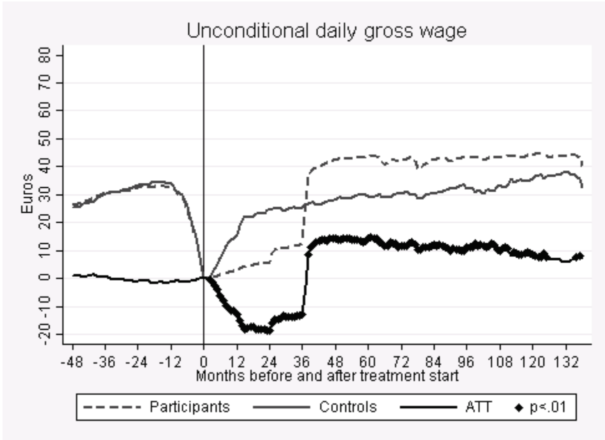
Figure 10
Effects of retraining versus further training on employment and wages for UI and welfare workers

UI workers

a: Employment

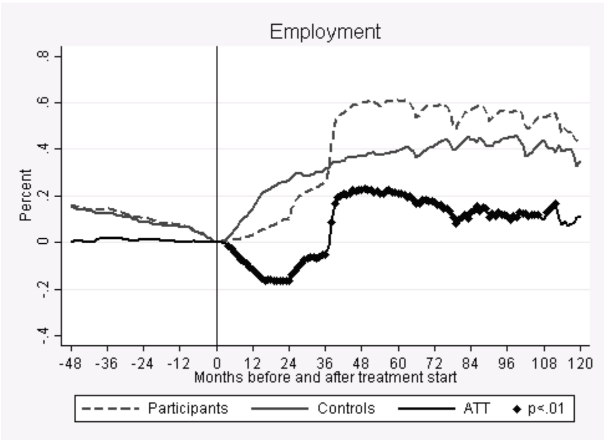


b: Wages

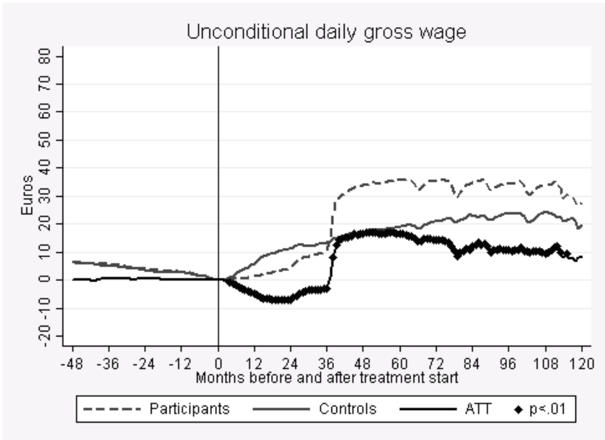


Welfare workers

c: Employment



d: Wages

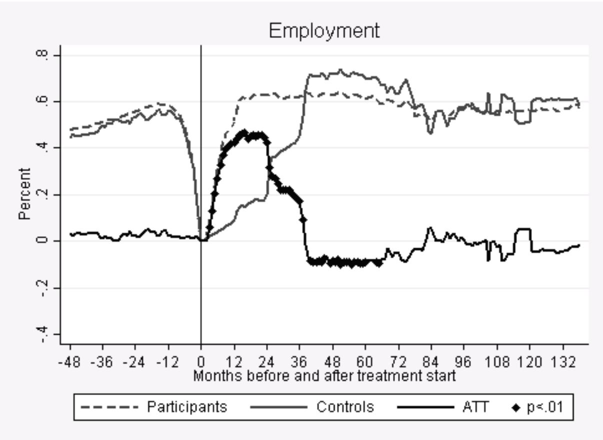


Source: IEB V12.01.00 – 160927. Own calculations.

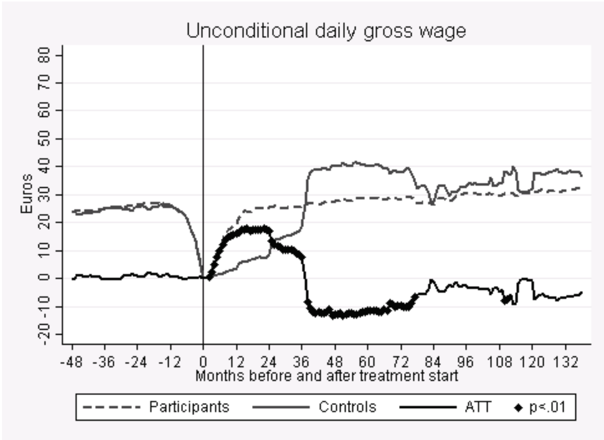
Figure 11
Effects of further training versus retraining on employment and wages for UI and welfare workers

UI workers

a: Employment

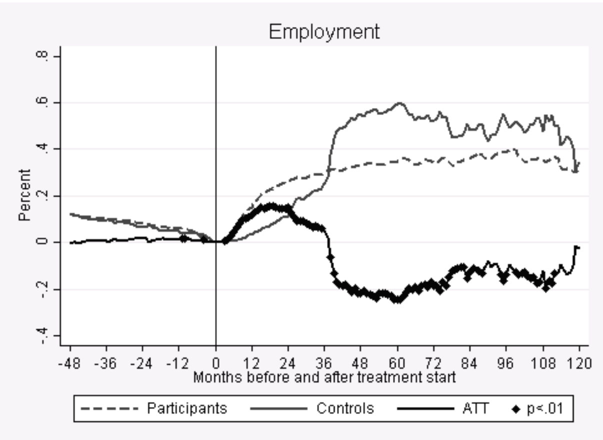


b: Wages

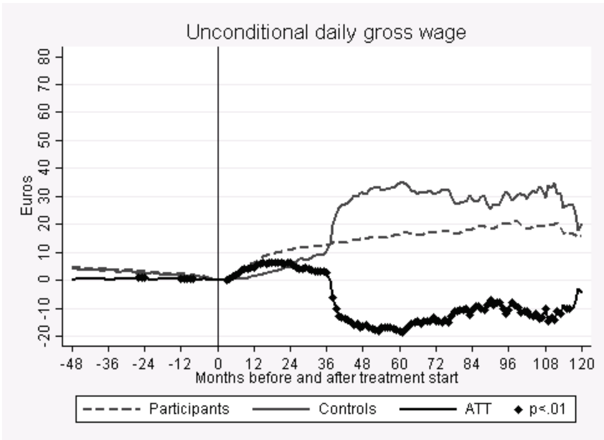


Welfare workers

c: Employment



d: Wages



Source: IEB V12.01.00 – 160927. Own calculations.

