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The Benefits of Adult Learning: Work-Related Training, Social Capital, and Earnings*

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Abstract

We propose a regression-adjusted matched difference-in-differences framework to estimate pecuniary and non-pecuniary returns to adult education. This approach combines kernel matching with entropy balancing to account for selection bias and sorting on gains. Using data from the German SOEP, we evaluate the effect of work-related training, which represents the largest portion of adult education in OECD countries, on individual social capital and earnings. As the related literature, we estimate positive monetary returns to work-related training. In addition, training participation increases participation in civic, political, and cultural activities while not crowding out social participation. Results are robust against a variety of potentially confounding explanations. These findings imply positive externalities from work-related training over and above the well-documented labor market effects.

JEL Codes: J24, I21, M53

Keywords: social capital, earnings, work-related training, matched difference-in-differences approach, entropy balancing

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1 Introduction

Updating skills and abilities over the life cycle is crucial for workers, firms, and entire economies seeking to prevent human capital depreciation and to remain competitive in a globalized and ever-changing work environment (**??**). Particularly in industrialized countries, participation in continuing education and training (CET) has become widespread. For example, according to the Survey of Adult Skills (PIAAC) 2015, approximately half of adults aged between 25 and 64 years took part in some CET activity (including open or distance-learning courses, private lessons, organized sessions for on-the-job training, and workshops or seminars—some of which might be of short duration) in OECD countries in a given year (**?**, p. 327). The majority of these activities are nonformal (approximately 92%), meaning that they are organized but are less institutionalized and structured than formal learning activities (which usually lead to the granting of credentials and certificates).[1]

While there are numerous studies showing that work-related training affects individual labor market outcomes and benefits the performance of the firm, there is rarely any causal evidence on the extent of further non-pecuniary benefits from CET (**?**).[2] Focusing on the case of Germany, where participation rates are close to the OECD average,[3] this paper provides an update on the monetary returns to CET and makes two key contributions to the literature on adult education. First, we address empirical challenges in the evaluation of wider benefits from training by transferring an extended flexible econometric framework from the labor economics literature into the literature that evaluates wider benefits of adult education. Second, we apply this framework to identify the effects of work-related training, which constitutes the majority (82%) of nonformal CET in Germany and elsewhere (**??**),[4] on measures of civic/political, cultural, and social participation—measures that are related to social capital at the individual level (**?**). Social capital outcomes are high on the political agenda because social capital is considered to facilitate collaboration and cooperation within a society, yielding positive economic and social externalities (see Section **??** for a discussion).

We use rich longitudinal panel data from the German Socio-Economic Panel Study (SOEP) from 1992 to 2014. These data offer detailed information on pecuniary and non-pecuniary

[1]The PIAAC survey shows that 39% of adults participate in nonformal education only, 4% participate in formal education only, 7% participate in both formal and nonformal education, and 50% do not participate in CET. *Formal education* is defined as "planned education provided in the system of schools, colleges, universities and other formal educational institutions" (**?**, p. 325) and *nonformal learning activities* are "sustained educational activity that does not correspond exactly to the definition of formal education."

[2]For example, **?** and **?** provide overview studies on individual labor market outcomes. **??**, **??**, and **?** provide studies on firm performance. **?** provide an overview of further non-pecuniary effects of formal education. In particular, there is some evidence that formal education can contribute to more civic engagement and political participation (**???**).

[3]In Germany, participation in CET in 2015 is equal to 53%, with 94% of participation taking place in the form of nonformal learning activities (**?**).

[4]Work-related training is also an important topic for firms because they allocate substantial resources to train their employees. For example, **?** estimate that the total costs for German firms amount to 33.5 billion euro for the year 2016.

outcomes, participation in work-related training activities, and a rich set of socio-economic background variables. In empirical studies, social capital often constitutes an aggregate of two dimensions: personal involvement in social activities and trust in people generally (**?**). While social capital is a multidimensional concept (**??**) with no consensus about the exact definition (**?**),[5] one can relate the first measure to a *structural* dimension of social capital (i.e., the channels and opportunities through which interaction can take place) and the second measure to a *relational* dimension (i.e., the level of trust, group identification, and the quality of social ties and networks) (**?**). We use eight non-pecuniary outcome variables to capture the structural dimension of social capital, which include interest in politics; participating in local politics; volunteering in clubs, organizations, and community services; attending artistic and musical events; being active in artistic/musical activities; and meeting with and assisting neighbors, friends, and relatives. To avoid ad-hoc definitions of how to combine the eight variables, we use a principal component analysis (PCA) that reveals and quantifies the underlying data structure. We also discuss the effects on trust in others and the number of close friends to capture the relational dimension of social capital. To measure participation in work-related training, the SOEP provides special survey modules in the years 2000, 2004, and 2008 that specifically ask the respondents about training activities in the last three years prior to the survey. Using this information, we define three periods before, one period during, and three periods after training participation for each of the modules.

Evaluating the effects of CET requires the construction of the counterfactual situation of what would have happened to training participants if they had not taken part in the training. Social experiments provide the gold standard for a causal evaluation because the treatment status is randomly assigned. However, data from randomized controlled trials and quasi-experiments are not available for many research questions that are interesting from a policy perspective. Moreover, (quasi-)experimental variation sometimes identifies a specific parameter that is hardly transferable to other interventions and population groups. Our approach therefore relies on methodological insights from the literature that studies the effects of training on labor market outcomes in a real world setting, considering the entire population that may be affected by the treatment. At the center of the framework is a regression-adjusted matched difference-in-differences approach (**???**), which requires panel data to model the decision to participate in training. Using information from two periods before the training, the method accounts for selection into the training based on the levels and the trends of a large set of observable characteristics. Moreover, our econometric framework incorporates the use of entropy balancing to refine conventional matching weights (**?**). By calibrating unit weights

[5] The most appropriate definition of social capital for this study refers to the view that social capital represents social connections and interactions, which have (productive) value (**?**). In the economy, those connections and interactions lead to social networks, norms of reciprocity, and mutual trust, which have the potential to improve the efficiency of society by facilitating coordination, collaboration, and cooperation (**???**). There also exist other definitions of social capital. For example, **?** uses his concept of social capital to explain class inequalities, and **?** argues that social capital is important for human capital formation because social capital facilitates collective aims.

in the non-participation group such that average covariates of the reweighted comparison group satisfy prespecified balancing conditions, the approach ensures exact balancing between the participant and non-participant groups not only on the mean but also on higher moments such as the variance of the covariates. This approach is meaningful because we show that the participant group is a more homogenous selection of the population than the non-participant group. The regression adjustment uses individual fixed effects to control for further selection on time-invariant unobserved heterogeneity. Although our results are not very sensitive to the choice of the econometric model, we carefully assess the robustness of each step and discuss how changes in the empirical specification affect the estimates.

We find that participation in work-related training yields positive non-pecuniary returns in the form of higher civic/political and cultural participation. Those increases do not crowd out social participation. We do not find that trust or the number of close friends increase after participation in work-related training. To establish the econometric model, we estimate earnings returns to work-related training of approximately 5% on average, which confirms previous findings in the literature (**???**). A series of robustness checks show that the results are not driven by selective sample attrition or functional form assumptions. While work-related training should primarily increase individual productive skills and abilities, thus leading to job promotions and earnings increases (**?**), further results suggest that these improvements in skills and labor market outcomes are unlikely to explain our findings. By contrast, we provide suggestive evidence that work-related training opens up opportunities for networking, social interactions, and information exchange, which then lead to higher participation in civic, political, and cultural activities. Supporting this view, we do not find effects for distance learning courses where people rarely meet and interact with each other. In that sense, these benefits come as a by-product of activities engaged in for other purposes (**?**). Because social participation, trust in others, and the number of close friends do not seem to be related to the participation in work-related training, we conclude that participation is characterized by low-intensity social interactions that do not foster relational dimensions of social capital immediately. Being aware that non-experimental data may still conceal correlations of unobserved factors with the treatment and outcome variables that may violate the identifying assumption of common trends in the participant and non-participant groups, we provide an extensive discussion to show that the results are unlikely to be driven by endogeneity bias.

Our paper is related to the literature that studies the returns to adult education. Supporting the widespread belief among researchers (e.g., **????**) and policy makers (e.g., **????**) that there are wider benefits of adult education, some studies relate participation in CET to well-being, health, job satisfaction, and worries (**??????**), social and political attitudes (**????**), and measures of social capital such as membership in civic groups, political interest, voting, social networks, and trust (**?????**). However, this evidence is almost entirely based on descriptive and qualitative studies, covering only specific questions (**????**). Many of these studies also do not differentiate by the type of learner, which limits the possibility of identifying causal mechanisms (**?**).

The paper proceeds as follows. Section **??** discusses the conceptual framework of this study by introducing the concept of social capital and how work-related training may contribute to social capital. Section **??** introduces the data, explains the basic structure of the dataset, develops our measures of social capital, and discusses the construction of the treatment and comparison groups. That section also sets out the conditioning variables for the matching procedure. Section **??** describes the empirical setup and the implementation of the estimator. Section **??** presents the results, discusses the identification assumption, and performs a series of robustness checks. Section **??** discusses potential mechanisms by looking at effect heterogeneity along individual and training characteristics. Section **??** concludes.

2 Conceptual Framework

2.1 Social Capital: Concept and Measurement

By studying the relationship between local social interactions and networks to explain economic development differences across Italian regions, **?** formulates the concept of *social capital*. He describes it broadly as features of social organizations, such as networks, norms, and trust, which can improve the efficiency of society by facilitating coordination, collaboration, and cooperation. Subsequently, this work has inspired a large literature that uses measures of social interaction, such as the frequency of socialization with others and trust in others, to explain economic performance.[6] However, social capital may provide further social externalities for society (e.g., **?**). For example, it has been noted that a democracy relies on individuals who engage with each other to organize the economy, actively take part in the political process by being interested in politics, voting, directly participating, and being willing to volunteer in clubs, organizations, and charities (**??**).[7]

However, measuring the level of social capital is demanding because social capital is a multidimensional concept (**??**). At the individual level, social capital is often seen as an aggregate of two dimensions: trust in people generally and personal involvement in social activities (**?**). The first measure is more associated with the *relational* dimension of social capital (i.e., the level of trust, group identification, and the quality of social ties and networks), whereas the second measure is more related to the *structural* dimension of social capital (i.e., the channels and opportunities through which interaction can take place) (**?**). While especially relational social capital is used to explain economic outcomes (e.g., **????**), it is believed that

[6] See, for example, **???????**. **??????** provide overviews.

[7] The European Union and the OECD promote *active citizenship* as the foundation of an open, democratic, and well-functioning society (**????**). Moreover, social capital and active citizenship may also contribute to social cohesion by reducing the social distance within a society (**??**). Social cohesion may also provide economic externalities because the absence of a common culture within a population undermines the efficiency of production and exchange (e.g., **???**).

structural social capital is an important prerequisite and foundation for the deployment of other social capital dimensions (**??**) and that the evolution of trust and norms are long-run outcomes of social interactions and networks (**?**). Moreover, recent research shows that employers often use personal networks and referrals to hire new employees (e.g., **???**.[8] The literature argues that structural social capital can be improved by interacting with others, for example, through active participation in civic-minded groups (e.g., political parties, sports clubs, and neighborhood associations) by individuals of equivalent status, which, in turn, has the potential to foster relational social capital dimensions (**????**).

This study focuses on structural social capital by examining participation behavior in social activities in three domains: civic/political participation (i.e., interest in politics, participation in local politics, and volunteering), cultural participation (i.e., attending classical and modern events and being active in musical and artistic activities), and social participation (i.e., socializing with and assisting friends, neighbors, and relatives). We also study trust and the number of close friends as measures of relational dimensions of social capital.

2.2 Social Capital and Work-Related Training

Broadly following the theoretical framework by **?** who examine the association between adult education and social capital, we argue that work-related training may affect social capital via at least three channels: (1) economic reasons and positional effects, (2) the development of abilities and cognitive/non-cognitive skills, and (3) peer effects.

Economic reasons and positional effects. The primary motive for firms to offer work-related training and for employees to participate in training is to increase productivity (**??**). Those productivity increases may lead to increasing wages and job promotions (**??**) and reduces unemployment threats (**?**). The resulting higher monetary resources may enable civic/political, cultural, and social activities directly (e.g., by being able to spend more money to go to the cinema, purchase books, meet friends, etc.) or indirectly (e.g., by having more freedom to spend time with others instead of working). Higher income levels and job promotions also have the potential to change both one's network and the recognition that one receives from family members, relatives, friends, and neighbors, thereby affecting an individual's (perceived and actual) social status (**??**). However, because leisure is getting more expensive with increasing monetary returns and because jobs with more responsibility could require more overtime work, we may also observe decreasing participation behavior. Promotions into higher positions can also be associated with social isolation if the individual is not able to adapt to the new social environment.

Development of abilities and cognitive/non-cognitive skills. **?** emphasize that adult education fosters generic cognitive (e.g., better cognitive skills facilitating self-management

[8] Using self-reported sociability and measures of participation in clubs in high school to assess individual social capital, **?** shows that social capital endowments are perceived to have growing importance for the performance of high-paying jobs because of an increasing demand to coordinate and collaborate efficiently.

and reflection) and personal development (e.g., the development of resilience and grit through learning experiences). Participating in training about how to organize and manage information at the workplace may also reduce the costs of gathering and processing information for other purposes (**?**). Personal development could also increase the awareness of political and societal issues. Moreover, successful participation in work-related training may increase self-confidence and self-esteem (**??**), which can be helpful for other activities as well.

Peer effects. Participation in training intensifies contact with other colleagues and creates an opportunity to connect with individuals who one would not otherwise have seen or interacted with (**??**). This contact creates opportunities for social networking with similar-minded and engaged persons, potentially leading to higher activity levels. Those new or existing relationships may also easily spill over into private life (**?**) because peers may provide useful information and learning opportunities on various topics. For example, breaks during the training session can be used to talk about volunteering opportunities, political and social issues, and the latest movie appearing at the cinema. Of course, gains from these interactions depend on the quality of the surrounding peers and how likely an interaction is.

In sum, while a comprehensive formal model of how work-related training affects social capital does not yet exist, theoretical considerations make a clear case for such a relationship. This is true even though it is more likely that workers participate in training because they want to develop skills to increase their occupational standing, keep up with new requirements of the workplace, and improve their income situation, rather than to foster their social capital.[9] It is also unlikely that employers who initiate most work-related training (**?**) are primarily concerned about the social capital of the majority of their employees.[10] This is in line with the conjecture that the creation of social capital is often unconscious and that the individual develops social capital as a by-product of activities engaged in for other purposes (**?**, p. 312).

3 Data

3.1 Basic Data Setup

We use data from the German Socio-Economic Panel Study (SOEP), one of the world's largest and longest panel studies (**??**). In the years 2000, 2004, and 2008, the SOEP contained special survey modules with questions about participation in work-related training in the *last three*

[9] For example, the Adult Education Survey (AES) reports for the year 2014 that workers took work-related training courses mainly to update their knowledge about economic issues and issues related to their work environment (38%), courses in science, IT, and technology (23%), followed by courses in the area of health and sports (19%). Only 9% of respondents reported that they took work-related training courses to foster social skills.

[10] In fact, the continuing vocational training survey (CVTS), which is a firm-level survey that is carried out by EUROSTAT, for the year 2015 shows that firms provide work-related training to foster mainly technical, practical, and workplace-related skills (64% of firms). With some difference, the firms report that they want to enhance customer-oriented behavior (27%) and IT skills (20%). Skills that are arguably more related to social capital follow with lower percentages: management skills (18%), problem-solving skills (17%), and teamwork skills (16%).

years.[11] To allow for the identification of a group of participants and non-participants at each point in time in the most comprehensible way, we set up each of the modules as a separate evaluation. Figure **??** illustrates the evaluation periods, marking the survey years that contain questions about work-related training in red. To maximize statistical power, the final dataset stacks all evaluation periods.

Insert Figure ?? here

The three years prior to the survey with the work-related training information (including the survey year) form the treatment period. Within this period, we assume that participation in work-related training can happen at any point in time.[12] We expect that training may already affect outcomes during this period because some people may participate in training at the beginning of the period. Because information about outcome variables is not equally distributed across the years, we assign two years to each pre- and posttreatment period. Whenever possible, we average the available information within each treatment period, which should reduce measurement error.[13] Pretreatment periods $t-1$ and $t-2$ are used to compare participants to non-participants prior to the training activity, which results in dropping all individuals with missing information in either of the two periods. To ensure a minimal degree of panel stability, we restrict the sample to individuals with at least one observation in either the treatment period $t=0$ or one of the first two posttreatment periods.

The estimation sample consists to individuals who are between 25 and 55 years old and with (potential) labor market entry before pretreatment period $t-2$ (labor market entry year equals birth year plus years of schooling (incl. apprenticeships and possible university education) plus six). We further distinguish between two occupational groups: blue collar worker and non-blue collar worker (including white collar workers and public servants). The reason is that we expect the content and the extent of training to differ by occupational status. To be in one of the two samples, we require that the worker has worked in one year of the pretreatment period $t-1$ and in one year of the pretreatment period $t-2$ in the respective occupational group. In a few cases where the assignment to one of the groups is not unique, we use the most recent occupational group for the classification. This sample restriction largely excludes apprentices, retired workers, unemployed individuals who are not in the labor force, and self-employed individuals (from the pretreatment observations).

[11] In the years 1989 and 1993, there are also modules with information about participation in work-related training. However, we concentrate on the more recent modules because the questionnaires are identical.

[12] While we have the start date of each course, we prefer to use this broader setting. The reason is that we observe a large bunching of start dates for the last three courses in the year prior to the survey (see Appendix Figure **??**). Because this reporting behavior may indicate recall bias, we do not use variation about the timing of the course start.

[13] Averaging takes place only in seven treatment periods because we average only when we have information on non-pecuniary outcomes (see Figure **??**).

3.2 Measures of Social Capital

Our measures of structural social capital rely on eight variables that are related to personal involvement in social activities and civic-minded groups and are frequently and coherently asked about throughout the study period. The first three variables are related to civic/political participation. *Interest in politics* asks whether the person has an interest in politics (see Table **??** for response categories). *Participate in politics* asks whether the person participates in local politics. The next variable, *volunteer*, is concerned with civic participation more generally. The question asks the person how often he/she volunteers in clubs, organizations, and community services. The second set of variables is related to cultural participation. *Active in artistic/musical activities* asks the person how often he/she actively participates in artistic (e.g., painting, photography, acting, and dance) or musical activities. *Attend classic events* asks the person how often he/she attends opera, classic concerts, theater, and exhibitions. *Attend modern events* asks the person how often he/she attends cinema, pop concerts, disco, and sporting events. Finally, a third set of variables proxies social participation. *Socialize* asks whether the person meets friends, neighbors, and relatives and *assist* asks whether the person assists friends, neighbors, and relatives when they need a helping hand.