Appendix

Table A.1
Average sample statistics for UI workers before propensity score matching

Variable Names	treated	pot. com- parisons	dif	p-value
Men	0.16	0.26	-0.09	0.00
Age	41.43	39.28	2.14	0.00
Age squared	1814.02	1681.50	132.51	0.00
Foreign	0.07	0.11	-0.04	0.00
No vocational degree	0.20	0.21	-0.01	0.00
Vocational degree	0.66	0.58	0.08	0.00
A-levels	0.03	0.02	0.01	0.00
A-levels and vocational degree	0.06	0.08	-0.02	0.00
Technical college	0.02	0.04	-0.02	0.00
University	0.03	0.07	-0.04	0.00
No school degree	0.04	0.07	-0.04	0.00
Hauptschule	0.36	0.36	0.00	0.04
Mittlere Reife	0.47	0.36	0.11	0.00
Fachhochschulreife	0.05	0.08	-0.03	0.00
A-levels	0.08	0.13	-0.06	0.00
Child <15 years in household	0.38	0.29	0.09	0.00
Single	0.25	0.37	-0.12	0.00
Not married	0.10	0.09	0.01	0.00
Single parent	0.11	0.08	0.04	0.00
Married	0.54	0.47	0.07	0.00
Occupation missing	0.00	0.01	-0.01	0.00
Occupations in farming	0.00	0.00	0.00	0.00
Occupations in gardening and floristy	0.01	0.01	0.00	0.11
Occupations in mining and glass- and ceramic-making and -processing	0.01	0.02	-0.01	0.00
Occupations in plastic-, rubber, and wood-making and processing	0.00	0.00	0.00	1.00
Occupations in paper-making and -processing, printing technology	0.02	0.02	0.00	0.98
Occupations in metal-making and -working, metal constructing and welding	0.01	0.01	0.00	0.25
Occupations in machine- and automobile-building	0.02	0.03	0.00	0.00
Occupations in mechatronics and electrical engineering	0.03	0.03	0.00	0.00
Occupations in technical research and development	0.01	0.01	0.00	0.00
Occupations in textile- and leather-making	0.01	0.01	0.00	0.00
Occupations in production of foodstuffs	0.01	0.01	0.00	0.00
Occupations in architecture, construction supervision	0.04	0.04	0.00	0.00
Occupations in building construction and civil engineering	0.00	0.00	0.00	0.00
Occupations in interior construction	0.01	0.02	-0.01	0.00
Occupations in building services	0.01	0.02	-0.01	0.00
Occupations in mathematics, physics, biology, and chemistry	0.01	0.01	0.00	0.00

Variable Names	treated	pot. comparisons	dif	p-value
Occupations in geology, geography, and environmental protection	0.01	0.01	0.00	0.00
Occupations in computer science	0.00	0.00	0.00	0.00
Occupations in traffic and logistics	0.00	0.01	-0.01	0.00
Occupations in driver of vehicles	0.07	0.06	0.01	0.00
Occupations in security and personal protection	0.02	0.03	-0.01	0.00
Occupations in cleaning services	0.01	0.01	0.00	0.00
Occupations in purchasing, sales, and trading	0.06	0.05	0.01	0.00
Occupations in sales	0.01	0.02	-0.01	0.00
Occupations in tourism, hotels, and gastronomy	0.12	0.12	0.00	0.08
Occupations in management and business organisation	0.05	0.05	0.00	0.01
Occupations in insurance and financial services	0.10	0.15	-0.05	0.00
Occupations in legal services and public administration	0.01	0.03	-0.02	0.00
Occupations in nursing and medicine	0.01	0.02	-0.01	0.00
Occupations in non-medical care/nursing	0.07	0.05	0.01	0.00
Occupations in social work and housekeeping	0.14	0.03	0.11	0.00
Occupations in teaching	0.09	0.04	0.05	0.00
Occupations in humanities, social sciences, economics	0.01	0.02	-0.01	0.00
Occupations in marketing and public relations	0.00	0.00	0.00	0.00
Occupations in product design and art	0.02	0.02	0.00	0.00
Occupations in performance and entertaining	0.00	0.00	0.00	0.17
Occupations in armed forces	0.00	0.01	0.00	0.00
Details on last employer				
Wage at last employer	42.59	52.45	-9.86	0.00
Last position apprentice or no last employer	0.10	0.14	-0.04	0.00
Last position fulltime worker	0.54	0.62	-0.08	0.00
Last position part-time worker	0.36	0.24	0.12	0.00
Last firm age missing	0.16	0.15	0.01	0.00
Last firm age 0-5 years	0.20	0.20	0.00	0.10
Last firm age 6-15 years	0.29	0.29	0.00	0.25
Last firm age 16-30 years	0.22	0.23	-0.01	0.00
Last firm age >30 years	0.13	0.14	-0.01	0.00
Last firm size missing	0.16	0.15	0.01	0.00
Last firm size 1-10 workers	0.17	0.22	-0.05	0.00
Last firm size 11-50 workers	0.23	0.23	0.00	0.14
Last firm size 51-200 workers	0.26	0.21	0.05	0.00
Last firm size >200 workers	0.18	0.19	-0.01	0.00
Mean wage at last firm	56.58	63.35	-6.77	0.00
Last firm agriculture, hunting and forestry, fishing	0.01	0.02	-0.00	0.00
Last firm mining and quarrying,	0.00	0.00	-0.00	0.00
Last firm manufacturing	0.12	0.13	-0.01	0.00
Last firm electricity, gas and water supply	0.00	0.00	-0.00	0.00
Last firm construction	0.02	0.05	-0.03	0.00
Last firm trade, maintenance and repair of motor vehicles, motor	0.12	0.15	-0.03	0.00

Variable Names	treated	pot. com-parisons	dif	p-value
Last firm hotels and restaurants	0.04	0.05	-0.01	0.00
Last firm transport and communication	0.03	0.04	-0.01	0.00
Last firm financial intermediation	0.01	0.02	-0.01	0.00
Last firm real estate	0.01	0.01	-0.00	0.00
Last firm liberal professions	0.17	0.17	-0.00	0.73
Last firm public adminstration	0.04	0.07	-0.03	0.00
Last firm health and social work	0.22	0.10	0.12	0.00
Last firm non-industrial organizations	0.05	0.05	-0.01	0.00
Last firm sector missing	0.16	0.15	0.01	0.00
Details on labor market career prior to unemployment (UE)				
Employed prior to UE	0.54	0.59	-0.05	0.00
In education prior to UE	0.05	0.08	-0.04	0.00
In the labor force prior to UE	0.02	0.02	0.00	0.00
Not in the labor force prior to UE	0.20	0.25	-0.05	0.00
In ALMP prior to UE	0.20	0.06	0.14	0.00
Employment in prior 14 days (days)	6.25	6.84	-0.60	0.00
Employment in prior 29 days (days)	13.27	14.61	-1.34	0.00
Employment in prior 1 years (days)	199.08	195.55	3.53	0.00
Employment in prior 2 years (days)	413.40	400.53	12.87	0.00
Employment in prior 3 years (days)	611.99	600.81	11.18	0.00
Employment in prior 4 years (days)	790.44	781.34	9.10	0.00
Employment in prior 5 years (days)	948.34	934.49	13.85	0.00
Number of employment spells in 14 days	0.46	0.51	-0.04	0.00
Number of employment spells in 29 days	0.49	0.53	-0.04	0.00
Number of employment spells in 1 years	0.87	0.79	0.09	0.00
Number of employment spells in 2 years	1.12	1.04	0.09	0.00
Number of employment spells in 3 years	1.31	1.17	0.13	0.00
Number of employment spells in 4 years	1.45	1.27	0.18	0.00
Number of employment spells in 5 years	1.58	1.35	0.23	0.00
Tenure without interruptions in prior 14 days (days)	6.24	6.84	-0.60	0.00
Tenure without interruptions in prior 29 days (days)	13.22	14.57	-1.35	0.00
Tenure without interruptions in prior 1 years (days)	164.97	169.96	-4.99	0.00
Tenure without interruptions in prior 2 years (days)	283.99	294.10	-10.10	0.00
Tenure without interruptions in prior 3 years (days)	362.98	384.98	-22.00	0.00
Tenure without interruptions in prior 4 years (days)	418.90	449.19	-30.28	0.00
Tenure without interruptions in prior 5 years (days)	459.22	493.32	-34.10	0.00
Recalls in prior 1 years (yes/no)	0.04	0.04	0.00	0.11
Recalls in prior 2 years (yes/no)	0.08	0.10	-0.02	0.00
Recalls in prior 3 years (yes/no)	0.11	0.13	-0.02	0.00
Recalls in prior 4 years (yes/no)	0.13	0.15	-0.03	0.00
Recalls in prior 5 years (yes/no)	0.14	0.17	-0.03	0.00
Benefit receipt in prior 14 days (days)	2.83	1.22	1.61	0.00

Variable Names	treated	pot. comparisons	dif	p-value
Benefit receipt in prior 29 days (days)	5.87	2.55	3.32	0.00
Benefit receipt in prior 1 years (days)	49.09	32.79	16.30	0.00
Benefit receipt in prior 2 years (days)	72.63	58.12	14.51	0.00
Benefit receipt in prior 3 years (days)	95.56	81.29	14.27	0.00
Benefit receipt in prior 4 years (days)	116.31	102.10	14.21	0.00
Benefit receipt in prior 5 years (days)	134.80	119.08	15.72	0.00
Number of benefit periods in prior 14 days	0.22	0.11	0.11	0.00
Number of benefit periods in prior 29 days	0.24	0.12	0.11	0.00
Number of benefit periods in prior 1 years	0.45	0.32	0.14	0.00
Number of benefit periods in prior 2 years	0.64	0.50	0.14	0.00
Number of benefit periods in prior 3 years	0.80	0.66	0.14	0.00
Number of benefit periods in prior 4 years	0.94	0.80	0.14	0.00
Number of benefit periods in prior 5 years	1.05	0.91	0.15	0.00
Unemployed job search in prior 14 days (days)	0.19	0.06	0.12	0.00
Unemployed job search in prior 29 days (days)	1.88	0.61	1.27	0.00
Unemployed job search in prior 1 years (days)	52.34	40.54	11.80	0.00
Unemployed job search in prior 2 years (days)	93.10	89.09	4.01	0.00
Unemployed job search in prior 3 years (days)	138.57	138.87	-0.30	0.77
Unemployed job search in prior 4 years (days)	185.75	186.94	-1.19	0.36
Unemployed job search in prior 5 years (days)	231.40	228.58	2.81	0.07
Number of unemployed job search periods in prior 14 days	0.07	0.02	0.05	0.00
Number of unemployed job search periods in prior 29 days	0.17	0.06	0.11	0.00
Number of unemployed job search periods in prior 1 years	0.58	0.39	0.19	0.00
Number of unemployed job search periods in prior 2 years	0.89	0.68	0.21	0.00
Number of unemployed job search periods in prior 3 years	1.20	0.96	0.25	0.00
Number of unemployed job search periods in prior 4 years	1.48	1.20	0.28	0.00
Number of unemployed job search periods in prior 5 years	1.73	1.39	0.33	0.00
Average daily unconditional wage in prior 14 days (wage=0 w/o BeH)	20.60	29.86	-9.25	0.00
Average daily unconditional wage in prior 29 days (wage=0 w/o BeH)	21.07	30.58	-9.52	0.00
Average daily unconditional wage in prior 1 years (wage=0 w/o BeH)	25.89	32.72	-6.83	0.00
Average daily unconditional wage in prior 2 years (wage=0 w/o BeH)	27.58	34.07	-6.49	0.00
Average daily unconditional wage in prior 3 years (wage=0 w/o BeH)	27.66	34.43	-6.77	0.00
Average daily unconditional wage in prior 4 years (wage=0 w/o BeH)	27.11	33.96	-6.85	0.00
Average daily unconditional wage in prior 5 years (wage=0 w/o BeH)	26.27	32.88	-6.60	0.00
Average daily benefits in prior 14 days	5.09	2.67	2.42	0.00
Average daily benefits in prior 29 days	5.42	2.96	2.46	0.00
Average daily benefits in prior 1 years	8.67	6.62	2.06	0.00
Average daily benefits in prior 2 years	10.50	8.89	1.61	0.00
Average daily benefits in prior 3 years	11.59	10.37	1.22	0.00

Variable Names	treated	pot. comparisons	dif	p-value
Average daily benefits in prior 4 years	12.22	11.23	0.99	0.00
Average daily benefits in prior 5 years	12.70	11.81	0.89	0.00
Welfare in prior 14 days (days)	0.30	0.46	-0.16	0.00
Welfare in prior 29 days (days)	0.64	0.91	-0.27	0.00
Welfare in prior 1 years (days)	12.33	16.64	-4.31	0.00
Welfare in prior 2 years (days)	35.90	43.53	-7.62	0.00
Welfare in prior 3 years (days)	69.26	75.78	-6.52	0.00
Welfare in prior 4 years (days)	107.19	109.14	-1.95	0.13
Welfare in prior 5 years (days)	145.10	138.75	6.35	0.00
Number of welfare spells in 14 days	0.02	0.04	-0.02	0.00
Number of welfare spells in 29 days	0.03	0.04	-0.02	0.00
Number of welfare spells in 1 years	0.09	0.12	-0.03	0.00
Number of welfare spells in 2 years	0.19	0.22	-0.02	0.00
Number of welfare spells in 3 years	0.29	0.31	-0.01	0.00
Number of welfare spells in 4 years	0.39	0.39	0.00	0.51
Number of welfare spells in 5 years	0.48	0.46	0.02	0.00
Local employment offices (188 dummies)	YES			
Year-month of UE start (156 dummies)	YES			
N	44,486	3,650,779		

Source: IEB V12.01.00 – 160927. Own calculations.