We construct three non-pecuniary outcome scores for each individual by using a principal component analysis (PCA) on the eight non-pecuniary outcome variables. This approach identifies underlying concepts because the outcome variables are related to each other (see correlation matrix in Appendix Table **??**), avoids ad-hoc definitions of how to aggregate the information and to increase the statistical discrimination between the outcome dimensions.[14] To facilitate the interpretation of the scores, we standardize each non-pecuniary outcome score such that the group of non-participants has a mean of 500 and a standard deviation of 100 in the pretreatment periods ($t-2$ and $t-1$) for each evaluation period.[15]

Constructing outcome scores based on the PCA requires that the individual has answered all eight questions within the same survey. However, in some years, the survey does not ask questions on *socialize*, *assist*, and *active in artistic/musical activities* (see Figure **??**). For the missing years, we therefore impute the values on these three variables from the survey that is closest to the year with the missing information (Appendix Section **??** provides more details). For posttreatment years, we use information that is closest to the treatment period $(t = 0)$. Given that we expect positive treatment effects, this imputation procedure provides a conservative approximation for the true values. In the regression analysis, we use dummy

[14] Factor loadings are based on the group of non-participants who answered all eight questions in pretreatment periods $t-1$ and $t-2$. We follow the criterion to retain components until the eigenvalue of the component is smaller than one to identify the optimal number of components that should be extracted. Appendix Table **??** shows the factor loadings of the PCA.

[15] Appendix Figures **??** and **??** plot average scores by educational degree and along the distribution of earnings. Both figures reiterate evidence from PIAAC, the OECD survey of adult skills, which shows a positive association between literacy skills and non-pecuniary outcomes such as volunteering and political efficacy (**?**). However, the reverse is true for social participation, which may indicate different time-use behaviors of high-skilled versus low-skilled individuals.

variables indicating imputed values for each outcome variable. The final non-pecuniary outcome scores are constructed by taking averages for each treatment period. According to Figure **??**, this is the case for the years 1994-95, 1996-97, and 1998-99 in the evaluation period 2000, years 1996-97, 1998-99, and 2007-08 in the evaluation period 2004, and years 2007-08 in the evaluation period 2008.

3.3 Work-Related Training

To define the treatment, we use information on whether the individual has participated in work-related training courses during the three years prior to the qualification surveys in the years 2000, 2004, and 2008 (including those that are currently running). According to this question, 34% of the sample reports participating in some form of work-related training (33% in the evaluation period 2000, 32% in 2004, 35% in 2008). These average numbers conceal substantial heterogeneity. For example, the incidence of training is unequally distributed between occupational groups. While blue-collar workers have a participation rate of only 16%, non-blue-collar workers (including white collar workers and public servants) have a participation rate of 44%.

The survey modules provide more detailed information about the last three courses the individual has taken.[16] For each course, we know the course duration, the costs of the course, who organized the course, and whether it took place during work-time. To construct a more homogenous treatment group, we concentrate on participants with more than ten hours of training. This restriction eliminates approximately 28% of the treated sample and reduces the incidence of training to 27% (28% in 2000, 25% in 2004, 27% in 2008).[17] Training participants completed an average of 208 course hours (median: 33 course hours). The comparison group consists of individuals who have not participated in any training activity in a given evaluation period. Pooling all evaluation periods, the baseline sample consists of a total of 49,100 person-year observations (6,492 unique persons) with valid information on all control variables. This number splits into 13,862 person-year observations (2,104 unique persons) in the treatment group and 35,238 person-year observations (4,987 unique persons) in the (potential) comparison group (before matching).

Because training motivation and outcomes may differ depending on who initiates the course, we try to distinguish between courses that are initiated by the employer (i.e., courses that took place during work-time, were financed by the employer, or were organized and hosted by the employer) and those that are due to the motivation of the employee. This distinction shows that

[16]The total number of courses could be larger. Appendix Figures **??**(a) and (b) show the distribution of the number of courses. The distribution shows that about one-third of the individuals having taken part in more than three courses.

[17]The density plot of the cumulative duration of the three training courses in Appendix Figure **??** indicates a bunching of short courses with fewer than ten hours of training. Appendix Figure **??**(c) shows the distribution of the sum of reported course hours for the restricted sample, and Appendix Figure **??**(d) provides the CDF for the unrestricted sample.

84% report employer-induced courses and only a minority of 16% mainly report having taken work-related courses entirely on their own.[18] Blue-collar workers are less likely to participate in employer-induced training (78%) than non-blue-collar workers (86%). Employer-induced courses are on average much shorter than non-employer-induced courses (mean: 144 hours versus 572 hours; median: 31 hours versus 171 hours) (see Appendix Figure **??** for the distribution of training hours). Participants in employer-induced courses also report (slightly) less often that they can transfer the new knowledge learned in the course to other work environments that are not related to their current job (63% versus 70%).

3.4 Conditioning Variables

Conditioning variables are important in order to find a comparison group that is, on average, very similar to the treated group prior to the training. Therefore, the set of conditioning variables should contain covariates that affect participation in training and may also have an impact on the change in the outcome variables. We select the variables according to the literature that investigates the determinants of training participation,[19] according to our own reasoning, and according to data availability. Important for our work is that previous papers have established that more educated workers are more likely to engage in training (**????**). Moreover, the literature has identified differences in training participation according to age; that is, younger workers are more likely to participate (**??**). More recently, **?** have found that personality characteristics, such as locus of control, can explain training participation as well. Furthermore, the probability of receiving training is higher in larger firms (**???**).

Table **??** provides an overview of the conditioning variables in this study. They are broadly classified into *demographic characteristics*, *education*, *labor market characteristics*, *satisfaction and worries*, and *outcomes before treatment*. Specifically, conditioning on pretreatment outcome variables is vital to find a valid comparison group. We therefore condition on the three composite scores as well as on each of the eight underlying variables of the scores.[20]

Insert Table ?? here

We again use simple averages of variables when there are treatment periods with more than one survey year. For indicator variables, we always use the information from the survey year

[18]To distinguish between training participants who take employer-induced versus non-employer-induced courses, we first define a course-level indicator that equals one if the course took place during work-time, was financed by the employer, or was organized and hosted by the employer, and zero otherwise. Using the training hours of each course as weights, we then take a weighted average of the course-level indicator for each individual to characterize the most prevalent nature of the individual training activities. Individuals have taken mainly employer-induced training if more than 50% of their course hours are employer-induced. The data show that 76% of the individuals took only employer-induced training, 12% took only non-employer-induced training, and the remaining 12% took both types of courses.

[19]See, e.g., **????** for overviews.

[20]To make the variable scales comparable, we z-standardize variables according to **?**. We do so by subtracting the mean of each variable and divide the difference by the standard deviation. Means and standard deviations are calculated from the comparison group in pretreatment periods $t-1$ and $t-2$.

within a treatment period that is closest to the treatment period $t = 0$. We use information from the other year of the same treatment period to impute missing categorical variables.

4 Empirical Approach

4.1 Setup and Identification

Since the early papers by **?**, **?** and **?**, economists have been interested in the labor market effects of training programs.[21] They acknowledge that selection into training is non-random and leads to biased conclusions about the effectiveness of a program. Over time, several papers have offered different approaches to solve the evaluation problem. **??** and **?** proposed matching estimators to construct counterfactual comparison groups. **?** show that matching is not the silver bullet to approach all evaluation problems, but they conclude that a matching difference-in-differences approach works best among the group of non-experimental estimators.

To identify non-pecuniary effects of work-related training, we adopt the empirical strategy from the literature mentioned before and employ a regression-adjusted difference-in-differences (DiD) matching approach (**???**). The estimator is described in Equation (**??**). In this setting, n_1 is the number of treated individuals, and group membership is indicated by I_1 (treated) and I_0 (comparison), respectively. S_P describes the group of individuals who share *common support*. The counterfactual comparison group is a weighted average of the change in outcome variables, with weights equal to $w(i,j)$. The estimator is similar to the traditional DiD estimator in that it partials out selection on unobservables that is time-invariant. In addition, however, it reweights each observation according to weights $w(i,j)$ that are obtained from matching.

$$\widehat{\alpha}_{DiD} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} \left[(Y_{1i}^{after} - Y_{0i}^{before}) - \sum_{j \in I_0 \cap S_P} w(i,j)(Y_{0j}^{after} - Y_{0j}^{before}) \right] \tag{1}$$

Equation (**??**) gives the identifying assumption for the matched DiD estimator. Y is the outcome of interest measured before and after the treatment, indicated by D. $P = P(D = 1|X)$ is the propensity score and gives the conditional probability of participating in work-related training conditional on a vector of background variables X.

$$E(Y_0^{after} - Y_0^{before}|P, D = 1) = E(Y_0^{after} - Y_0^{before}|P, D = 0) \tag{2}$$

The condition states that the expected change in the outcome of the treatment group must be equal to the expected change in the outcome of the comparison group in the absence of treatment (indicated by subscript 0). Hence, the estimator identifies a causal effect if there are

[21] There are at least three strands of literature: The first strand of the literature studies the effects of work-related training (**?????????**) and adult learning activities (**???**). The second strand of the literature focuses on adults who return to upper-secondary schooling or college (**???**), often after displacement (**??**). And the third strand of the literature looks at the effects of training for unemployed individuals, including the effectiveness of active labor market policies (**????**). See **?** and **?** for overviews and **?** for a current overview of the main takeaways from the literature.

no unobserved factors that determine participation in work-related training and simultaneously influence a *change* in the outcome variable of interest. This is the *common trend assumption* that requires that treated individuals would be on the same trend as individuals in the comparison group in the absence of treatment. Using the matched comparison group makes it more plausible that this assumption holds. The regression adjustment, including covariates that vary over time and explicitly take care of the level of the outcome variable prior to the treatment, has the advantage that it partials out remaining pretreatment differences that have remained after matching (**?**).

4.2 Implementation

We implement the estimator in five major steps.

First step: propensity score estimation. We estimate a logit model to predict participation in work-related training before treatment. Based on a large number of observable covariates, we construct for each individual the propensity to participate in work-related training, $P = P(D = 1|X)$. Table **??** provides an overview of the variables that we use in the matching function, including demographic characteristics, education, labor market characteristics, satisfaction and worries, and, most importantly, a series of outcome variables prior to the treatment. We include all conditioning variables for pretreatment period $t-1$. To control flexibly for differences in individual time trends, we also include labor market characteristics, health, satisfaction and worries, and outcomes before treatment for pretreatment period $t-2$.[22] Pooling observations over all evaluation periods, we have 9,555 observations (6,492 unique persons) in this step. The model contains 40 covariates and 208 conditioning variables.

Second step: trimming and re-estimation. In propensity score matching, identification depends on matching individuals with similar propensity scores (or the corresponding odds ratios). If the propensity score is close to one or close to zero, it is hard to argue that participation (if the score is close to one) or non-participation (if the score is close to zero) can be random. Therefore, **?** and **?** recommend trimming observations with propensity scores below 0.1 or above 0.9. This practice also ensures common support and yields more robust results. We therefore follow their recommendation and drop those observations. Appendix Table **??** shows the pretreatment sample size before and after trimming. Trimming drops 25% of the sample in the pretreatment period. As a result of the strong self-selection into training, almost everyone who is dropped come from the comparison group and has a very low probability participating in training.[23] The model does not predict propensity scores that are above 0.9, suggesting that the model is not overfitted. After trimming the propensity scores, we rerun the same logit model

[22] Because other demographic characteristics and the educational background do not show substantial variation within the four years of the pretreatment periods $t-1$ and $t-2$, we only include them in period $t-1$. We do not weight individuals by sampling weights because the matching function produces a propensity score that acts as a balancing score of the covariates and should not yield inference about the underlying population (**??**).

[23] For the treatment group, Appendix Figures **??** and **??** show that trimming causes mainly a parallel shift in the outcome profile, which has no consequences for the subsequent analysis that eliminates level differences entirely.

described before on the trimmed sample and compute propensity scores and odds ratios for further analysis.

Third step: matching on odds ratios. We construct kernel matching weights, $w(i, j)$, for the comparison group based on the odds ratios of participating in work-related training. Equation (**??**) describes these weights, with OR being the odds ratio of individuals i and j, $G(\cdot)$ equal to a kernel function and a_n equal to a bandwidth parameter. We use the Epanechnikov kernel with a bandwidth of $a_n = 0.06$, also applied in **?**.[24]

$$w(i, j) = \frac{G[(OR_j - OR_i)/a_n]}{\sum_{k \in I_0} G[(OR_k - OR_i)/a_n]} \tag{3}$$

There is no consensus about how to incorporate sampling weights into propensity score matching (**?**). However, sampling weights are usually important in longitudinal surveys to correct for panel mortality and (non-random) sample attrition. With incorrect or unknown sampling weights, **?** and **?** recommend matching on the odds ratios $(P/(1-P))$ (or on the log odds ratios) because they show that the odds ratios obtained from an estimation with these incorrect or unknown sampling weights is a scalar multiple of the true odds ratios.[25] We follow this recommendation in this study and favor matching on the odds ratios over matching on the propensity score.[26]

We scale the odds ratios to allow for exact matching on evaluation periods, occupation sample (blue-collar worker versus non-blue-collar worker), previous work-related training, and earnings tertiles. This choice acknowledges, first, that individuals should only be compared with individuals from the same year. This is important because time-specific shocks, e.g., business cycle movements, can affect the probability of participation in work-related training as well as pecuniary and non-pecuniary outcomes. Second, different occupations lead to participation in different types of work-related training. Moreover, because individuals choose occupations based on various observable and unobservable characteristics, we suspect that occupational background is a potentially important confounding variable. Third, because 66% (26%) of individuals in the treatment (comparison) group have participated in work-related training before, we match exactly on treatment status in previous evaluation periods.[27] This large gap in the probability of participating in training conditional on previous training participation also suggests other (observed and unobserved) individual characteristics that are different between these two groups. Fourth, we match exactly on the tertile position in the earnings distribution[28] because there is a strong presumption that many workers take up training to improve their

[24] Matching is implemented by using the `psmatch2` command in Stata (**?**).

[25] Sampling weights do not affect single-nearest-neighbor matching (in contrast to kernel matching and local linear matching) because the weights do not affect the ranking of the potential neighbors, and thus the same set of pairs is selected regardless of being matched on the odds ratios or the propensity scores (**??**).

[26] Matching on the propensity score does not change the results (not shown).

[27] For training in the first evaluation period 2000, we assess participation in previous training by referring to the qualification survey in the year 1993.

[28] Tertiles are computed for log monthly gross earnings in 2010 euros averaged over $t-1$ and $t-2$. Calculations are based on the sample before matching.

income situation. Thus, it is likely that training participation and the type of training chosen depend on the initial earnings position. We also assume that earnings represent a summary measure of all sorts of (observed and unobserved) input factors (such as noncognitive skills, school and family environment, peers, and occupational choices) that may also determine training participation and outcomes.

Fourth step: entropy balancing. We use entropy balancing to overhaul the conventional matching weights (**??**).[29] Entropy balancing is a nonparametric data preprocessing method for observational studies that ensures exact balancing between prespecified covariates of the treatment and comparison group. Weights are adjusted for the comparison group to match sample moments (i.e., mean, variance, and potentially also higher moments) of the treatment group covariate distribution. The method calculates these weights by minimizing a loss function, which accounts for the sample moment restrictions (Appendix Section **??** provides more details on the method.). However, with many covariates and a limited number of observations, it could be difficult for the method to converge on a set of weights that satisfies all moment restrictions. Therefore, **?** also shows that the method can refine matching weights from conventional matching procedures where the matching weights already try to make the samples comparable. Entropy balancing then keeps the weights as close as possible to the conventional matching weights to prevent loss of information, but at the same time ensures exact balancing on important covariates.

Because it is important for identification that we achieve pretreatment balancing on outcome variables, we require that entropy balancing overhauls the matching weights for the comparison group such that they have the same mean and variance as the treatment group on the three non-pecuniary outcome scores, log monthly earnings, and log hours worked per week. We impose separate restrictions for periods $t-1$ and $t-2$ and for each of the three evaluation periods. The main advantage of this approach is that the weights now also take into account differences in the variances of the outcome variables between the two groups. This seems to be important because the treatment group is a more homogenous group of individuals than the comparison group. For example, the standard deviation in log monthly earnings is equal to 1.43 in the treatment group versus 1.59 in the comparison group in the pretreatment periods. Lower standard deviations in the treatment group than in the comparison group can also be observed for civic/political (97 vs. 115), cultural (92 vs. 97), and social participation (92 vs. 98). Another advantage of entropy balancing is that we do not have to check pretreatment balancing for included variables because weights are constructed such that mean and variance differences are exactly zero.

Fifth step: regression analysis. Including only individuals with common support and by weighting observations by their matching weights, we finally apply a regression analysis to

[29] We implement entropy balancing by using the `ebalance` command in Stata (**?**).

estimate the following model:

$$Y_{iet} = \gamma + \alpha_{t-2}\left(\text{Training}_{ie} \times \text{pre}_{t-2}\right) + \alpha_{t=0}\left(\text{Training}_{ie} \times \text{treat}_{t=0}\right) + \sum_{j=1}^{J=3} \alpha_{t+j}\left(\text{Training}_{ie} \times \text{post}_{t+j}\right) + \mathbf{X}'_{iet}\beta + (\mu_i \times \mu_e) + (\mu_t \times \mu_e) + \varepsilon_{iet} \tag{4}$$

In our main analysis, Y_{iet} is one of the three non-pecuniary outcome scores of individual i in evaluation period e at treatment period t. $Training_{ie}$ is equal to one if individual i has participated in work-related training in evaluation period e and zero otherwise. Pre_{t-2} is a lead dummy variable indicating pretreatment period $t-2$. $Treat_{t=0}$ is a dummy variable indicating the treatment period. $Post_{t+j}$ is a dummy variable indicating j's period after treatment. $\mathbf{X}_{iet}$ is a vector of time-variant control variables. As control variables, we use German citizen (dummy), marital status (dummy), homeowner (dummy), children (dummy), vocational degree (dummy), university degree (dummy), school degree (four categories), state of residence (14 categories), and election year to the national parliament (dummy). Including these basic variables should increase the precision of the estimates. $\mu_t \times \mu_e$ are treatment-by-evaluation period fixed effects and purge out all variation that is common to each individual within the same treatment and evaluation period. $\mu_i \times \mu_e$ are individual-by-evaluation period fixed effects and eliminate all individual-specific time-invariant variation within each evaluation period. We weight individual observations according to the matching weights that are provided by the matching algorithm outlined above. Standard errors ε_{iet} are clustered at the individual level.

Because standard errors should take into account the uncertainty that arises due to the estimation and refinement of propensity scores (**??**), we also provide bootstrapped standard errors (see Appendix Table **??**). The bootstrap comprises 3,000 replications of steps one to five on bootstrap samples of equal size and work-related training status, evaluation period, tertile position, previous training status, and occupation sample (blue-collar worker versus non-blue-collar worker) as strata. The comparison of clustered and bootstrapped standard errors shows that our conclusion about the significance of the results does not change by taking into account the uncertainty of the estimates. Because of computational advantages, we therefore report clustered standard errors throughout.

5 Results

5.1 Covariate Balancing

In line with the literature, Table **??** confirms that there is strong selection into the treatment. For example, comparing treated individuals in Column (1) with the non-matched comparison group in Column (2), we find that training participants are younger, more likely to be male, much better educated, more likely to be full-time employed, more likely to work in large firms, work more hours per week, and therefore earn more on a monthly and hourly basis. Considering the non-pecuniary outcome scores, we find that treated individuals have a civic/political participation score that is 31% of a standard deviation larger compared to the comparison group. For cultural participation, we find an even larger gap of 47% of a standard deviation. However, both groups show no differences with respect to social participation. Looking at the eight underlying variables, we also find a very similar pattern of strong positive self-selection. Thus, the overall picture shows that treated individuals are highly selected along several pecuniary and non-pecuniary dimensions. Comparing them to the average individual who has not participated in any type of training may therefore lead to biased conclusions about the effectiveness of work-related training.

Insert Table ?? here

While we do not have to check balancing for variables included in entropy balancing, we need to assess the balancing quality for the remaining variables. We use two indicators: First, according to Equation (**??**), we calculate normalized differences in average covariates ($\tilde{\Delta}_{X,k}$) for the element X_k of the covariate vector $\mathbf{X}$ of the treated ($\overline{X}_{t,k}$) and comparison groups ($\overline{X}_{c,k}$) (non-matched and matched) as a percentage of the square root of the average of the sample variances in both groups ($S^2_{X,t,k}$ and $S^2_{X,c,k}$) (**??**). **?** suggest that one should regard matching as unsuccessful when the normalized difference in means exceeds 5%. Columns (3) and (7) of Table **??** show the results.

$$\tilde{\Delta}_{X,k} = \frac{\overline{X}_{t,k} - \overline{X}_{c,k}}{\sqrt{0.5\left(S^2_{X,t,k} + S^2_{X,c,k}\right)}} \tag{5}$$

Second, we use $t-$tests to test the equality of means in the treated and the comparison samples (**?**). The tests are based on a regression of the specific variable on the treatment, using evaluation-period fixed effects. We report the coefficient of that regression in Columns (4) and (8) with the corresponding p-values of the t-test in Columns (5) and (9).

Overall, the balancing table reveals that matching was successful in eliminating the large pretreatment gaps. Almost all p-values are well above conventional levels, which would indicate statistical significance. The average and median standardized differences across all 96 covariates are greatly reduced. Before reweighting, 70% of covariates yield standardized differences larger than 5%. After reweighting, this is the case for only 2% of variables. We do not expect these very small differences to affect our results significantly because remaining pretreatment differences are taken care of explicitly by the regression adjustment (**???**).

5.2 Pecuniary Benefits of Work-Related Training: Earnings and Labor Supply

In this section, we establish the empirical model by studying the pecuniary returns to participation in work-related training and comparing them with the extensive literature on pecuniary returns to work-related training. Then, we proceed by discussing the wider benefits of work-related training in the next section.

By plotting coefficient estimates and 90% confidence intervals, Figure **??** shows the results from the regression analysis using log monthly earnings.[30] The top left panel in Figure **??** already shows large treatment gaps before treatment. The DiD estimator on the non-matched sample (top right panel) reveals that treated individuals are not only ahead in terms of higher average earnings but also exhibit higher earnings growth prior to the treatment. Thus, selection on earnings growth is very likely (**??**). The bottom two panels show the results using the matched comparison group. There, we cannot find significant pretreatment differences in the cross-sectional setup (bottom left panel). Finally, applying the DiD estimator on the matched sample (bottom right panel), we find similar results with smaller confidence bands. In terms of effect sizes, we find that the effect of work-related training increases gradually from 3.9% in the treatment period to 7.2% three periods (approximately five years) later (Appendix Table **??**, Column (6)). On average, we find earnings gains of 5.1% after participation in training (regression not shown). This effect seems to confirm the existing literature that uses the same data source (i.e., training information from the qualification modules in the SOEP) and similar identification strategies (i.e., fixed effects, matching, DiD, and matched DiD estimators).[31]

Insert Figure ?? here

Further analysis reveals that introducing control variables (such as German citizenship, martial status, homeownership status, presence of children, educational degrees, and state of residence) slightly reduces standard errors (Appendix Table **??**, Column (5)). In addition, we test how much of the earnings gain can be attributed to (endogenous) changes in labor-market characteristics (such as weekly hours worked, unemployment experience, tenure with the current firm, employment position, occupational position, industry, and firm size). The result shows a substantial decrease in the average effect from 5.1% to 3.5%, indicating that higher monthly earnings are partly driven by changes in labor-market characteristics. For example, Appendix Tables **??** and **??** show that training participation increases both log weekly hours worked by 3.3% (significant at the 1% level) on average and log hourly earnings by 1.7% (significant at the 10% level) on average.

The extent to which these estimates can be interpreted as causal are highly debated in the literature. The main reason is that studies exploiting situations with random non-participation (**??**) and using randomly distributed training vouchers (**???**) usually do not find strong effects of training participation on earnings and employment. However, these studies use rather specific variation to identify training effects, particularly by evaluating adult learning activities in general and by relying on specific random variation in training assignment. While

[30] Appendix Table **??** shows the corresponding regression results. Appendix Figure **??** plots average log monthly earnings by treatment period.

[31] See **??????**. Appendix Table **??** provides an overview. Most of these studies also use a fixed effects difference-in-differences (DiD) strategy, controlling for selection into the treatment based on the earnings level and prior earnings growth. However, none of them combine the regression-adjusted difference-in-differences (DiD) matching approach with entropy balancing in a multiple event study setting.

these limitations question the generalizability of the results to other forms of training, we have to acknowledge that our results may still partly be driven by unobserved time-varying heterogeneity.

5.3 Wider Benefits of Work-Related Training: Social Capital

We now turn to the effects of participating in work-related training on our measures of social capital. In Figure **??**, we plot coefficients and 90% confidence intervals for the same empirical models as in the earnings analysis.[32] Turning directly to our preferred specification in the bottom right panel, we find that civic/political and cultural participation gradually increase after participation in training. We do not find any substantial treatment effects for social participation even though there is a small (insignificant) increase in treatment period $t = 0$.

Insert Figure ?? here

For effect sizes, we look at the regression results in Table **??**. For civic/political participation, Column (1) of Panel A shows that participation in training increases the participation score by 8.6% of a standard deviation in the treatment period. That decreases slightly to 4.5% in $t+1$ and increases again to 12.2% in $t+2$ and 10.6% in $t+3$. We find similar increases in the cultural participation score by 6.5%, 10.8%, and 11.0% in the posttreatment periods (Column (3) of Panel A) and a small insignificant effect of 3.6% in $t = 0$. Note, however, that the effects in period $t = 0$ are difficult to interpret because these effects are a mixture of effects for treated and not-yet-treated individuals and could be crowded out by the participation in work-related training. Again, for social participation, we do not see any noteworthy changes in the participation score. In Panel B of Table **??**, we calculate treatment effects by comparing the averaged effect of the three posttreatment periods to the averaged effect in the two pretreatment periods. The coefficients show that civic/political participation and cultural participation increase on average by 8.6% and 8.8%, respectively (Columns (1) and (3) of Panel B). To get an idea about the size of the effect, we can compare the coefficients to the average difference in civic/political and cultural participation between individuals with an university degree (those most engaged) and those with no educational degree (those least engaged) (see Appendix Figure **??**). The comparison reveals a rather modest effect, which amounts to 13% $(= 8.6/(545-477))$ and 9% $(= 8.8/(566-464))$ of the differences in civic/political participation and cultural participation, respectively. The effect on social participation is close to zero (Column (5)). Appendix Section **??** provides extensive evidence that the results are not due to selective sample attrition and robust to various choices of the matching procedure.

Insert Table ?? here

[32] The detailed regression results can be found in Appendix Tables **??** to **??**, Columns (1), (3), (4), and (6). Appendix Figure **??** plots treatment-period averages of the non-pecuniary outcome scores and Appendix Figure **??** depicts the same plots for the eight subdimensions.

While the non-effect on social participation seems to be puzzling in the first instance, one should remember that the domain captures social activities with friends, neighbors, and relatives. If at all, participation in work-related training together with training-induced increases in other activities should crowd out social activities with neighbors and relatives. To the extent that the participants of the courses are other colleagues in most instances, any effect on this dimension therefore depends on whether respondents regard former colleagues as new friends with whom they interact more because of the training participation *and* that this effect is larger than the potential crowding out from having less time for meeting and assisting neighbors and relatives. Transforming former colleagues into new friends requires high-intensity and repeated interactions. Further below we show that at least the number of *close* friends seems to be unaffected by the training participation, which makes high-intensity interactions due to training participation unlikely. Therefore, we conclude that other activities do not crowd out social participation.

Appendix Table **??** shows regressions for each subdimension. Effects are positive and significant for participating in local politics, being active in artistic/musical activities, and attending classic events. We further find economically meaningful effects on volunteering in clubs, organizations, and community services and on attending modern events. Treatment effects are small for interest in politics, socializing, and assisting.

In further analysis, we provide evidence for the effects on two measures of social capital that are more related to the relational dimension of social capital: trust in others and the number of close friends (Appendix Sections **??** and **??**). We show that both concepts are strongly linked to each of our three participation measures, but we do not find that participation in work-related training affects trust or the number of close friends, respectively. While the number of close friends is a very rigid measure of one's social network (the average (median) number of close friends reported is 4 (4.4)) and trust in others is a rather long-run outcome that may not change over the six years we are covering in our analysis, we conclude that work-related training does not affect these relational measures of social capital directly. However, data coverage for these two concepts is relatively weak in the SOEP (trust is measured in three years and number of friends is measured in four years only), which prevents us from drawing strong conclusions from this analysis.

5.4 Identification

The most important identifying assumption is the *common trend assumption* (see Section **??**). Because outcome measures from $t-1$ and $t-2$ are used in the entropy balancing approach and therefore forced to be comparable between treatment and comparison group, the coefficient on $\text{training}_{ie} \times \text{pre}_{t-2}$ in Table **??** is not informative about the common trend assumption. Hence, to assess the plausibility of the assumption, we extend the sample to pretreatment period $t-3$ (which has not been used in the matching procedure) and test whether training participation in

$t = 0$ predicts outcomes relative to the pretreatment periods $t-1$ and $t-2$.[33] Running the model in Equation (**??**), we must be concerned about common trends when we observe significant estimates for γ_1. Specifically, $\gamma_1 < 0$ is problematic because it implies that individuals in the treatment group are on different trends than individuals in the comparison group prior to the treatment.

$$Y_{iet} = \gamma_0 + \gamma_1 \left(\text{Training}_{ie} \times \text{pre}_{t-3}\right) + (\mu_i \times \mu_e) + (\mu_t \times \mu_e) + \eta_{iet} \quad (6)$$

Table **??** shows the results of the test for log monthly earnings and the three participation scores. For all outcome variables, we run the regression on the full sample (attrition in t+2/t+3: yes) and on a sample that keeps only individuals who are still in the panel in periods $t+2$ and $t+3$ (attrition in t+2/t+3: no). Because the results are particularly strong in these latter periods, the worry is that respondents in periods $t+2$ and $t+3$ are differently selected. Panel A of Table **??** shows the results for the non-matched sample. Negative and significant coefficients on log monthly earnings confirm the literature and the results from the previous section that training participants are positively selected based on monetary gains from training. However, we do not find any economically meaningful or statistically significant coefficients on non-pecuniary outcomes (Panel A, Columns (3) to (8)). The results for the matched sample in Panel B suggest that the empirical approach successfully addresses the pretreatment trends in earnings (Columns (1) and (2)). Other outcomes are still not affected.[34] Specifically, the non-findings for non-pecuniary outcomes in the non-matched sample imply that selection into the training is not driven by anticipated non-pecuniary gains from participation. In fact, this suggests that selection into the treatment based on these non-pecuniary outcomes is individual-specific and time-invariant.

Insert Table ?? here

The main selection mechanism in work-related training comes down to monetary gains, which may or may not be anticipated in advance. At the same time, it could also be true that pursuing higher pecuniary returns correlate with improvements in civic engagement. For example, individuals may increase their social activities to find other people who are able to provide access to higher-paying jobs. It is also possible that training-induced increases in monetary resources lead to more possibilities for participation (see *economic reasons* as a potential mechanism in Section **??**). In Columns (2), (4), and (6) of Table **??**, we therefore include potentially endogenous controls for labor market characteristics such as log monthly earnings, log hours worked, employment status, occupational status, civil service indicator, unemployment experience, tenure with the current firm, industry indicators, and firm size.

[33] Alternatively, one could include an interaction for period $t-3$ into the main model (Appendix Table **??**). This does not change the conclusion.

[34] The findings are in line with the estimation results from the DiD estimator on the non-matched sample, which revealed significant pretreatment trends for log monthly earnings (Figure **??**, top right panel) but no pretreatment trends for the non-pecuniary outcomes (Figure **??**, top right panels).

However, controlling for these variables does not affect the coefficients on work-related training very much, which lends additional support to the validity of the identifying assumption.

Nevertheless, one may still worry that anticipated monetary gains correlate with changes in unobservable characteristics, which correlates with non-pecuniary outcomes. Therefore, we test whether our results are similar when we split the treatment group into one group that has experienced positive monetary returns after training participation, i.e., the training had presumably high monetary value, and one group that has not experienced positive monetary returns, i.e., the training had low monetary value. To classify training participants into these two groups, we compare their log *hourly* earnings trajectory in posttreatment periods $t+1$, $t+2$, and $t+3$ to the average performance of the weighted comparison group. Training participants are in the *high value* group when the average difference over the three periods is positive, and they are in the *low value* group otherwise. Interestingly, this splits the treatment sample by almost half (53% of participants are in the high-value group and 47% are in the low-value group).[35] Reassuringly, Table **??** shows that positive monetary returns arise only for the high-value group (Columns (1) and (2)).[36] While there is some heterogeneity for participation in civic/political, cultural, and social participation, the results imply that the monetary value of the treatment does not systematically affect the conclusions of positive non-pecuniary returns.

Insert Table ?? here

To conclude, the identification checks indicate that the common trend assumption holds. Specifically, the results imply that individuals do not take up training to invest in their civic engagement. We therefore interpret the non-pecuniary returns identified above as a by-product of work-related training (in addition to the effects on labor market outcomes). However, two further identification issues deserve some attention. First, our approach partials out selection on a large set of observables and partials out time-invariant selection on unobservables. Thus, one may worry about selection on unobservables that varies over time and is correlated with the timing of the treatment. We argue above that this is unlikely to be a concern because the non-pecuniary outcomes we study are not a decisive factor in the decision to take up work-related training.

Second, our analysis relies on retrospective information about training participation. One may worry that individuals only remember and report training activities when those activities had positive non-pecuniary returns. Because the survey asks explicitly for work-related training that is more associated with labor market outcomes, we argue that the opposite is more likely. Thus, it is very likely that individuals do not report trainings that are directly related to fostering

[35] While average training hours in the low-value group are higher (228 hours) than in the high-value group (132 hours), median training hours are comparable (33 versus 32 hours). High-value trainings are slightly more often induced by the employer than are low-value trainings (91% versus 83%).

[36] Matching weights from the baseline model are refined by using entropy balancing within the sample splits. The same procedure as outlined in step four of Section **??** is used. To analyze balancing quality, the bottom of Table **??** reports average normalized differences for different points in the normalized differences distribution.

non-pecuniary outcomes but are pursued during leisure time. In fact, the majority of courses that are highly beneficial for civic engagement should be outside the firm. However, our treatment does not cover those non-work-related courses such as language courses, courses on political and societal issues, and courses to become an exercise instructor at the local sports club. Participation in those courses would probably deliver larger treatment effects, but identification would be more problematic due to a more complicated self-selection mechanism. Therefore, on the one hand, our 0/1 treatment setting almost certainly classifies some individuals to the treatment group who do not gain strongly in terms of non-pecuniary outcomes. On the other hand, we also assign some individuals to the comparison group who may have participated in trainings that had been highly beneficial to their participation behavior but did not report that to the interviewer. This misclassification works against our findings of positive non-pecuniary returns from work-related training, leading to a lower bound interpretation of the results.

6 Mechanism

In Section **??**, we laid out three mechanisms that may explain a connection between participation in work-related training and our non-pecuniary outcomes: (i) economic reasons and positional effects, (ii) development of abilities and cognitive/non-cognitive skills, and (iii) peer effects. While direct evidence on the exact mechanism is impossible to establish due to limited available information in the survey, we use several sample splits to learn more about the origins of the average effect. In Figures **??** and **??**, we present estimates on different subsamples along individual characteristics and different features of the training. For each analysis, we refine the baseline matching weights using entropy balancing that imposes exact matching on the outcome variables (log monthly earnings, log weekly hours worked, three participation scores), separately for pretreatment periods $t-1$ and $t-2$.[37]

Splitting the sample by individual characteristics (Figure **??**) reveals that the effects are much stronger for females than for males. For other sample splits, we find that the effect on civic/political participation is largest for individuals with a university degree, in the upper part of the wage distribution (measured prior to the treatment as an average of the log monthly earnings distribution in periods $t-1$ and $t-2$), and working in a non-blue-collar job. This suggests a positive interaction between high levels of civic-mindedness and interests in politics and work-related training. For individuals without a university degree and especially for blue-collar workers, training does not increase civic/political participation. In fact, this finding limits the expectation that participation in work-related training may be able to contribute to social cohesion in terms of civic/political participation (see also **??**). By contrast, while training participation seems to affect cultural participation for all subgroups positively, the effects are largest for blue-collar workers. We also split the sample by family status, expecting that the

[37] Appendix Tables **??** to **??** provide further information on the subsamples, regression results, and statistics on balancing properties within each subsample.

effect is mainly due to childless singles who have the largest amount of spare time available when compared to married individuals and singles with children. The results strongly support this view.