Table A.2
Average sample statistics for welfare workers before propensity score matching

Variable Names	treated	pot. comparisons	dif	p-value
Men	0.20	0.26	-0.06	0.00
Age	37.57	38.64	-1.06	0.00
Age squared	1509.00	1616.02	-107.02	0.00
Foreign	0.11	0.20	-0.09	0.00
No vocational degree	0.38	0.45	-0.06	0.00
Vocational degree	0.51	0.43	0.08	0.00
A-levels	0.03	0.03	0.00	0.81
A-levels and vocational degree	0.04	0.04	0.00	0.00
Technical college	0.01	0.02	-0.01	0.00
University	0.02	0.04	-0.01	0.00
No school degree	0.11	0.22	-0.11	0.00
Hauptschule	0.45	0.41	0.04	0.00
Mittlere Reife	0.35	0.26	0.09	0.00
Fachhochschulreife	0.03	0.04	-0.01	0.00
A-levels	0.06	0.07	-0.01	0.00
Child <15 years in household	0.49	0.35	0.15	0.00
Single	0.35	0.37	-0.02	0.00
Not married	0.13	0.12	0.01	0.00
Single parent	0.30	0.18	0.12	0.00
Married	0.23	0.33	-0.11	0.00

Variable Names	treated	pot. comparisons	dif	p-value
Occupation missing	0.02	0.06	-0.04	0.00
Occupations in farming	0.00	0.00	0.00	0.64
Occupations in gardening and floristy	0.01	0.01	0.00	0.00
Occupations in mining and glass- and ceramic-making and -processing	0.02	0.02	-0.01	0.00
Occupations in plastic-, rubber, and wood-making and processing	0.00	0.00	0.00	0.03
Occupations in paper-making and -processing, printing technology	0.01	0.01	0.00	0.00
Occupations in metal-making and -working, metal constructing and welding	0.01	0.01	0.00	0.64
Occupations in machine- and automobile-building	0.02	0.02	-0.01	0.00
Occupations in mechatronics and electrical engineering	0.01	0.02	0.00	0.00
Occupations in technical research and development	0.01	0.01	0.00	0.00
Occupations in textile- and leather-making	0.00	0.01	0.00	0.04
Occupations in production of foodstuffs	0.01	0.01	0.00	0.00
Occupations in architecture, construction supervision	0.06	0.06	0.00	0.02
Occupations in building construction and civil engineering	0.00	0.00	0.00	0.00
Occupations in interior construction	0.01	0.03	-0.02	0.00
Occupations in building services	0.01	0.02	-0.01	0.00
Occupations in mathematics, physics, biology, and chemistry	0.01	0.01	0.00	0.00
Occupations in geology, geography, and environmental protection	0.00	0.00	0.00	0.21
Occupations in computer science	0.00	0.00	0.00	0.51
Occupations in traffic and logistics	0.00	0.00	0.00	0.00
Occupations in driver of vehicles	0.08	0.09	0.00	0.00
Occupations in security and personal protection	0.02	0.02	-0.01	0.00
Occupations in cleaning services	0.02	0.02	0.00	0.03
Occupations in purchasing, sales, and trading	0.11	0.13	-0.02	0.00
Occupations in sales	0.01	0.01	0.00	0.44
Occupations in tourism, hotels, and gastronomy	0.13	0.13	0.00	0.31
Occupations in management and business organisation	0.08	0.07	0.01	0.00
Occupations in insurance and financial services	0.07	0.07	-0.01	0.00
Occupations in legal services and public administration	0.01	0.01	0.00	0.00
Occupations in nursing and medicine	0.00	0.01	0.00	0.00
Occupations in non-medical care/nursing	0.04	0.02	0.02	0.00
Occupations in social work and housekeeping	0.10	0.03	0.07	0.00
Occupations in teaching	0.08	0.04	0.04	0.00
Occupations in humanities, social sciences, economics	0.01	0.01	0.00	0.00
Occupations in marketing and public relations	0.00	0.00	0.00	0.00
Occupations in product design and art	0.03	0.02	0.01	0.00
Occupations in performance and entertaining	0.00	0.00	0.00	0.12
Occupations in armed forces	0.00	0.00	0.00	0.00
Details on last employer				

Variable Names	treated	pot. com-parisons	dif	p-value
Wage at last employer	26.47	25.00	1.47	0.00
Last position apprentice or no last employer	0.33	0.40	-0.07	0.00
Last position fulltime worker	0.43	0.41	0.02	0.00
Last position part-time worker	0.24	0.18	0.05	0.00
Last firm age missing	0.29	0.38	-0.09	0.00
Last firm age 0-5 years	0.10	0.09	0.01	0.00
Last firm age 6-15 years	0.27	0.24	0.03	0.00
Last firm age 16-30 years	0.24	0.19	0.04	0.00
Last firm age >30 years	0.11	0.10	0.01	0.00
Last firm size missing	0.29	0.38	-0.09	0.00
Last firm size 1-10 workers	0.13	0.13	-0.01	0.00
Last firm size 11-50 workers	0.17	0.16	0.02	0.00
Last firm size 51-200 workers	0.23	0.18	0.05	0.00
Last firm size >200 workers	0.19	0.15	0.03	0.00
Mean wage at last firm	41.44	36.28	5.15	0.00
Last firm agriculture, hunting and forestry, fishing	0.01	0.02	0.00	0.00
Last firm mining and quarrying	0.00	0.00	0.00	0.03
Last firm manufacturing	0.05	0.06	0.00	0.00
Last firm electricity, gas and water supply	0.00	0.00	0.00	0.51
Last firm construction	0.02	0.03	-0.01	0.00
Last firm trade, maintenance and repair of motor vehicles	0.09	0.08	0.00	0.17
Last firm hotels and restaurants	0.06	0.05	0.00	0.00
Last firm transport and communication	0.02	0.02	0.00	0.02
Last firm financial intermediation	0.00	0.00	0.00	0.85
Last firm real estate	0.01	0.01	0.00	0.28
Last firm liberal professions	0.17	0.16	0.01	0.00
Last firm public adminstration	0.08	0.07	0.01	0.00
Last firm health and social work	0.13	0.06	0.07	0.00
Last firm non-industrial organizations	0.06	0.05	0.01	0.00
Last firm sector missing	0.29	0.38	-0.09	0.00
Details on labor market career prior to unemployment (UE)				
Employed prior to UE	0.34	0.25	0.08	0.00
In education prior to UE	0.04	0.08	-0.04	0.00
In the labor force prior to UE	0.02	0.07	-0.05	0.00
Not in the labor force prior to UE	0.25	0.46	-0.22	0.00
In ALMP prior to UE	0.36	0.13	0.23	0.00
Employment in prior 14 days (days)	0.51	0.61	-0.10	0.00
Employment in prior 29 days (days)	1.19	1.40	-0.21	0.00
Employment in prior 1 years (days)	19.67	19.32	0.35	0.26
Employment in prior 2 years (days)	48.20	43.24	4.96	0.00
Employment in prior 3 years (days)	85.23	75.48	9.75	0.00
Employment in prior 4 years (days)	129.04	115.96	13.08	0.00
Employment in prior 5 years (days)	180.51	163.78	16.73	0.00
Number of employment spells in 14 days	0.04	0.05	-0.01	0.00
Number of employment spells in 29 days	0.05	0.06	-0.01	0.00