Insert Figure ?? here

Some interesting effect heterogeneity arises when we split the sample by training characteristics (Figure **??**). In general, the treatment effect tends to be stronger with a longer training duration,[38] more courses taken, and when we split the treatment group by whether the individual has participated in training before. In further analysis, the results are not different between trainings teaching firm-specific and general skills. We also split the sample by firm size and find that training has a larger non-pecuniary return on civic/political participation in smaller- and medium-sized firms than in large firms. Interestingly, when we split the treatment group by whether the participant reports that the majority of the last three courses substantially paid off in the job versus the respondent did not experience that the training yields a payoff in the job or is not yet sure about the payoff, we do not find substantial differences. Finally, splitting the treatment group by whether the individual has taken at least one distance learning course yields the clear picture that the effect is driven by courses where people have to meet each other in person.

Insert Figure ?? here

Based on the evidence, we conclude that participation in work-related training affects structural social capital mainly by opening up opportunities for social networking and information exchange rather than by increasing monetary resources, inducing shifts in job positions, or improving skills and abilities. We largely rule out channel (i) because controlling for endogenous labor market characteristics does not change the results (see Section **??**). Using insights from mediation analysis (see, e.g., **???**), it is likely that the effect of training would be mediated by other factors (such as labor market outcomes) if the coefficient of the treatment indicator decreases (in absolute size) and the adjusted R-squared substantially increases after the inclusion of the additional covariates. This would suggest that some part of the variation in the effect of training on civic/political and cultural participation is channeled through the effect of the training on labor market outcomes. While there are concerns about endogeneity, omitted variable bias, and measurement error, which potentially invalidate such an interpretation, we do not observe any effect of adding labor market outcomes on coefficient movements or changes in the adjusted R-squared (Table **??**). Hence, we can conclude that the effect is not mediated via the labor market by increasing monetary resources, shifts in occupational and employment status, or switches to other (larger) firms and industries. The interpretation of an unlikely strong effect of monetary resource gains as an effect mediator is supported by similar non-pecuniary

[38] For the training-duration subsamples, we split the treated sample at median training hours (33 hours).

returns to treatments with and without high monetary returns (Table **??**). Moreover, results are fairly similar when splitting the treatment group by whether the individual experienced a payoff in the job from the course.

The effects through channel (ii) are more difficult to address because there is no direct assessment of acquired skills and abilities in the survey. This channel finds some support by the fact that the effects on civic/political participation are stronger for more educated workers (i.e., non-blue-collar versus blue-collar workers and university-educated versus non-university-educated workers) who presumably undertake more abstract training courses. However, given that it seems that the effects are not mediated through changes in labor market characteristics, we can rule out a strong mediating effect of training-related changes in ability and skills—at least as long as they are also associated with changes in earnings and job positions. Another indication of a limited role of this channel is that there are very similar results by whether individuals attended trainings to foster general or firm-specific skills. Usually, one would assume that general training should be teaching more abstract skills than trainings that teach firm-specific skills. Finally, the larger effect for females than for males is not compatible with the view that cognitive and non-cognitive abilities are the driving force because it would presume that females seek trainings raising cognitive and non-cognitive abilities more than men do.

By contrast, there is suggestive evidence supporting channel (iii), which argues that the effect could be due to opening up opportunities for new contacts and information sharing. First evidence comes again from the fact that the effect is mainly due to females. This may be explained by the findings of **?** and **?** who argue that females seek to be socially connected to a higher degree than men are, which makes it plausible that women take up networking opportunities to a larger degree than men do. It may also indicate that women select more into trainings that offer more opportunities for social interactions. Second, effects only materialize for courses that are not distance learning courses (Figure **??**). This implies that personal involvement is key to establish non-pecuniary effects from work-related training. Third, splitting the sample by family status (Figure **??**) suggests that spare time seems to be the largest constraint on the effect of training on civic/political and cultural participation. Fourth, given that training-induced economic perceptions and realizations do not strongly interfere with the effect of training on civic/political and cultural participation, it seems more likely that the effect comes from who you meet at the training and not from what you learn there. This conclusion is in line with the notion of social capital formulated by (**?**, p. 67) who argues that "it's not *what* you know, but it's *who* you know" that matters.

In conclusion, it seems that work-related training fosters the structural dimension of social capital through creating more opportunities to engage in social interactions and to exchange information with colleagues and other course participants. However, these new interactions do not seem to be strong because we do not observe significant changes for the number of close friends, which is a very rigid measure of one's social network, the degree of social participation, which should have been affected if colleagues become friends, or trust in others, which we expect to change only over a long time of high-intensity and repeated social interactions. This conclusion also seems most reasonable given the rather short average duration of work-related training. Nevertheless, there is the potential that these new social interactions lead to economic and social externalities by facilitating coordination, collaboration, and cooperation within the population.

7 Conclusions

This paper contributes to the literature on adult learning by describing the implementation of a five-step econometric framework that uses panel data to evaluate treatment effects. The main methodological problem in the evaluation is to address selection bias, which would confound any empirical analysis on the effects of work-related training. To mitigate this bias, we use rich longitudinal data from the German Socio-Economic Panel (SOEP) to implement a regression-adjusted matched difference-in-differences approach. The matching procedure combines propensity score matching with entropy balancing. We match on pretreatment outcome variables and various covariates to obtain a comparison group that is similar in observable characteristics to the treated group. Entropy balancing is used to refine conventional matching weights such that the comparison group has not only the same mean but also the same variance in the outcome variables in the pretreatment period. After calculating the weights, we use a difference-in-differences estimator on the matched sample to eliminate time-invariant fixed effects and remaining pretreatment differences. In addition, we control for labor market outcomes pre- and posttreatment to net out selection bias that is based on pecuniary returns.

We illustrate the implementation of this framework by focusing on non-pecuniary outcomes such as civic/political, cultural, and social participation. Although work-related training and lifelong learning are high on the political agenda in many countries, there is no causal study on the effect of work-related training on those non-pecuniary outcomes. After documenting strong self-selection into treatment, which is also found in terms of non-pecuniary outcomes, we find significant positive effects of participation in work-related training on civic/political and cultural participation. Specifically, participating in local politics, volunteering in clubs, organizations, and community services, being active in artistic/musical activities, and attending classic and modern events show improvements after participation in training. We do not document changes in terms of social participation. This finding indicates that increased activities in other domains do not crowd out socializing with and assisting friends, family, and neighbors. Of course, this does not imply that there are no other life and social domains that could be negatively affected. We do not find any effects on trust in others or the number of close friends.

The results are robust to a series of identification and robustness checks. We validate our model with an update on the evidence of pecuniary returns to work-related training. We find earnings effects of 4.6% to 7.2% of additional earnings after participation in work-related training. These numbers are comparable to what has been found in the existing literature. We also extensively study pretreatment trends and cannot find substantial differences between the treatment and the comparison group in periods before participation in training. We further show that treatment effects are comparable when splitting the sample by whether the training generated pecuniary returns, suggesting that selection into the treatment that is potentially based on anticipated pecuniary returns does not strongly affect our results.

We conclude that participation in work-related training affects structural social capital, potentially yielding beneficial externalities for societies (over and above direct training effects) in the long run. These effects arise mainly as a by-product of participation in work-related training because it is more plausible that workers and firms consider the improvement of individual productive capacity to be a first-order concern when taking up training. By studying subsamples, we document that the results are much stronger for females than for males. The analysis further reveals that civic/political participation increases most strongly for an affluent group of individuals (highly educated, working in better-paying occupations), which limits the expectation that participation in work-related training improves the civic/political participation of the disadvantaged. This disparity may contribute to the persistence of social inequalities and therefore raise concerns about distributional effects.

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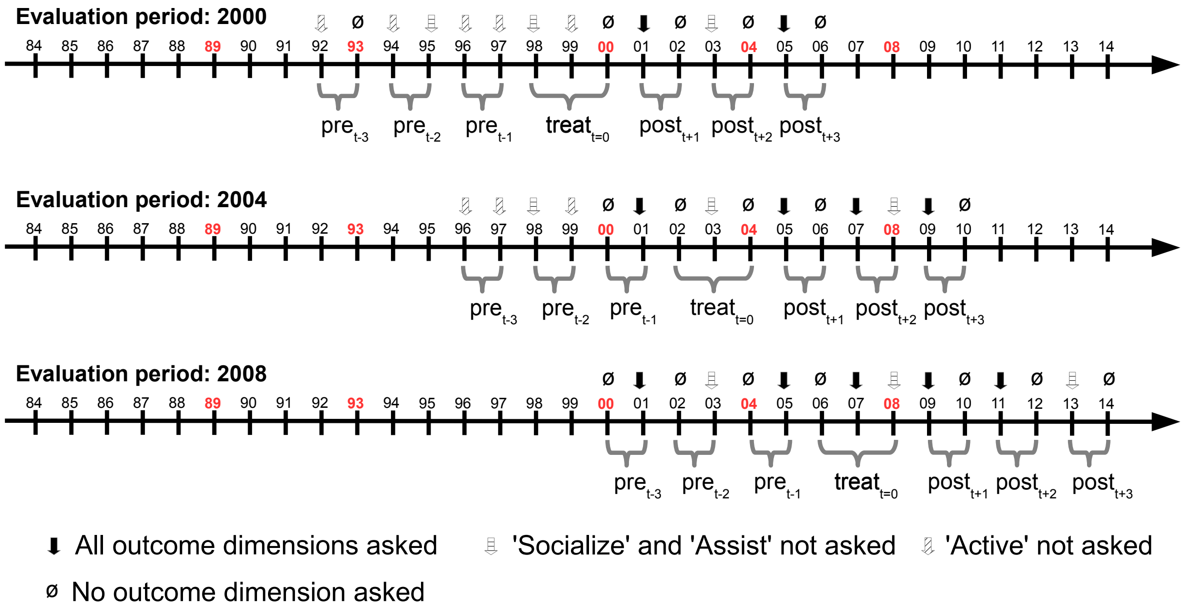
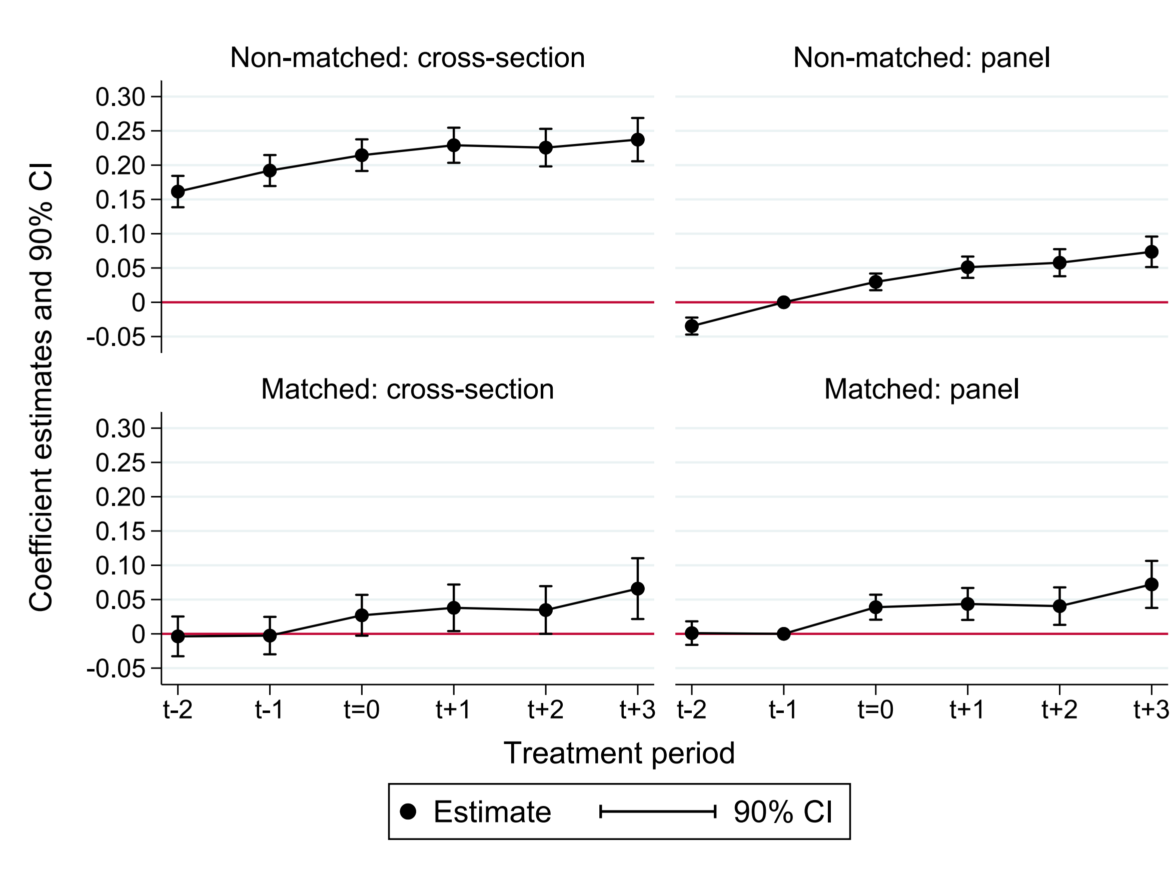
Figures and Tables

Figure 1: Description of Treatment and Evaluation Periods



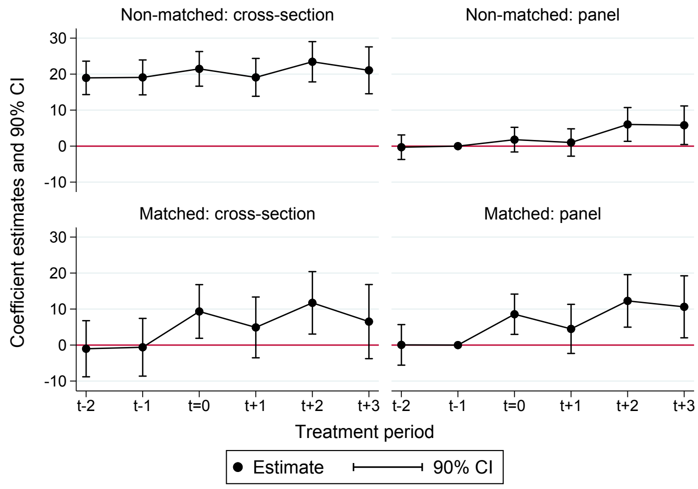
Notes: The figure describes the evaluation periods. Years marked in red indicate survey years with qualification survey modules in the SOEP. We evaluate the years 2000, 2004, and 2008. Treatment periods are centered around most reported treatment years, which in all cases is the year prior to the survey. Matching and standardization of variables is based on information in pretreatment years $t-1$ and $t-2$. Symbols above years indicate what information about the outcome dimensions is available.

Figure 2: Estimation Results for Log Monthly Earnings

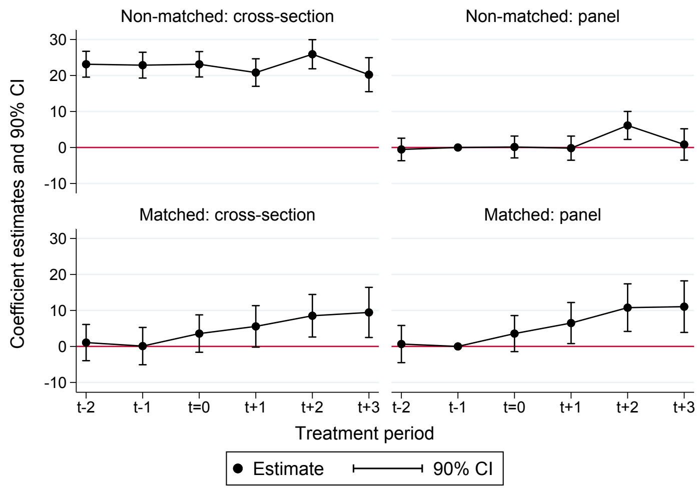


Notes: The figure displays coefficients and 90% confidence intervals for different regression models. Explanations are provided in the text. Regression results can be found in Appendix Table **??**, Columns (1), (3), (4), and (6).

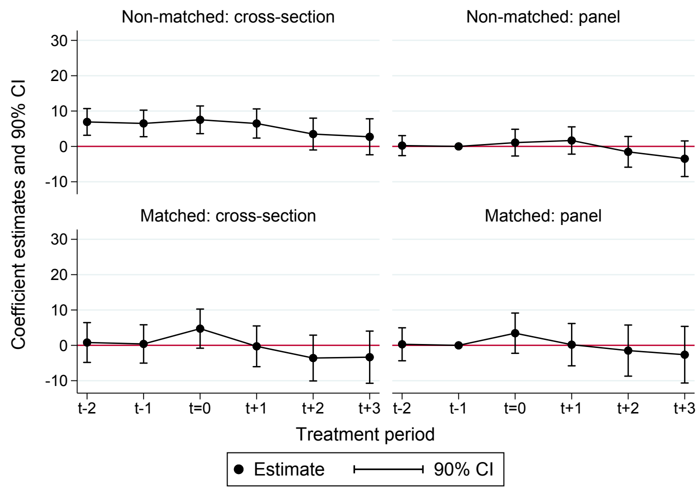
Figure 3: Estimation Results for Social Capital



(a) Civic/political participation



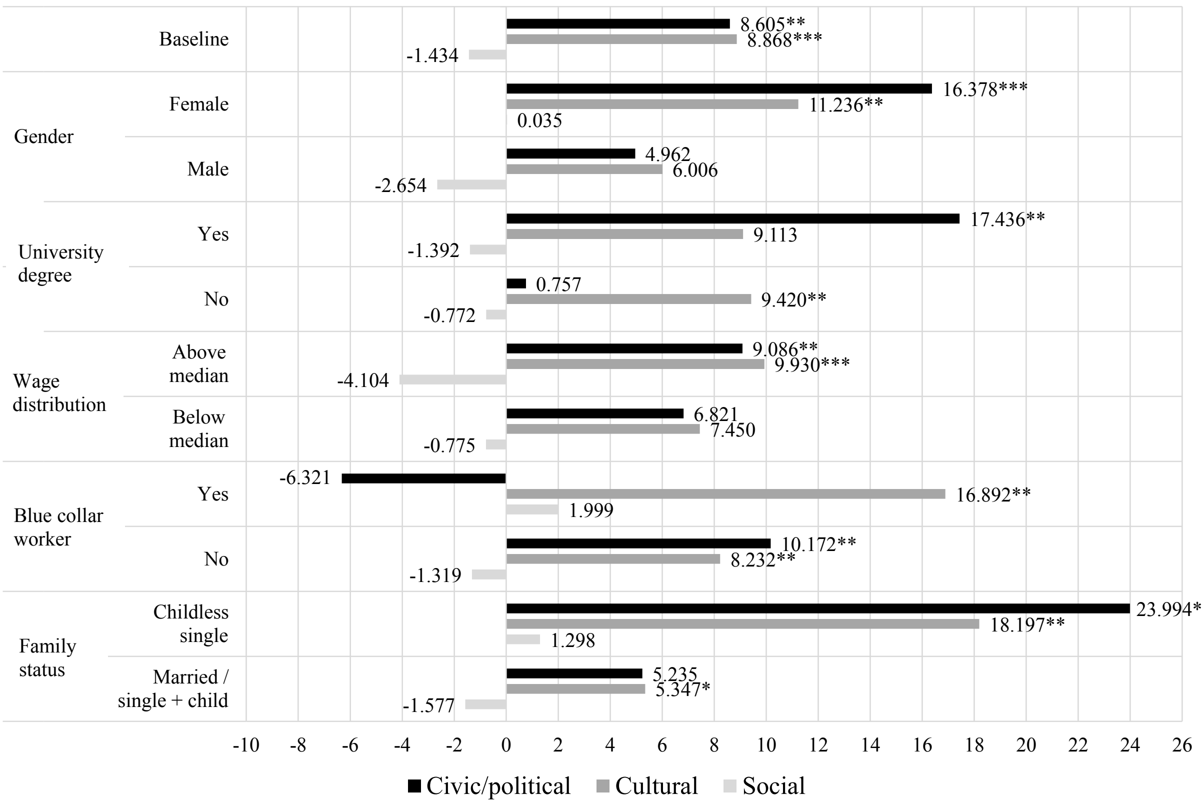
(b) Cultural participation



(c) Social participation

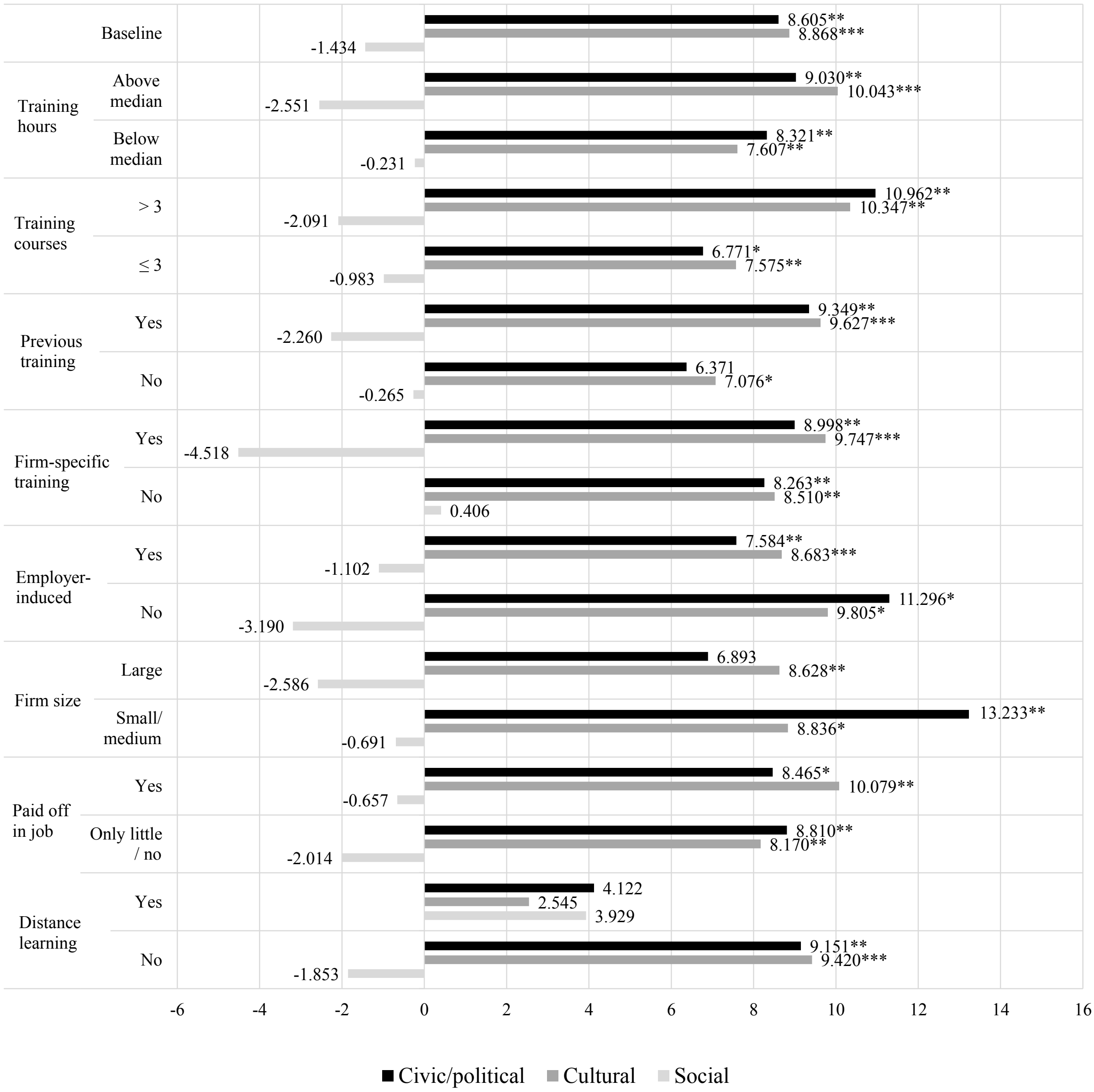
Notes: The figure displays coefficients and 90% confidence intervals for different regression models. Explanations are provided in the text. Regression results can be found in Appendix Tables **??** to **??**, Columns (1), (3), (4), and (6).

Figure 4: Heterogeneity of Treatment Effects: Individual Characteristics



Notes: The figure shows coefficients on the variable $Training_{ie} \times post_{t+1,t+2,t+3}$ from baseline regression models on the subsample indicated. Table **??** provides description of samples; especially for *position in wage distribution* and *blue collar worker*. *Family status* is assessed in period $t-1$ and is based on the two variables *married* and *children*. In the category *childless single*, the respondent is not married and has no child under the age of 16. All other respondents are assigned to the category *married / single + child*. All regressions use entropy-balancing adjusted matching weights to reweight the comparison group. Baseline weights are used, which are further refined to match within specific subsamples (covariates: log monthly earnings, log hours worked, and the three non-pecuniary outcomes in periods $t-1$ and $t-2$). Appendix Tables **??** and **??** provide regression results, including treatment period-specific heterogeneity analysis. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Figure 5: Heterogeneity of Treatment Effects: Training Characteristics



Notes: The figure shows coefficients on the variable $Training_{ie} \times post_{t+1,t+2,t+3}$ from baseline regression models on the subsample indicated. *Training hours* splits treatment group at median training hours (33 hours). *Previous training* splits treatment group by whether the respondent has already received training in the past. *Firm-specific training* splits treatment group by whether the respondent has received firm-specific or general training. To categorize the nature of courses, we use information received in response to the following question: *"To what extent could you use the newly acquired skills if you got a new job in a different company?"*. Response categories "for the most part" and "completely" are categorized as general training, while "not at all" and "only to a limited extend" are categorized as specific training. Following **?**, we use the most recent course to categorize whether training is firm-specific or not. *Employer-induced* splits treatment group by whether the respondent has taken mainly employer-induced training, i.e., the majority of courses took place during work-time, were financed by the employer, or were organized and hosted by the employer. *Paid off in job* splits treatment group by whether the participant reports that the majority of the last three courses substantially paid off in the job versus the respondent did not experience that the training yields a (substantial) payoff in the job or is not yet sure about the payoff. *Distance learning* splits the treatment group by whether the participant has attended at least one distance learning training course (among the last three reported courses). All regressions use entropy-balancing adjusted matching weights to reweight the comparison group. Baseline weights are used, which are further refined to match within specific subsamples (covariates: log monthly earnings, log hours worked, and the three non-pecuniary outcomes in periods $t-1$ and $t-2$). Appendix Tables **??** and **??** provide regression results, including treatment period-specific heterogeneity analysis. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 1: Overview of Conditioning Variables

Demographic characteristics	
Age[a]	3 categories (25-35, 36-45, 46-55)
Female	0 = male, 1 = female
Migrant	1 = individual or parents moved to Germany, 0 else
German citizen	1 = German, 0 foreign citizen
Married	1 = yes, 0 = no
Homeowner	1 = home owner, 0 = tenant
Children	1 = children under the age of 16 in household, 0 else
Self-rated health[b] $(t-1; t-2)$	5 categories (1 bad - 5 very good)
Federal state[d]	14 categories
Evaluation period[a]	3 categories (2000, 2004, 2008)
Occupational sample[a,e]	2 categories (blue collar worker; non-blue collar worker)
Education	
Vocational	0 = no vocational training, 1 = vocational training
University	0 = no university degree, 1 = university degree
Schooling	4 categories (no degree/basic school; intermediate/other school; technical school; academic school track (Abitur))
Previous work-related training	1 = participated in work-related training before, 0 else
Labor market characteristics	
Log monthly earnings[c] $(t-1; t-2)$	Log monthly gross earnings in 2010 euros
Log hours worked per week[c] $(t-1; t-2)$	Log hours worked per week
Earnings tertile[a,f]	3 categories (bottom; middle; top)
Full-time employed $(t-1; t-2)$	1 = yes, 0 = no
Occupational status $(t-1; t-2)$	7 categories (blue collar; white collar; public servant; self-employed; unemployed; non-working; apprentice, retired)
Civic service $(t-1; t-2)$	1 = public service, 0 else
Unemployment experience	3 categories (no experience; 0-2 years; more than two years)
Tenure with the current firm	4 categories (0-2 years; 2-8 years; 8-15 years; more than 15 years)
Firm size $(t-1; t-2)$	3 categories (small < 20, medium 20-200, large > 200 employees)
Industry $(t-1; t-2)$	10 categories
Satisfaction and worries	
Life satisfaction[b] $(t-1; t-2)$	11 categories (0 low - 10 high)
Worries: economic situation[b] $(t-1; t-2)$	3 categories (1 no worries, 2 some worries, 3 big worries)
Worries: own economic situation[b] $(t-1; t-2)$	3 categories (1 no worries, 2 some worries, 3 big worries)
Worries: job situation[b] $(t-1; t-2)$	3 categories (1 no worries, 2 some worries, 3 big worries)
Outcomes before treatment	
Civic/political participation score[c,g] $(t-1; t-2)$	Score from PCA
Cultural participation score[c,g] $(t-1; t-2)$	Score from PCA
Social participation score[c,g] $(t-1; t-2)$	Score from PCA
Interest in politics[b] $(t-1; t-2)$	4 categories (1 not at all, 2 not so strongly, 3 strongly, 4 very strongly)
Participate in politics[b] $(t-1; t-2)$	3 categories (1 never, 2 rarely, 3 often)
Volunteer[b] $(t-1; t-2)$	4 categories (1 never, 2 rarely, 3 every month, 4 every week)
Active in artistic/musical activities[b] $(t-1; t-2)$	4 categories (1 never, 2 rarely, 3 every month, 4 every week)
Attend classic events[b] $(t-1; t-2)$	4 categories (1 never, 2 rarely, 3 every month, 4 every week)
Attend modern events[b] $(t-1; t-2)$	4 categories (1 never, 2 rarely, 3 every month, 4 every week)
Socialize[b] $(t-1; t-2)$	4 categories (1 never, 2 rarely, 3 every month, 4 every week)
Assist[b] $(t-1; t-2)$	4 categories (1 never, 2 rarely, 3 every month, 4 every week)

Notes: All variables are included for period $t-1$ if not indicated otherwise. [a]Propensity score matching is exact on these variables. [b]Variable x is z-standardized by $(x - mean_x)/sd_x$ (see **?**). Mean and SD are based on the comparison group in periods $t-1$ and $t-2$. [c]Balancing on first and second moments of these variables in the entropy balancing stage to refine conventional matching weights. [d]Bremen and Hamburg are grouped together with Lower Saxony and Schleswig-Holstein, respectively, due to small samples. [e]To belong to the blue-collar worker sample, the individual has to report to work in a blue-collar occupation at least in one year during $t-1$ and at least in one year during $t-2$. To belong to the non-blue-collar worker sample, the individual has to report to work in a white-collar occupation or as a public servant at least in one year during $t-1$ and at least in one year during $t-2$. Most recent occupation is assigned in the case of multiple group membership assignment options. The variable is only used for exact matching and not included in the matching function (instead: matching in detailed occupational status). [f]Tertiles computed for log monthly gross earnings in 2010 euros averaged over $t-1$ and $t-2$. Calculations are based on the sample before matching. [g]Scores are rescaled by evaluation period such that the comparison group has, on average, mean 500 and SD 100 in periods $t-1$ and $t-2$.

Table 2: Balancing Table – Before Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Treated	Comparison							
		Non-matched				Matched			
	Mean	Mean	$\tilde{\Delta}$	*t*-test		Mean	$\tilde{\Delta}$	*t*-test	
				coef	pvalue			coef	pvalue
Demographic characteristics									
Age: 25-35	0.36	0.31	9.28	0.044	0.000	0.35	2.37	0.011	0.522
Age: 35-45	0.44	0.45	-1.60	-0.006	0.567	0.43	1.18	0.006	0.734
Age: 45-55	0.21	0.24	-8.61	-0.038	0.000	0.22	-4.18	-0.017	0.245
Female	0.42	0.45	-5.90	-0.031	0.019	0.41	1.24	0.006	0.754
Migrant	0.12	0.23	-28.18	-0.098	0.000	0.12	0.18	0.001	0.962
German citizen	0.97	0.88	34.52	0.085	0.000	0.97	-1.20	-0.002	0.726
Married	0.70	0.73	-8.20	-0.034	0.002	0.69	1.54	0.007	0.682
Homeowner	0.52	0.47	11.24	0.053	0.000	0.49	5.56	0.028	0.137
Children	0.51	0.53	-4.77	-0.021	0.082	0.48	4.90	0.025	0.186
East Germany	0.31	0.26	10.55	0.044	0.000	0.30	0.90	0.004	0.823
Self-rated health	0.05	0.00	5.00	0.043	0.041	0.06	-1.48	-0.014	0.659
Attrition from sample	0.32	0.36	-8.68	-0.039	0.000	0.32	-1.15	-0.005	0.761
Education									
Degree: vocational	0.73	0.73	0.08	0.001	0.944	0.75	-4.05	-0.018	0.289
Degree: university	0.36	0.17	46.30	0.185	0.000	0.35	1.97	0.009	0.630
School degree: no/basic school	0.16	0.34	-41.29	-0.161	0.000	0.16	1.93	0.007	0.608
School degree: intermediate/other school	0.42	0.45	-5.94	-0.030	0.020	0.44	-3.45	-0.017	0.376
School degree: technical school	0.07	0.04	13.35	0.029	0.000	0.07	-1.23	-0.003	0.759
School degree: academic school track (Abitur)	0.33	0.16	41.24	0.162	0.000	0.32	1.85	0.009	0.647
School degree: no info	0.01	0.01	0.81	0.000	0.878	0.01	4.43	0.005	0.129
Previous work-related training[a]	0.66	0.26	87.30	0.371	0.000	0.65	0.97	0.005	0.789
Labor market characteristics									
Log gross monthly earnings (in 2010 euro)[b]	7.93	7.63	51.99	0.279	0.000	7.93	0.00	0.000	1.000
Log hours worked per week[b]	3.68	3.59	25.57	0.086	0.000	3.68	0.01	0.000	0.998
Earnings tertile: bottom[a]	0.17	0.37	-46.22	-0.184	0.000	0.16	1.05	0.004	0.769
Earnings tertile: middle[a]	0.32	0.34	-5.40	-0.022	0.051	0.32	-1.00	-0.005	0.796
Earnings tertile: top[a]	0.51	0.29	46.98	0.206	0.000	0.51	0.16	0.001	0.968
Entry age	19.91	18.40	61.53	1.409	0.000	19.82	3.24	0.083	0.422
Employment: full-time	0.84	0.78	15.21	0.058	0.000	0.84	-0.90	-0.003	0.801
Employment: part-time	0.14	0.17	-7.80	-0.031	0.000	0.14	0.66	0.002	0.856
Employment: marginal/unregular	0.01	0.03	-15.63	-0.019	0.000	0.01	0.09	0.000	0.974
Employment: non-working	0.01	0.02	-7.02	-0.008	0.000	0.01	0.57	0.001	0.831
Occupation sample: blue collar worker[a]	0.86	0.54	73.58	0.292	0.000	0.85	1.35	0.005	0.709
Occupation sample: non-blue collar worker[a]	0.14	0.46	-73.58	-0.292	0.000	0.15	-1.35	-0.005	0.709
Civic service	0.41	0.22	42.81	0.178	0.000	0.40	1.48	0.007	0.699
Unemployment experience: 0 years	0.71	0.63	17.85	0.076	0.000	0.72	-0.45	-0.002	0.909
Unemployment experience: 0-2 years	0.26	0.31	-10.58	-0.043	0.000	0.26	0.59	0.003	0.882
Unemployment experience: more than 2 years	0.02	0.06	-18.03	-0.033	0.000	0.03	-0.62	-0.001	0.858
Tenure: 0-2 years	0.15	0.17	-4.86	-0.015	0.026	0.14	4.65	0.016	0.105
Tenure: 2-8 years	0.35	0.36	-1.84	-0.011	0.265	0.37	-3.01	-0.014	0.357
Tenure: 8-15 years	0.26	0.26	0.87	0.006	0.502	0.25	2.16	0.009	0.521
Tenure: more than 15 years	0.23	0.20	5.22	0.018	0.066	0.24	-3.00	-0.013	0.433
Firm size: small firms (<20)	0.13	0.24	-29.03	-0.100	0.000	0.13	-1.99	-0.007	0.574
Firm size: medium firms (20-200)	0.23	0.30	-15.89	-0.065	0.000	0.23	-0.57	-0.002	0.869
Firm size: large firms (>200)	0.62	0.42	39.43	0.177	0.000	0.61	1.61	0.008	0.650
Firm size: no info	0.03	0.04	-6.88	-0.012	0.000	0.03	0.76	0.001	0.781
Satisfaction and worries									
Life satisfaction	0.10	0.03	8.12	0.065	0.001	0.11	-0.78	-0.007	0.815
Satisfaction with job situation	0.07	0.01	6.65	0.053	0.007	0.08	-1.76	-0.015	0.597
Worries: economic situation	0.09	0.06	2.58	0.008	0.665	0.10	-1.01	-0.009	0.739
Worries: own economic situation	-0.25	0.00	-25.91	-0.221	0.000	-0.25	0.22	0.002	0.950
Worries: job	-0.20	0.00	-22.05	-0.190	0.000	-0.21	0.18	0.002	0.959
Non-pecuniary outcomes (before treatment)									
Civic/political participation score[b]	533	502	29.48	29.202	0.000	533	0.00	-0.005	0.999
Cultural participation score[b]	549	502	49.83	42.990	0.000	549	0.00	0.000	1.000
Social participation score[b]	501	500	1.35	0.605	0.780	501	0.01	0.010	0.997
Interest in politics	0.40	0.02	39.70	0.350	0.000	0.37	3.14	0.030	0.388
Participate in politics	0.16	0.01	14.12	0.145	0.000	0.20	-3.30	-0.040	0.412
Volunteer	0.27	0.02	23.84	0.232	0.000	0.25	2.05	0.023	0.583
Active in artistic/musical activities	0.30	0.00	29.19	0.280	0.000	0.28	1.77	0.019	0.598
Attend classic events	0.41	0.04	39.97	0.339	0.000	0.43	-2.04	-0.019	0.530
Attend modern events	0.26	0.01	28.14	0.237	0.000	0.27	-1.10	-0.010	0.752
Socialize	0.10	0.01	9.66	0.079	0.000	0.10	-0.14	-0.001	0.967
Assist	0.00	0.00	-0.26	-0.007	0.757	0.00	0.48	0.004	0.892
Mean/median/P75 absolute $\tilde{\Delta}$ (96 variables)			18.24/9.39/28.60				1.49/1.16/1.98		