Variable Names	treated	pot. com-parisons	dif	p-value
Number of employment spells in 1 years	0.18	0.15	0.02	0.00
Number of employment spells in 2 years	0.31	0.26	0.05	0.00
Number of employment spells in 3 years	0.45	0.37	0.08	0.00
Number of employment spells in 4 years	0.58	0.48	0.10	0.00
Number of employment spells in 5 years	0.72	0.59	0.13	0.00
Tenure without interruptions in prior 14 days (days)	0.51	0.61	-0.10	0.00
Tenure without interruptions in prior 29 days (days)	1.18	1.39	-0.21	0.00
Tenure without interruptions in prior 1 years (days)	17.19	16.90	0.28	0.32
Tenure without interruptions in prior 2 years (days)	36.11	32.28	3.83	0.00
Tenure without interruptions in prior 3 years (days)	55.25	49.21	6.04	0.00
Tenure without interruptions in prior 4 years (days)	74.73	67.93	6.81	0.00
Tenure without interruptions in prior 5 years (days)	95.24	87.70	7.54	0.00
Recalls in prior 1 years (yes/no)	0.00	0.01	0.00	0.03
Recalls in prior 2 years (yes/no)	0.02	0.02	0.00	0.19
Recalls in prior 3 years (yes/no)	0.03	0.03	0.00	0.92
Recalls in prior 4 years (yes/no)	0.04	0.04	0.00	0.37
Recalls in prior 5 years (yes/no)	0.04	0.05	0.00	0.17
Benefit receipt in prior 14 days (days)	0.46	0.20	0.26	0.00
Benefit receipt in prior 29 days (days)	0.99	0.44	0.55	0.00
Benefit receipt in prior 1 years (days)	16.59	10.82	5.77	0.00
Benefit receipt in prior 2 years (days)	35.54	26.39	9.15	0.00
Benefit receipt in prior 3 years (days)	52.61	41.57	11.03	0.00
Benefit receipt in prior 4 years (days)	70.21	57.33	12.88	0.00
Benefit receipt in prior 5 years (days)	88.18	73.82	14.36	0.00
Number of benefit periods in prior 14 days	0.04	0.02	0.02	0.00
Number of benefit periods in prior 29 days	0.04	0.02	0.02	0.00
Number of benefit periods in prior 1 years	0.13	0.09	0.04	0.00
Number of benefit periods in prior 2 years	0.23	0.17	0.06	0.00
Number of benefit periods in prior 3 years	0.32	0.25	0.07	0.00
Number of benefit periods in prior 4 years	0.42	0.34	0.08	0.00
Number of benefit periods in prior 5 years	0.52	0.43	0.09	0.00
Unemployed job search in prior 14 days (days)	0.18	0.09	0.09	0.00
Unemployed job search in prior 29 days (days)	1.87	0.90	0.97	0.00
Unemployed job search in prior 1 years (days)	124.55	101.59	22.96	0.00
Unemployed job search in prior 2 years (days)	270.85	241.82	29.03	0.00
Unemployed job search in prior 3 years (days)	405.10	374.55	30.55	0.00
Unemployed job search in prior 4 years (days)	537.08	505.06	32.02	0.00
Unemployed job search in prior 5 years (days)	662.67	627.49	35.18	0.00
Number of unemployed job search periods in prior 14 days	0.07	0.03	0.04	0.00
Number of unemployed job search periods in prior 29 days	0.19	0.08	0.11	0.00
Number of unemployed job search periods in prior 1 years	1.01	0.77	0.24	0.00

Variable Names	treated	pot. com-parisons	dif	p-value
Number of unemployed job search periods in prior 2 years	1.59	1.26	0.33	0.00
Number of unemployed job search periods in prior 3 years	2.10	1.69	0.41	0.00
Number of unemployed job search periods in prior 4 years	2.60	2.11	0.48	0.00
Number of unemployed job search periods in prior 5 years	3.04	2.48	0.56	0.00
Average daily unconditional wage in prior 14 days (wage=0 w/o BeH)	1.43	1.84	-0.41	0.00
Average daily unconditional wage in prior 29 days (wage=0 w/o BeH)	1.58	2.02	-0.44	0.00
Average daily unconditional wage in prior 1 years (wage=0 w/o BeH)	1.97	2.05	-0.08	0.02
Average daily unconditional wage in prior 2 years (wage=0 w/o BeH)	2.45	2.29	0.16	0.00
Average daily unconditional wage in prior 3 years (wage=0 w/o BeH)	2.95	2.73	0.23	0.00
Average daily unconditional wage in prior 4 years (wage=0 w/o BeH)	3.41	3.24	0.17	0.00
Average daily unconditional wage in prior 5 years (wage=0 w/o BeH)	3.86	3.73	0.13	0.02
Average daily benefits in prior 14 days	0.58	0.29	0.29	0.00
Average daily benefits in prior 29 days	0.65	0.35	0.30	0.00
Average daily benefits in prior 1 years	2.05	1.50	0.55	0.00
Average daily benefits in prior 2 years	3.21	2.55	0.66	0.00
Average daily benefits in prior 3 years	4.15	3.47	0.68	0.00
Average daily benefits in prior 4 years	5.07	4.42	0.65	0.00
Average daily benefits in prior 5 years	6.01	5.35	0.66	0.00
Welfare in prior 14 days (days)	12.70	11.10	1.60	0.00
Welfare in prior 29 days (days)	26.05	22.68	3.38	0.00
Welfare in prior 1 years (days)	305.40	274.06	31.34	0.00
Welfare in prior 2 years (days)	574.87	521.91	52.96	0.00
Welfare in prior 3 years (days)	818.54	745.99	72.55	0.00
Welfare in prior 4 years (days)	1038.85	947.14	91.72	0.00
Welfare in prior 5 years (days)	1230.24	1121.19	109.06	0.00
Number of welfare spells in 14 days	0.92	0.82	0.10	0.00
Number of welfare spells in 29 days	0.93	0.83	0.10	0.00
Number of welfare spells in 1 years	1.10	1.03	0.07	0.00
Number of welfare spells in 2 years	1.27	1.20	0.07	0.00
Number of welfare spells in 3 years	1.45	1.38	0.07	0.00
Number of welfare spells in 4 years	1.63	1.55	0.08	0.00
Number of welfare spells in 5 years	1.82	1.73	0.10	0.00
Local employment offices (176 dummies)	YES			
Year-month of UE start (156 dummies)	YES			
N	39,687	3,823,477		

Source: IEB V12.01.00 – 160927. Own calculations

Table A.3
Treatment characteristics for UI participants

	All	Women		Men	
		Retraining	Further training	Retraining	Further training
Enrollment length (days)	397	858	180	806	219
Duration from UE to enrollment (days)	100	99	99	105	102
UE duration (days)	555	971	354	945	418
Training successfully completed (percent)	90	86	92	83	89
Training drop out (percent)	10	14	8	17	11
Training examination failed (percent)	0	0	0	0	0
Prior to UE: employment (percent)	54	55	53	56	54
Prior to UE: education (percent)	5	9	3	8	5
Prior to UE: in the labor force (percent)	2	1	2	3	4
Prior to UE: not in the labor force (percent)	20	17	23	11	14
Prior to UE: ALMP (percent)	20	18	20	22	23
	44,485	10,522	26,673	3,776	3,514

Source: IEB V12.01.00 – 160927. Own calculations.