Notes: The table shows group means before and after matching for treatment and comparison group, averaged over both pretreatment periods $t-1$ and $t-2$. Appendix Tables **??** and **??** show balancing tables separately by treatment period. Sample consists of working-age males and females (25-55 years old), working in each of the two pretreatment periods at least in one year in a white-collar occupation, a blue-collar occupation, or as a public servant. $\tilde{\Delta}$ is the standardized difference in group means. *coef* and *pvalue* are based on a regression of the specific variable on the treatment indicator and evaluation-period fixed effects. Observations are not weighted before matching and by matching weights after matching. Matching also considers ten (plus one for missing) industry dummies, 14 state dummies, and three evaluation period dummies. Variables are not displayed, but included in the average absolute standardized difference calculations. [a]Exact matching on these variables in the propensity score matching stage. [b]Balancing on these variables in the entropy balancing stage.

Table 3: Social Capital and Work-Related Training

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: treatment effects by treatment period						
	Civic/political		Cultural		Social	
$\text{Training}_{ie} \times \text{post}_{t+3}$	10.624**	10.330**	11.047**	10.945**	–2.646	–2.506
	(5.234)	(5.218)	(4.352)	(4.352)	(4.868)	(4.842)
$\text{Training}_{ie} \times \text{post}_{t+2}$	12.273***	12.301***	10.774***	10.449***	–1.481	–0.929
	(4.435)	(4.460)	(4.018)	(4.022)	(4.394)	(4.422)
$\text{Training}_{ie} \times \text{post}_{t+1}$	4.492	4.493	6.496*	5.597	0.190	0.466
	(4.147)	(4.155)	(3.468)	(3.421)	(3.637)	(3.630)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	8.567**	8.915***	3.569	2.667	3.440	3.374
	(3.402)	(3.402)	(3.045)	(3.051)	(3.461)	(3.459)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.053	0.147	0.661	0.710	0.298	0.619
	(3.426)	(3.422)	(3.137)	(3.118)	(2.834)	(2.830)
R-squared	0.677	0.678	0.601	0.605	0.537	0.539
Observations	20,997	20,997	20,997	20,997	20,997	20,997
H_0: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.018	0.018	0.023	0.033	0.886	0.921
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.037	0.039	0.031	0.038	0.925	0.925
Panel B: treatment effects averaged over post-treatment periods						
	Civic/political		Cultural		Social	
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.605**	8.485**	8.868***	8.428***	–1.434	–1.267
	(3.697)	(3.710)	(3.046)	(3.027)	(3.579)	(3.582)
R-squared	0.657	0.658	0.583	0.588	0.538	0.541
Observations	17,159	17,159	17,159	17,159	17,159	17,159
Treatment-by-evaluation FE	x	x	x	x	x	x
Control variables	x	x	x	x	x	x
Individual-by-evaluation FE	x	x	x	x	x	x
Labor-market control variables		x		x		x
Mean in $t-1 \cap t-2$	533	533	549	549	501	501

Notes: The sample is restricted to male and female individuals who are between 25 and 55 years old. In the matched sample, the comparison group is reweighted to match the treatment group by using entropy-balancing adjusted matching weights. Participation scores are standardized to have mean 500 and standard deviation 100 in the pre-treatment comparison group for each evaluation period. In Panel A, $Training_{ie}$ is equal to one if person i in evaluation period e has participated in at least ten hours of work-related training in the last three years and zero if the person has not participated in that period. $Treat_{t=0}$ is equal to one for the averaged three-year treatment period and zero otherwise. $Post_{t+\kappa}$ indicates averaged post-treatment periods $\kappa = \{1,2,3\}$ and $Pre_{t-\kappa}$ indicates averaged pre-treatment periods $\kappa = \{1,2\}$. In Panel B, the variable $\text{post}_{t+1,t+2,t+3}$ is equal to one if post_{t+1}, post_{t+2}, or post_{t+3} are equal to one and zero otherwise; period $t = 0$ is not considered. *Treatment-by-evaluation FE* are treatment period by evaluation period fixed effects and *Individual-by-evaluation FE* are individual by evaluation period fixed effects (see Figure **??**). *Control variables:* German citizen, married, homeowner, children, vocational degree, university degree, school degree (four categories), state of residence (14 categories), elections to the national parliament. *Labor-market control variables:* log monthly earnings, missing earnings dummy, log weekly hours worked, missing hours worked dummy, employment status (six categories), occupational status (eight categories), civil service, unemployment experience (three categories), tenure (four categories)), industry (ten categories)), and firm size (three categories). All regressions contain dummy variables for outcome scores that are based on imputed *socialize*, *assist*, and *active* values. *Mean in $t-1 \cap t-2$* is computed for the comparison group. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Common Trends in Pretreatment Period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log earnings		Civic/political		Cultural		Social	
	Attrition in $t+2/t+3$		Attrition in $t+2/t+3$		Attrition in $t+2/t+3$		Attrition in $t+2/t+3$	
	No	Yes	No	Yes	No	Yes	No	Yes
				Panel A: non-matched sample				
Training$_{ie}$ × pre$_{t-3}$	–0.060***	–0.047***	–1.900	0.779	2.631	1.017	0.179	2.649
	(0.014)	(0.010)	(3.354)	(2.510)	(2.820)	(2.126)	(3.636)	(2.789)
R-squared	0.841	0.859	0.676	0.693	0.700	0.694	0.568	0.577
Observations	14,966	26,744	14,869	26,567	14,869	26,567	14,869	26,567
				Panel B: matched sample				
Training$_{ie}$ × pre$_{t-3}$	–0.011	–0.012	1.993	5.317	–0.426	–0.816	–3.182	0.347
	(0.021)	(0.015)	(4.858)	(3.999)	(4.330)	(3.338)	(5.476)	(4.179)
R-squared	0.801	0.825	0.708	0.716	0.681	0.671	0.562	0.593
Observations	6,693	11,316	6,655	11,261	6,655	11,261	6,655	11,261
Treatment-by-evaluation FE	x	x	x	x	x	x	x	x
Individual-by-evaluation FE	x	x	x	x	x	x	x	x
Mean in $t-1 \cap t-2$	7.933	7.933	533	533	549	549	501	501

Notes: The sample is restricted to the three pre-treatment periods. Pre_{t-3} is equal to one if the period is equal to pre-treatment period 3 and zero if the period is equal to pre-treatment periods 1 or 2, respectively. *Attrition in* $t+2/t+3$*: no* indicates that individuals are dropped when they do not report a participation score. *Attrition in* $t+2/t+3$*: yes* allows individuals to report a participation score in one of the periods only. In the matched sample, the comparison group is reweighted to match the treatment group by using entropy-balancing adjusted matching weights. Table **??** provides further information on the sample and the variables. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

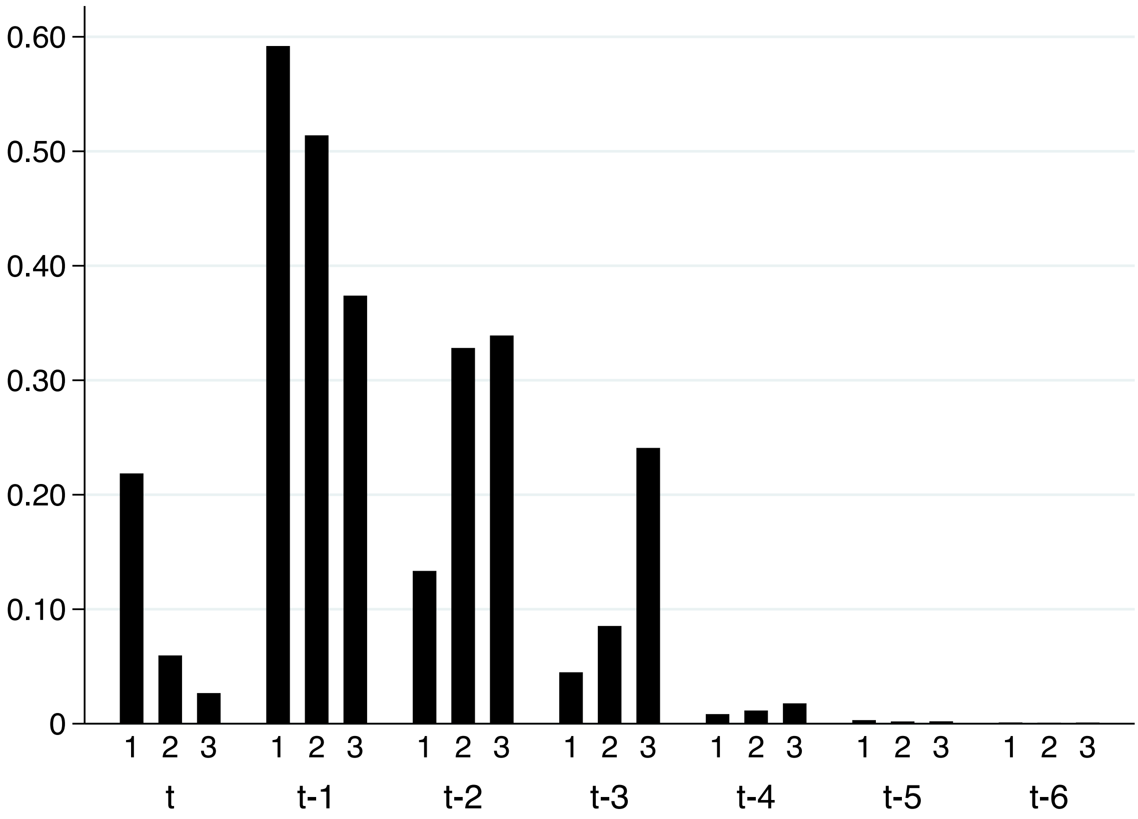
Table 5: Heterogeneity by Monetary Value of the Training

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log earnings		Civic/political		Cultural		Social	
	Monetary value		Monetary value		Monetary value		Monetary value	
	High	Low	High	Low	High	Low	High	Low
				Panel A: treatment effects by treatment period				
Training$_{ie}$ × post$_{t+3}$	0.152***	–0.002	5.441	14.994**	11.982**	10.344*	–8.117	3.336
	(0.027)	(0.029)	(6.744)	(6.543)	(5.573)	(5.389)	(6.167)	(6.100)
Training$_{ie}$ × post$_{t+2}$	0.126***	–0.041*	10.938*	14.025**	9.635**	11.445**	0.265	–1.839
	(0.019)	(0.024)	(5.865)	(5.641)	(4.875)	(5.074)	(5.174)	(5.421)
Training$_{ie}$ × post$_{t+1}$	0.100***	–0.015	3.577	5.658	8.051*	5.816	–1.619	2.533
	(0.015)	(0.023)	(5.519)	(5.354)	(4.502)	(4.401)	(4.418)	(4.816)
Training$_{ie}$ × treat$_{t=0}$	0.060***	0.019	7.621	10.741**	1.459	5.893	4.276	3.068
	(0.012)	(0.016)	(4.710)	(4.205)	(3.925)	(3.754)	(4.431)	(4.453)
Training$_{ie}$ × pre$_{t-2}$	–0.000	0.003	–0.019	0.147	0.083	1.135	0.112	0.184
	(0.013)	(0.014)	(4.307)	(4.214)	(4.218)	(3.540)	(3.271)	(3.918)
R-squared	0.759	0.722	0.683	0.667	0.598	0.601	0.554	0.520
Observations	14,270	14,044	14,419	14,351	14,419	14,351	14,419	14,351
H_0: post$_{t+1,t+2} = 0$ (pvalue)	0.000	0.203	0.149	0.039	0.094	0.079	0.888	0.555
H_0: post$_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.209	0.269	0.052	0.118	0.124	0.380	0.652
				Panel B: treatment effects averaged over post-treatment periods				
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	0.123***	–0.021	6.303	10.893**	10.055***	7.993**	–2.693	0.633
	(0.017)	(0.022)	(4.841)	(4.737)	(3.689)	(3.879)	(4.171)	(4.567)
R-squared	0.742	0.697	0.666	0.645	0.580	0.583	0.556	0.521
Observations	11,606	11,343	11,798	11,714	11,798	11,714	11,798	11,714
Treatment-by-evaluation FE	x	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x	x
Individual-by-evaluation FE	x	x	x	x	x	x	x	x
Mean absolute $\tilde{\Delta}$	3.84	2.61	3.84	2.61	3.84	2.61	3.84	2.61
Median absolute $\tilde{\Delta}$	3.22	2.19	3.22	2.19	3.22	2.19	3.22	2.19
P75 absolute $\tilde{\Delta}$	5.74	3.98	5.74	3.98	5.74	3.98	5.74	3.98

Notes: The table splits the treatment group into two categories: training participants whose hourly earnings have increased more than in the comparison group (group *high*) and training participants whose hourly earnings have increased not more than in the comparison group (group *low*). All regressions use entropy-balancing adjusted matching weights to reweight the comparison group. Baseline weights are used, which are further refined to match within specific subsamples (covariates: log monthly earnings, log hours worked, and the three non-pecuniary outcomes in periods $t-1$ and $t-2$). Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

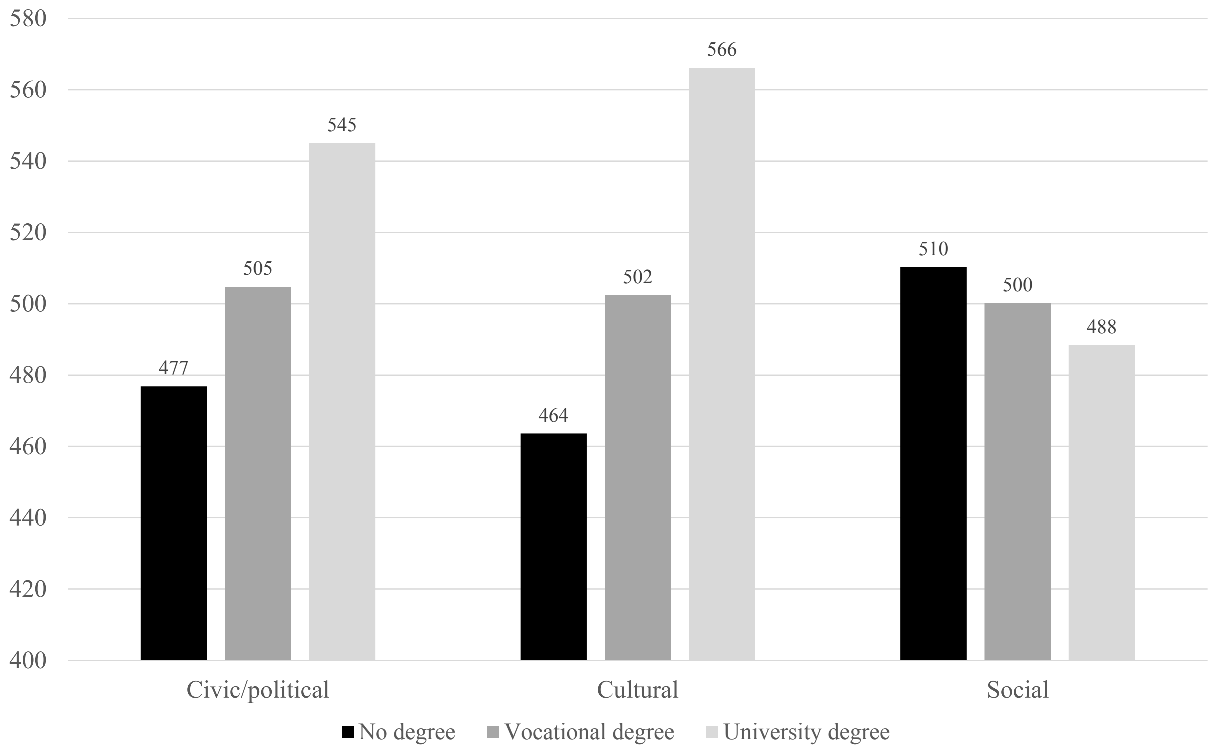
A Appendix Figures and Tables

Figure A-1: Start Years of Work-Related Training Courses



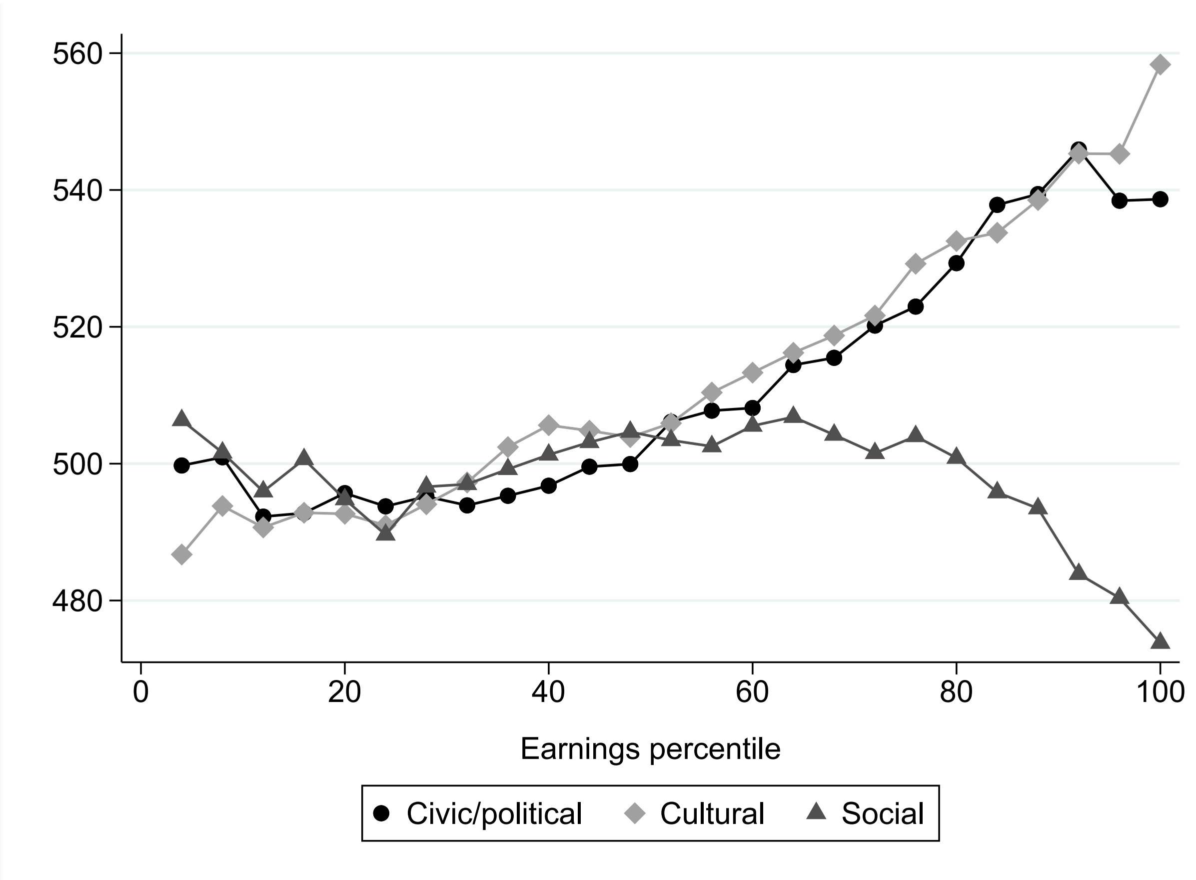
Notes: The figure shows the distribution of start years (relative to the qualification survey) for the last three courses of the individual.

Figure A-2: Non-Pecuniary Outcome Scores by Educational Degree



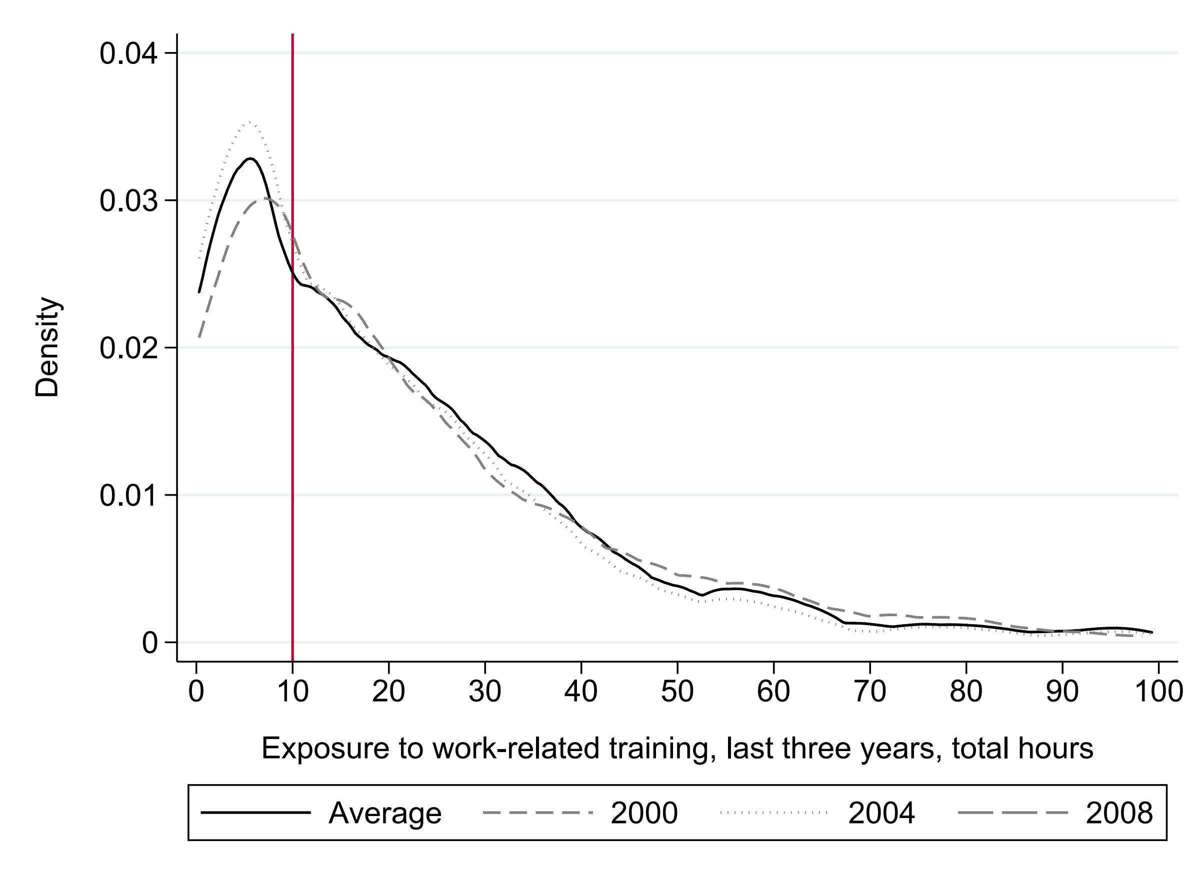
Notes: The figure shows average values of the three non-pecuniary outcome variables by educational degree of the individual. Averages are calculated over all available individual observations in all evaluation periods. Number of observations: no degree: $8,299$; vocational degree: $43,719$; university degree: $9,096$.

Figure A-3: Non-Pecuniary Outcome Scores by Position in the Monthly Earnings Distribution



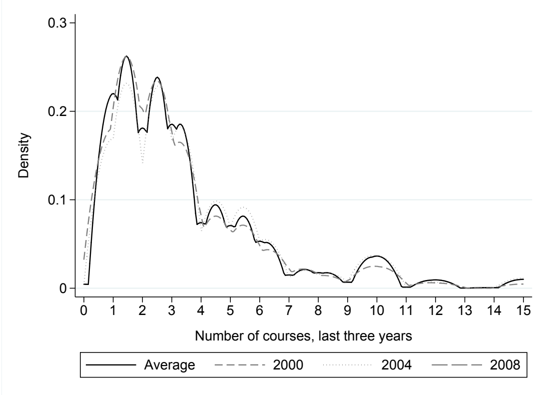
Notes: The figure shows average values of the three non-pecuniary outcome variables by position of the individual in the monthly earnings distribution. Earnings are in 2010 euro.

Figure A-4: Distribution of Course Hours

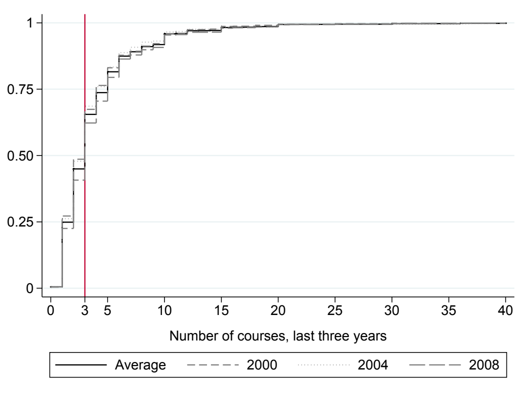


Notes: The figure shows the distribution of individual training course hours. Individual training course hours are calculated as the sum of the three reported training courses. The distribution is based on the sample in the pretreatment period $t-1$. For illustrative purpose, the distribution is capped at 100 course hours.

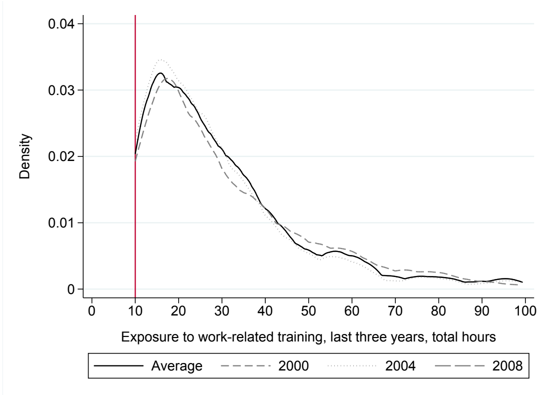
Figure A-5: Distribution of Courses and Course Hours



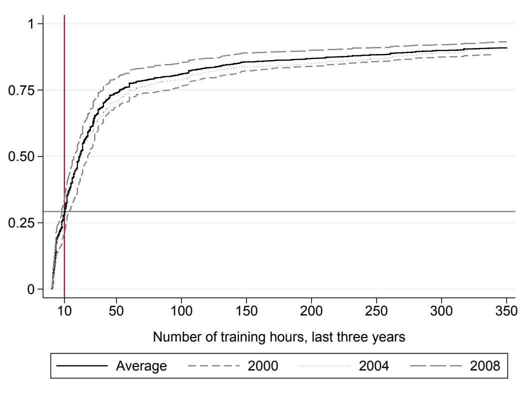
(a) Number of courses (pdf)



(b) Number of courses (cdf)



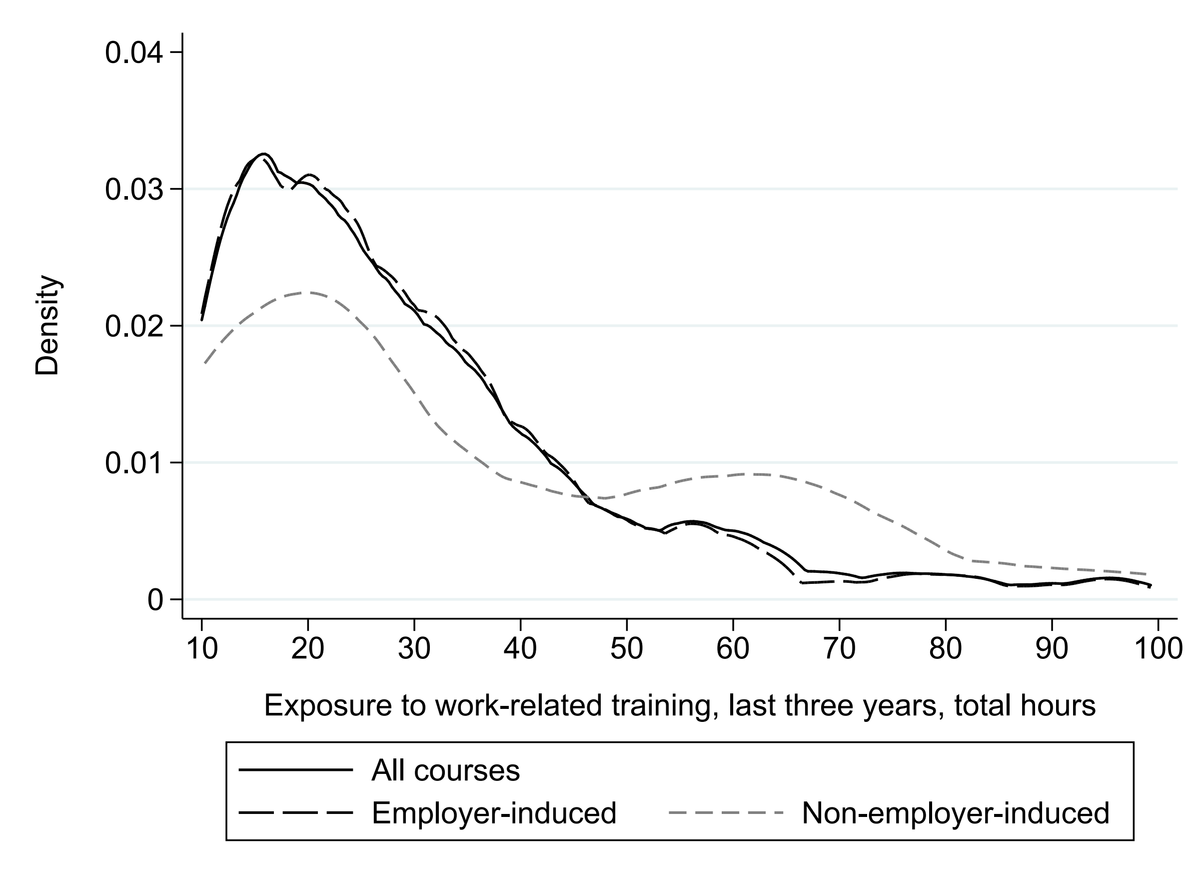
(c) Number of course hours (pdf)



(d) Number of course hours (cdf)

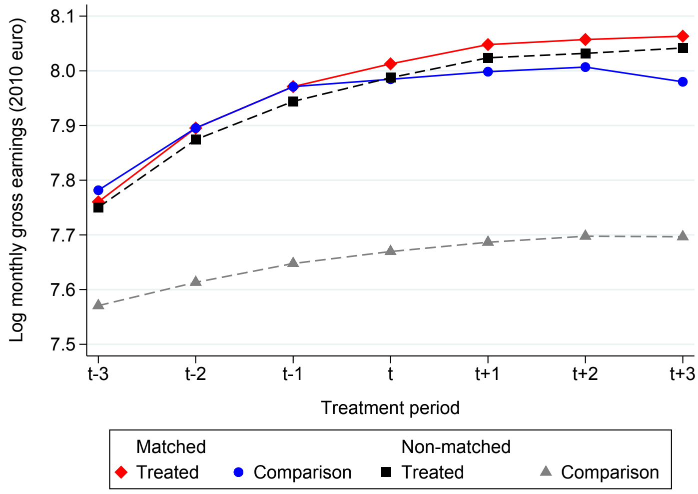
Notes: The figures show the distribution of courses and course hours. Distributions are based on the sample in the pretreatment period $t-1$. For illustrative purpose, distributions are capped at the last value displayed. For number of courses in Figures **??**(a) and **??**(b), the mean is equal to 3.9, the median is equal to 3, and the largest value is equal to 99. Figure **??**(c) shows the distribution of course hours after restricting the sample to individuals with at least 10 hours of training. Figure **??**(d) provides the CDF for the unrestricted sample. The mean in the restricted (unrestricted) sample is equal to 208 (149), the median is equal to 33 (22), and the largest value is equal to 13,757.

Figure A-6: Distribution of Employer- and Non-Employer-Induced Course Hours

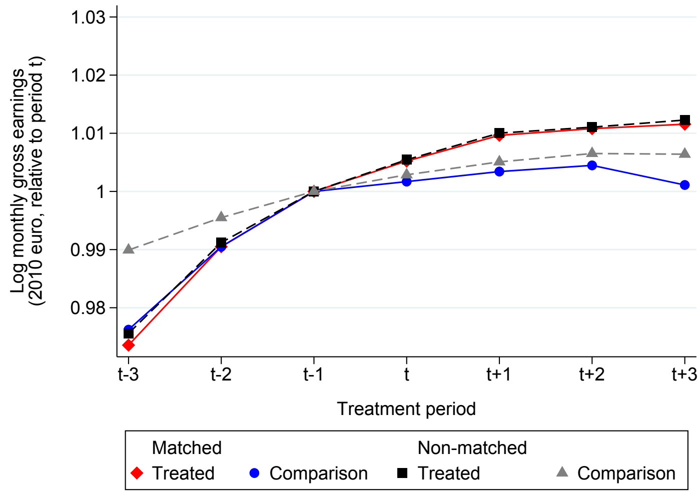


Notes: The figure shows the distribution of individual training course hours. Individual training course hours are calculated as the sum of the three reported training courses. The distribution is based on the sample in the pretreatment period $t-1$. For illustrative purpose, the distribution is capped at 100 course hours. An individual has participated in employer-induced courses if the majority of training courses took place during work-time, are financed by the employer, or organized and hosted by the employer.