Table A.4
Treatment characteristics for welfare participants

	All	Women		Men	
		Retraining	Further training	Retraining	Further training
Enrollment length (days)	287	722	209	704	200
Duration from UE to enrollment (days)	113	105	115	103	114
UE duration (days)	715	963	666	949	688
Training successfully completed (percent)	87	79	90	74	87
Training drop out (percent)	12	20	10	26	13
Training examination failed (percent)	0	0	0	0	0
Prior to UE: employment (percent)	34	30	33	31	38
Prior to UE: education (percent)	4	8	4	9	4
Prior to UE: in the labor force (percent)	2	0	2	2	3
Prior to UE: not in the labor force (percent)	25	21	28	13	18
Prior to UE: ALMP (percent)	36	41	34	46	37
	39,687	4,663	27,197	1,539	6,288

Source: IEB V12.01.00 – 160927. Own calculations.

Table A.5
Average sample statistics for participants in retraining and further training before propensity score matching

	UI workers		Welfare workers	
Variable Names	retraining	further training	retraining	further training
Men	0.26	0.12	0.25	0.19
Age	37.20	43.43	33.63	38.30
Age squared	1451.02	1985.96	1190.01	1568.08
Foreign	0.05	0.08	0.09	0.11
No vocational degree	0.18	0.21	0.28	0.40
Vocational degree	0.68	0.65	0.57	0.50
A-levels	0.04	0.02	0.05	0.03
A-levels and vocational degree	0.06	0.06	0.06	0.04
Technical college	0.02	0.02	0.01	0.01
University	0.03	0.03	0.02	0.02
No school degree	0.02	0.05	0.04	0.12
Hauptschule	0.27	0.40	0.32	0.48
Mittlere Reife	0.57	0.42	0.53	0.32
Fachhochschulreife	0.05	0.05	0.05	0.03
A-levels	0.08	0.08	0.07	0.05
Child <15 years in household	0.48	0.33	0.54	0.49
Single	0.27	0.25	0.34	0.35
Not married	0.11	0.09	0.13	0.13
Single parent	0.14	0.10	0.30	0.30
Married	0.48	0.57	0.22	0.23
Occupation missing	0.00	0.00	0.01	0.02
Occupations in farming	0.00	0.00	0.00	0.00
Occupations in gardening and floristy	0.01	0.01	0.01	0.01
Occupations in mining and glass- and ceramic-making and -processing	0.01	0.01	0.01	0.02
Occupations in plastic-, rubber, and wood-making and processing	0.00	0.00	0.00	0.00
Occupations in paper-making and -processing, printing technology	0.02	0.01	0.01	0.01
Occupations in metal-making and -working, metal constructing and welding	0.01	0.01	0.01	0.01
Occupations in machine- and automobile-building	0.03	0.02	0.02	0.02
Occupations in mechatronics and electrical engineering	0.03	0.02	0.02	0.01
Occupations in technical research and development	0.01	0.01	0.01	0.01
Occupations in textile- and leather-making	0.01	0.01	0.01	0.00
Occupations in production of foodstuffs	0.01	0.01	0.01	0.01
Occupations in architecture, construction supervision	0.03	0.04	0.04	0.06
Occupations in building construction and civil engineering	0.00	0.00	0.00	0.00
Occupations in interior construction	0.02	0.00	0.02	0.01
Occupations in building services	0.01	0.00	0.01	0.01
Occupations in mathematics, physics, biology, and chemistry	0.01	0.01	0.01	0.01

Variable Names	UI workers retraining	UI workers further training	Welfare workers retraining	Welfare workers further training
Occupations in geology, geography, and environmental protection	0.01	0.01	0.00	0.00
Occupations in computer science	0.00	0.00	0.00	0.00
Occupations in traffic and logistics	0.00	0.00	0.01	0.00
Occupations in driver of vehicles	0.08	0.07	0.07	0.09
Occupations in security and personal protection	0.02	0.01	0.02	0.01
Occupations in cleaning services	0.01	0.01	0.02	0.02
Occupations in purchasing, sales, and trading	0.04	0.07	0.07	0.11
Occupations in sales	0.01	0.01	0.01	0.01
Occupations in tourism, hotels, and gastronomy	0.10	0.12	0.13	0.13
Occupations in management and business organisation	0.04	0.06	0.07	0.08
Occupations in insurance and financial services	0.08	0.10	0.06	0.07
Occupations in legal services and public administration	0.01	0.01	0.01	0.01
Occupations in nursing and medicine	0.01	0.01	0.00	0.00
Occupations in non-medical care/nursing	0.07	0.07	0.05	0.04
Occupations in social work and housekeeping	0.19	0.12	0.15	0.09
Occupations in teaching	0.07	0.10	0.08	0.08
Occupations in humanities, social sciences, economics	0.00	0.01	0.01	0.01
Occupations in marketing and public relations	0.00	0.00	0.00	0.00
Occupations in product design and art	0.03	0.02	0.03	0.02
Occupations in performance and entertaining	0.00	0.00	0.00	0.00
Occupations in armed forces	0.00	0.00	0.00	0.00
Details on last employer				
Wage at last employer	47.70	40.17	27.67	26.25
Last position apprentice or no last employer	0.09	0.10	0.33	0.34
Last position fulltime worker	0.64	0.50	0.46	0.42
Last position part-time worker	0.28	0.40	0.22	0.24
Last firm age missing	0.12	0.18	0.26	0.29
Last firm age 0-5 years	0.22	0.19	0.12	0.09
Last firm age 6-15 years	0.35	0.27	0.31	0.27
Last firm age 16-30 years	0.24	0.21	0.22	0.24
Last firm age >30 years	0.07	0.15	0.08	0.11
Last firm size missing	0.12	0.18	0.26	0.29
Last firm size 1-10 workers	0.16	0.17	0.14	0.12
Last firm size 11-50 workers	0.25	0.22	0.19	0.17
Last firm size 51-200 workers	0.27	0.25	0.23	0.22
Last firm size >200 workers	0.19	0.17	0.17	0.19
Mean wage at last firm	59.00	55.43	42.34	41.27
Last firm agriculture, hunting and forestry, fishing	0.01	0.01	0.02	0.01
Last firm mining and quarrying	0.00	0.00	0.00	0.00
Last firm manufacturing	0.14	0.11	0.06	0.05
Last firm electricity, gas and water supply	0.00	0.00	0.00	0.00

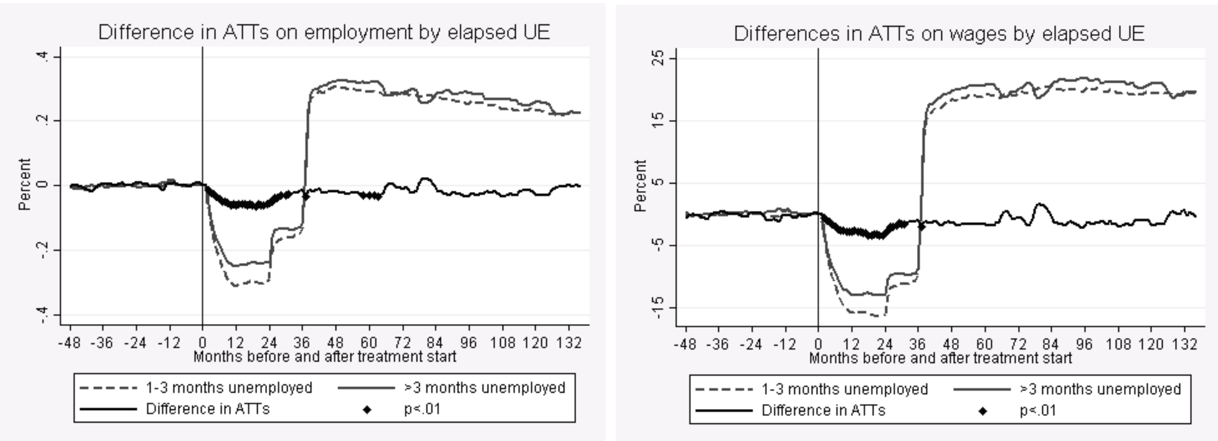
Variable Names	UI workers retraining	UI workers further training	Welfare workers retraining	Welfare workers further training
Last firm construction	0.03	0.01	0.02	0.02
Last firm trade, maintenance and repair of motor vehicles	0.11	0.13	0.09	0.08
Last firm hotels and restaurants	0.04	0.05	0.06	0.06
Last firm transport and communication	0.04	0.03	0.03	0.02
Last firm financial intermediation	0.01	0.01	0.00	0.00
Last firm real estate	0.01	0.01	0.01	0.01
Last firm liberal professions	0.16	0.17	0.17	0.17
Last firm public adminstration	0.04	0.04	0.08	0.09
Last firm health and social work	0.24	0.20	0.15	0.13
Last firm non-industrial organizations	0.05	0.05	0.06	0.06
Last firm sector missing	0.12	0.18	0.26	0.29
Details on labor market career prior to unemployment (UE)				
Employed prior to UE	0.56	0.53	0.34	0.34
In education prior to UE	0.09	0.03	0.04	0.04
In the labor force prior to UE	0.02	0.02	0.02	0.02
Not in the labor force prior to UE	0.15	0.22	0.26	0.26
In ALMP prior to UE	0.19	0.20	0.35	0.35
Employment in prior 14 days (days)	6.57	6.09	0.52	0.52
Employment in prior 29 days (days)	13.94	12.95	1.21	1.21
Employment in prior 1 years (days)	212.23	192.85	19.11	19.11
Employment in prior 2 years (days)	439.09	401.23	46.24	46.24
Employment in prior 3 years (days)	650.39	593.80	80.82	80.82
Employment in prior 4 years (days)	824.24	774.42	121.90	121.90
Employment in prior 5 years (days)	955.93	944.75	170.42	170.42
Number of employment spells in 14 days	0.49	0.45	0.04	0.04
Number of employment spells in 29 days	0.51	0.48	0.05	0.05
Number of employment spells in 1 years	0.90	0.86	0.17	0.17
Number of employment spells in 2 years	1.14	1.12	0.30	0.30
Number of employment spells in 3 years	1.28	1.32	0.43	0.43
Number of employment spells in 4 years	1.36	1.49	0.56	0.56
Number of employment spells in 5 years	1.45	1.64	0.69	0.69
Tenure without interruptions in prior 14 days (days)	6.56	6.09	0.52	0.52
Tenure without interruptions in prior 29 days (days)	13.89	12.90	1.20	1.20
Tenure without interruptions in prior 1 years (days)	179.16	158.25	16.65	16.65
Tenure without interruptions in prior 2 years (days)	308.01	272.62	34.53	34.53
Tenure without interruptions in prior 3 years (days)	391.56	349.44	52.51	52.51
Tenure without interruptions in prior 4 years (days)	445.83	406.15	70.83	70.83
Tenure without interruptions in prior 5 years (days)	478.34	450.17	90.51	90.51
Recalls in prior 1 years (yes/no)	0.03	0.04	0.00	0.00
Recalls in prior 2 years (yes/no)	0.07	0.09	0.01	0.01
Recalls in prior 3 years (yes/no)	0.10	0.11	0.03	0.03

Variable Names	UI workers retraining	UI workers further training	Welfare workers retraining	Welfare workers further training
Recalls in prior 4 years (yes/no)	0.12	0.13	0.03	0.03
Recalls in prior 5 years (yes/no)	0.12	0.14	0.04	0.04
Benefit receipt in prior 14 days (days)	3.30	2.61	0.43	0.43
Benefit receipt in prior 29 days (days)	6.82	5.42	0.91	0.91
Benefit receipt in prior 1 years (days)	54.27	46.64	15.68	15.68
Benefit receipt in prior 2 years (days)	80.59	68.85	33.39	33.39
Benefit receipt in prior 3 years (days)	105.73	90.74	49.54	49.54
Benefit receipt in prior 4 years (days)	127.38	111.06	66.30	66.30
Benefit receipt in prior 5 years (days)	144.97	129.99	83.26	83.26
Number of benefit periods in prior 14 days	0.25	0.20	0.03	0.03
Number of benefit periods in prior 29 days	0.27	0.22	0.04	0.04
Number of benefit periods in prior 1 years	0.50	0.43	0.12	0.12
Number of benefit periods in prior 2 years	0.71	0.60	0.21	0.21
Number of benefit periods in prior 3 years	0.90	0.75	0.30	0.30
Number of benefit periods in prior 4 years	1.05	0.88	0.39	0.39
Number of benefit periods in prior 5 years	1.16	1.00	0.48	0.48
Unemployed job search in prior 14 days (days)	0.18	0.19	0.18	0.18
Unemployed job search in prior 29 days (days)	2.14	1.75	1.80	1.80
Unemployed job search in prior 1 years (days)	62.98	47.30	122.70	122.70
Unemployed job search in prior 2 years (days)	111.30	84.48	269.18	269.18
Unemployed job search in prior 3 years (days)	161.56	127.68	404.88	404.88
Unemployed job search in prior 4 years (days)	210.75	173.92	539.24	539.24
Unemployed job search in prior 5 years (days)	252.24	221.52	667.84	667.84
Number of unemployed job search periods in prior 14 days	0.07	0.07	0.06	0.06
Number of unemployed job search periods in prior 29 days	0.21	0.15	0.18	0.18
Number of unemployed job search periods in prior 1 years	0.63	0.55	1.00	1.00
Number of unemployed job search periods in prior 2 years	0.97	0.86	1.59	1.59
Number of unemployed job search periods in prior 3 years	1.30	1.16	2.10	2.10
Number of unemployed job search periods in prior 4 years	1.58	1.43	2.60	2.60
Number of unemployed job search periods in prior 5 years	1.79	1.69	3.05	3.05
Average daily unconditional wage in prior 14 days (wage=0 w/o BeH)	23.83	19.07	1.45	1.45
Average daily unconditional wage in prior 29 days (wage=0 w/o BeH)	24.40	19.49	1.61	1.61
Average daily unconditional wage in prior 1 years (wage=0 w/o BeH)	30.85	23.54	1.90	1.90
Average daily unconditional wage in prior 2 years (wage=0 w/o BeH)	32.75	25.14	2.33	2.33
Average daily unconditional wage in prior 3 years (wage=0 w/o BeH)	32.74	25.26	2.78	2.78
Average daily unconditional wage in prior 4 years (wage=0 w/o BeH)	31.34	25.10	3.19	3.19
Average daily unconditional wage in prior 5 years (wage=0 w/o BeH)	29.23	24.87	3.62	3.62

Variable Names	UI workers retraining	UI workers further training	Welfare workers retraining	Welfare workers further training
Average daily benefits in prior 14 days	6.48	4.43	0.52	0.52
Average daily benefits in prior 29 days	6.84	4.75	0.59	0.59
Average daily benefits in prior 1 years	10.64	7.74	1.89	1.89
Average daily benefits in prior 2 years	12.87	9.38	2.96	2.96
Average daily benefits in prior 3 years	14.08	10.41	3.84	3.84
Average daily benefits in prior 4 years	14.60	11.10	4.71	4.71
Average daily benefits in prior 5 years	14.84	11.68	5.61	5.61
Welfare in prior 14 days (days)	0.69	0.12	12.69	12.69
Welfare in prior 29 days (days)	1.43	0.26	26.03	26.03
Welfare in prior 1 years (days)	20.81	8.31	306.66	306.66
Welfare in prior 2 years (days)	48.68	29.85	580.82	580.82
Welfare in prior 3 years (days)	84.28	62.14	831.48	831.48
Welfare in prior 4 years (days)	123.45	99.48	1059.99	1059.99
Welfare in prior 5 years (days)	157.89	139.04	1259.90	1259.90
Number of welfare spells in 14 days	0.05	0.01	0.92	0.92
Number of welfare spells in 29 days	0.06	0.01	0.93	0.93
Number of welfare spells in 1 years	0.14	0.07	1.09	1.09
Number of welfare spells in 2 years	0.25	0.16	1.26	1.26
Number of welfare spells in 3 years	0.36	0.26	1.44	1.44
Number of welfare spells in 4 years	0.47	0.36	1.62	1.62
Number of welfare spells in 5 years	0.56	0.45	1.81	1.81
Local employment offices (176 dummies)	YES	YES	YES	YES
Year-month of UE start (156 dummies)	YES	YES	YES	YES
N	14,299	30,187	6,202	33,484

Source: IEB V12.01.00 – 160927. Own calculations.

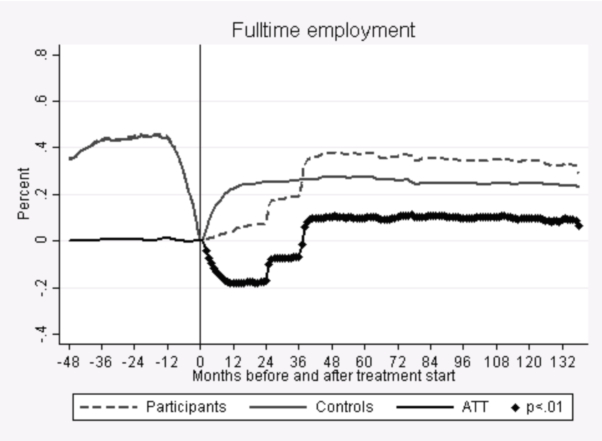
Figure A.1
Differences in ATTs on employment and wages between workers in UI unemployed for at most three months and workers unemployed for at least three months



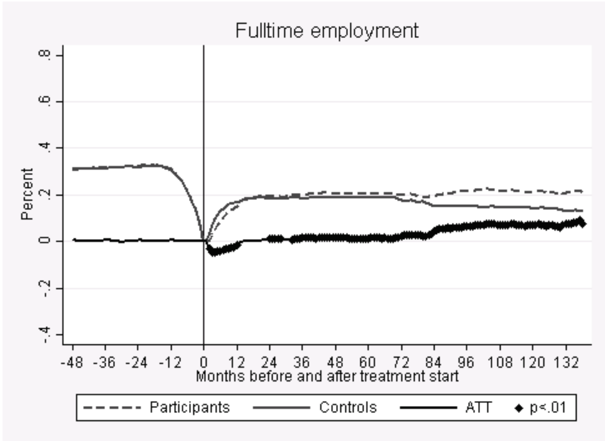
Source: IEB V12.01.00 – 160927. Own calculations.

Figure A.2
Effects of retraining and further training on fulltime and part-time employment for unemployed workers in UI

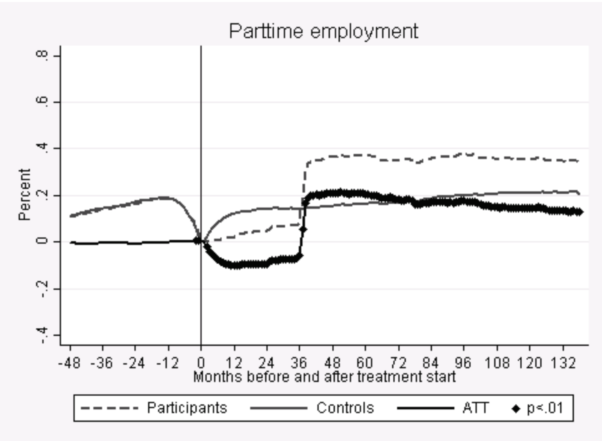
a: Retraining



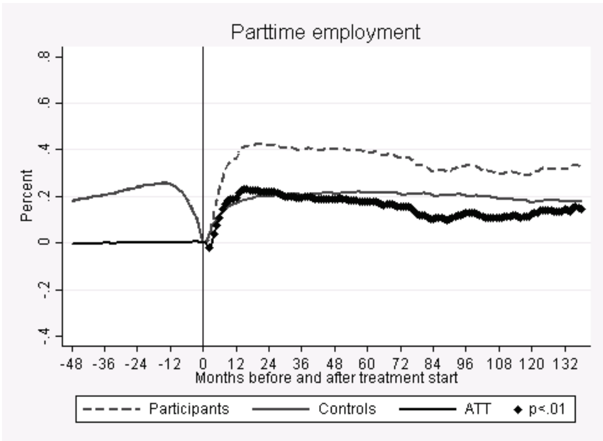
b: Further training



c: Retraining



d: Further training



Source: IEB V12.01.00 – 160927. Own calculations.

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