Figure A-7: Descriptive Relationship between Work-Related Training and Earnings



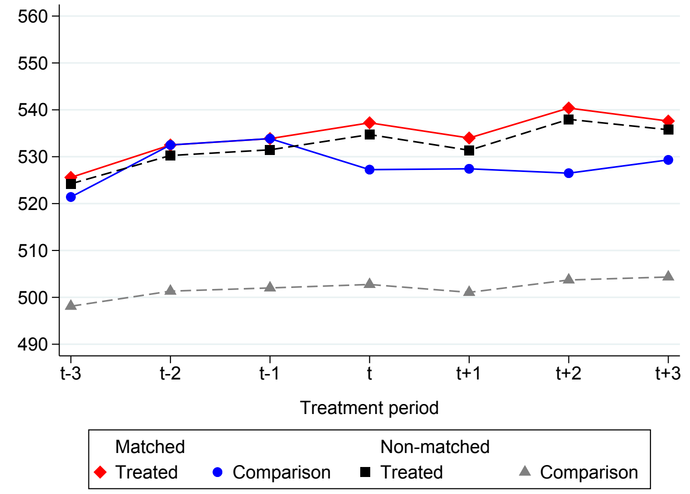
(a) Log monthly earnings



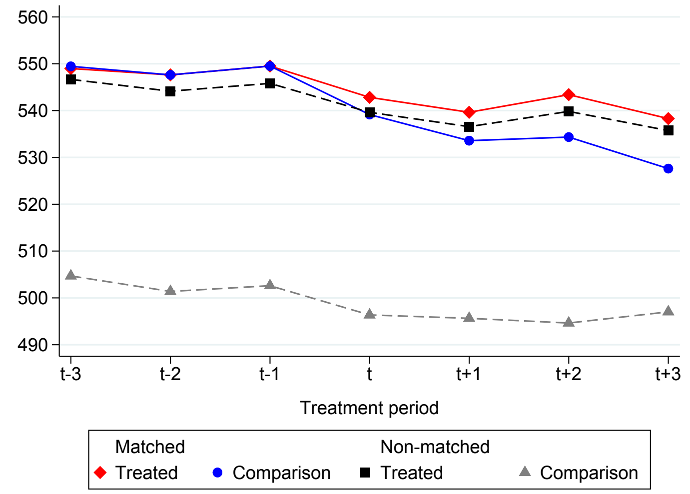
(b) Log monthly earnings relative to pretreatment period $t-1$

Notes: The figures show treatment-period averages of log monthly gross earnings. Observations in the comparison group are weighted by matching weights in the matched sample.

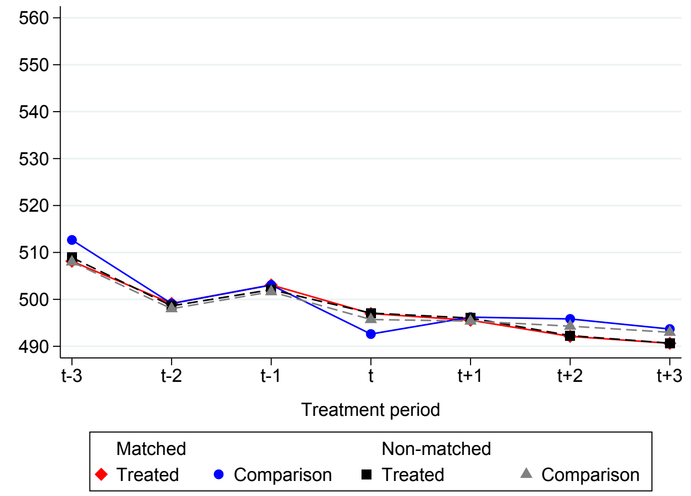
Figure A-8: Descriptive Relationship between Work-Related Training and Participation Domains



(a) Civic/political participation



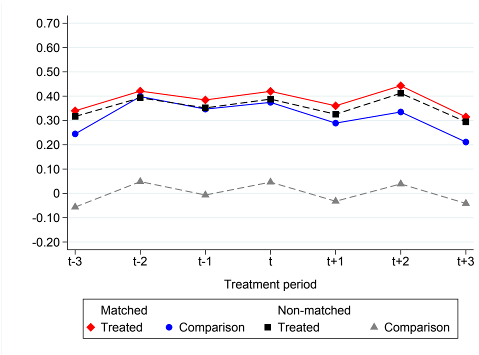
(b) Cultural participation



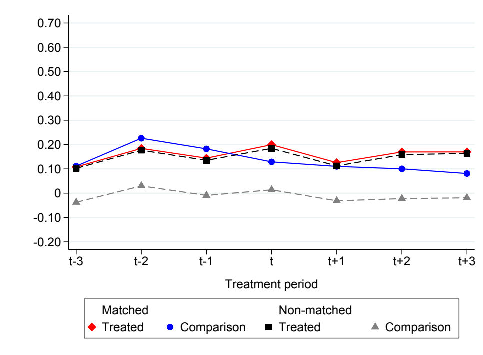
(c) Social participation

Notes: The figures show treatment-period averages of participation scores. Observations in the comparison group are weighted by matching weights in the matched sample.

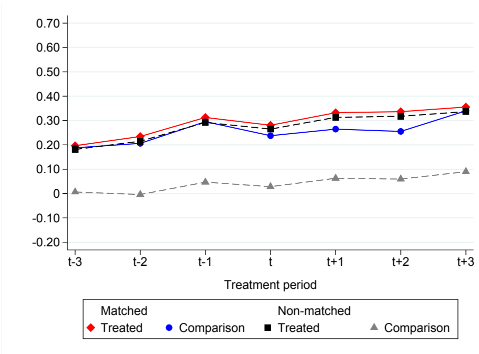
Figure A-9: Treatment-Period Averages of Subdimensions



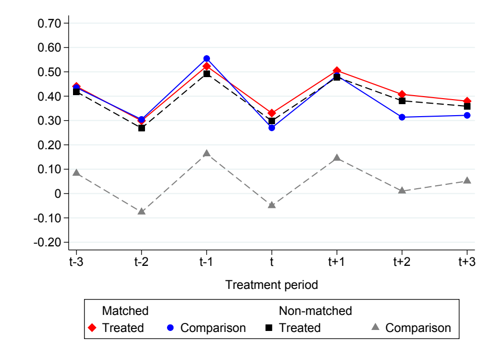
(a) Interest in politics



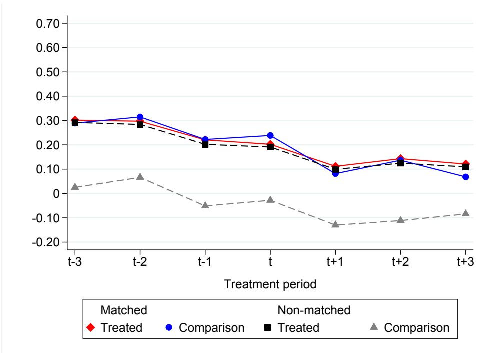
(b) Participate in politics



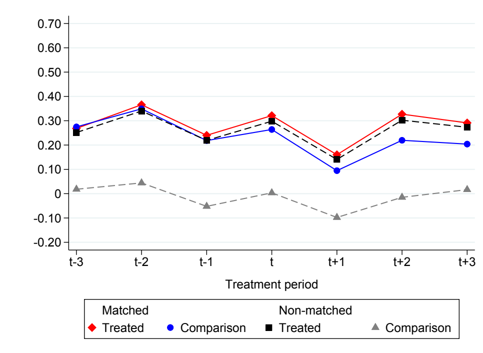
(c) Volunteer



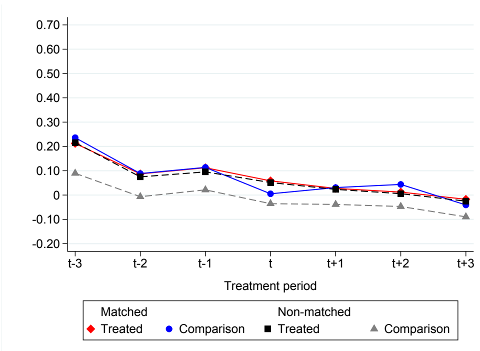
(d) Attend cultural events



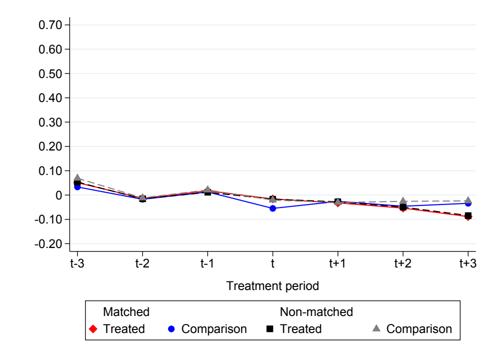
(e) Attend modern events



(f) Active



(g) Socialize



(h) Assist

Notes: The figures show treatment-period averages of participation scores. Observations in the comparison group are weighted by matching weights in the matched sample.

Table A-1: Correlation Matrix of Participation Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Interest in politics	1.000							
(2) Participate in politics	0.230	1.000						
(3) Volunteer	0.137	0.349	1.000					
(4) Active in artistic/musical activities	0.120	0.142	0.204	1.000				
(5) Attend classic events	0.224	0.171	0.199	0.319	1.000			
(6) Attend modern events	0.133	0.059	0.115	0.182	0.399	1.000		
(7) Socialize	0.049	0.033	0.087	0.109	0.157	0.219	1.000	
(8) Assist	0.006	0.073	0.158	0.049	0.083	0.112	0.387	1.000

Notes: The table shows the correlation matrix of outcome variables. The sample for these calculations is restricted to observations in the comparison group in pre-treatment periods $t-1$ and $t-2$. No imputations are used for the calculations.

Table A-2: Factor Loadings

Variable	Non-pecuniary outcome dimensions		
	Civic/political	Cultural	Social
Interest in politics	0.324	0.243	–0.170
Participate in politics	0.682	–0.052	–0.022
Volunteer	0.604	–0.008	0.126
Active in artistic/musical activities	0.129	0.426	–0.062
Attend classic events	0.043	0.610	–0.037
Attend modern events	–0.170	0.597	0.100
Socialize	–0.074	0.138	0.652
Assist	0.097	–0.083	0.716

Notes: The table shows the loadings from the principal component analysis of the outcome variables. The sample for these calculations is restricted to observations in the comparison group in pre-treatment periods $t-1$ and $t-2$. No imputations are used for the calculations.

Table A-3: Sample Size for Subsamples with the Propensity Score between 0.1 and 0.9

	(1)	(2)	(3)	(4)
	Low $P < 0.1$	Middle $0.1 \leq P \leq 0.9$	High $P > 0.9$	All
Comparison	2,300	4,598	0	6,898
Treatment	124	2,533	0	2,657
All	2,424	7,131	0	9,555

Notes: The table shows sample sizes for subsamples that have a very low probability to participate in training ($P < 0.1$) and a very high probability to participate in training ($P > 0.9$). We drop those individuals from the analysis. Sample is based on pretreatment period $t-1$. Number of unique persons is equal to 6,492. *Treatment* covers individuals who have participated in at least ten hours of work-related training in the last three years. *Comparison* covers individuals who have not participated in any work-related training in the last three years.

Table A-4: Balancing Table – Before Treatment (period $t-1$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Treated	Comparison							
		Non-matched				Matched			
	Mean	Mean	$\tilde{\Delta}$	t-test		Mean	$\tilde{\Delta}$	t-test	
				coef	pvalue			coef	pvalue
Demographic characteristics									
Age: 25-35	0.31	0.27	8.75	0.039	0.000	0.31	0.18	0.001	0.962
Age: 35-45	0.45	0.45	-0.10	0.002	0.854	0.43	2.93	0.015	0.431
Age: 45-55	0.25	0.28	-8.87	-0.041	0.000	0.26	-3.54	-0.015	0.353
Female	0.42	0.45	-5.90	-0.031	0.019	0.41	1.24	0.006	0.754
Migrant	0.12	0.23	-28.18	-0.098	0.000	0.12	0.18	0.001	0.962
German citizen	0.97	0.88	34.00	0.082	0.000	0.97	-1.72	-0.003	0.617
Married	0.71	0.74	-8.49	-0.036	0.002	0.71	-1.14	-0.005	0.771
Homeowner	0.54	0.48	11.76	0.055	0.000	0.52	4.85	0.024	0.216
Children	0.50	0.51	-3.13	-0.013	0.308	0.47	4.84	0.024	0.214
East Germany	0.31	0.26	10.39	0.043	0.000	0.31	0.54	0.003	0.893
Self-rated health	0.02	-0.04	5.88	0.052	0.026	0.02	-0.96	-0.009	0.798
Attrition from sample	0.32	0.36	-8.59	-0.039	0.000	0.32	-1.15	-0.005	0.761
Education									
Degree: vocational	0.73	0.73	1.08	0.006	0.621	0.75	-4.32	-0.019	0.274
Degree: university	0.37	0.17	46.85	0.187	0.000	0.36	2.07	0.010	0.615
School degree: no/basic school	0.16	0.33	-41.90	-0.162	0.000	0.15	1.58	0.006	0.681
School degree: intermediate/other school	0.42	0.46	-6.69	-0.034	0.009	0.44	-3.76	-0.019	0.342
School degree: technical school	0.08	0.04	14.23	0.031	0.000	0.08	-1.16	-0.003	0.779
School degree: academic school track (Abitur)	0.33	0.16	41.74	0.164	0.000	0.32	2.47	0.012	0.542
School degree: no info	0.01	0.01	0.67	0.000	0.908	0.01	4.12	0.004	0.170
Previous work-related training[a]	0.66	0.26	87.29	0.371	0.000	0.65	0.97	0.005	0.789
Labor market characteristics									
Log gross monthly earnings (in 2010 euro)[b]	7.97	7.65	55.97	0.297	0.000	7.97	0.00	0.000	1.000
Log hours worked per week[b]	3.69	3.59	27.18	0.090	0.000	3.69	0.01	0.000	0.998
Earnings tertile: bottom[a]	0.17	0.37	-46.22	-0.184	0.000	0.16	1.05	0.004	0.769
Earnings tertile: middle[a]	0.32	0.34	-5.40	-0.022	0.051	0.32	-1.00	-0.005	0.796
Earnings tertile: top[a]	0.51	0.29	46.98	0.206	0.000	0.51	0.16	0.001	0.968
Entry age	19.91	18.40	61.52	1.409	0.000	19.82	3.24	0.083	0.422
Employment: full-time	0.84	0.78	14.80	0.058	0.000	0.84	-0.20	-0.001	0.960
Employment: part-time	0.15	0.17	-6.61	-0.027	0.003	0.15	-0.05	0.000	0.990
Employment: apprenticeship	0.00	0.00	-2.95	0.000	0.084	0.00		0.000	
Employment: marginal/unregular	0.01	0.03	-19.52	-0.023	0.000	0.01	-1.55	-0.001	0.632
Employment: non-working	0.01	0.02	-5.85	-0.007	0.008	0.01	2.11	0.002	0.546
Occupation sample: blue collar worker	0.86	0.54	73.64	0.292	0.000	0.85	1.35	0.005	0.709
Occupation sample: non-blue collar worker	0.14	0.46	-73.64	-0.292	0.000	0.15	-1.35	-0.005	0.709
Civil service	0.41	0.21	43.95	0.182	0.000	0.41	1.79	0.009	0.654
Unemployment experience: 0 years	0.71	0.62	18.35	0.078	0.000	0.71	-0.61	-0.003	0.877
Unemployment experience: 0-2 years	0.27	0.32	-10.94	-0.045	0.000	0.26	0.50	0.002	0.900
Unemployment experience: more than 2 years	0.03	0.06	-17.94	-0.033	0.000	0.03	0.11	0.000	0.975
Tenure: 0-2 years	0.11	0.14	-8.58	-0.024	0.001	0.11	1.00	0.003	0.777
Tenure: 2-8 years	0.36	0.36	-0.64	-0.006	0.607	0.36	-0.94	-0.005	0.804
Tenure: 8-15 years	0.28	0.28	0.74	0.006	0.580	0.27	2.34	0.010	0.536
Tenure: more than 15 years	0.25	0.22	6.24	0.023	0.034	0.26	-2.35	-0.010	0.553
Firm size: small firms (<20)	0.12	0.24	-31.47	-0.106	0.000	0.13	-2.94	-0.010	0.435
Firm size: medium firms (20-200)	0.24	0.30	-15.30	-0.064	0.000	0.24	-0.67	-0.003	0.859
Firm size: large firms (>200)	0.62	0.42	40.54	0.181	0.000	0.61	1.88	0.009	0.625
Firm size: no info	0.02	0.04	-6.80	-0.011	0.002	0.02	2.33	0.003	0.483
Satisfaction and worries									
Life satisfaction	0.10	0.01	9.69	0.078	0.001	0.09	0.69	0.006	0.852
Satisfaction with job situation	0.04	-0.01	5.56	0.046	0.042	0.05	-1.44	-0.013	0.711
Worries: economic situation	0.08	0.05	2.89	0.005	0.833	0.11	-2.69	-0.025	0.444
Worries: own economic situation	-0.27	-0.01	-27.30	-0.241	0.000	-0.28	0.32	0.003	0.935
Worries: job	-0.19	0.01	-21.41	-0.193	0.000	-0.19	-0.08	-0.001	0.982
Non-pecuniary outcomes (before treatment)									
Civic/political participation score[b]	534	502	29.26	29.458	0.000	534	-0.01	-0.007	0.999
Cultural participation score[b]	550	503	50.29	43.115	0.000	550	0.00	0.000	1.000
Social participation score[b]	503	502	1.54	0.462	0.840	503	0.01	0.010	0.998
Interest in politics	0.38	-0.01	40.35	0.359	0.000	0.35	3.90	0.038	0.313
Participate in politics	0.14	-0.01	14.05	0.144	0.000	0.18	-3.12	-0.038	0.466
Volunteer	0.31	0.05	24.74	0.245	0.000	0.30	1.55	0.017	0.697
Active in artistic/musical activities	0.24	-0.05	28.48	0.267	0.000	0.22	2.03	0.022	0.581
Attend classic events	0.52	0.16	38.30	0.330	0.000	0.55	-3.43	-0.032	0.367
Attend modern events	0.22	-0.05	31.25	0.254	0.000	0.22	-0.18	-0.002	0.963
Socialize	0.11	0.02	9.70	0.075	0.001	0.11	-0.16	-0.001	0.966
Assist	0.02	0.02	-0.35	-0.010	0.661	0.01	0.51	0.005	0.892
Mean/median/P75 absolute $\tilde{\Delta}$ (96 variables)			18.51/9.69/28.86				1.58/1.18/2.34		

Notes: The table shows group means before and after matching for treatment and comparison group for pretreatment period $t-1$. Sample consists of working-age males and females (25-55 years old), working in each of the two pretreatment periods at least in one year in a white collar occupation, a blue collar occupation, or as a public servant. $\tilde{\Delta}$ is the standardized difference in group means. *coef* and *pvalue* are based on a regression of the specific variable on the treatment indicator and evaluation-period fixed effects. Observations are not weighted before matching and by matching weights after matching. Matching also considers ten (plus one for missing) industry dummies, 14 state dummies, and three evaluation period dummies. Variables are not displayed, but included in the average absolute standardized difference calculations. [a]Exact matching on these variables in the propensity score matching stage. [b]Balancing on these variables in the entropy balancing stage.

Table A-5: Balancing Table – Before Treatment (period $t-2$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Treated	Comparison							
		Non-matched				Matched			
	Mean	Mean	$\tilde{\Delta}$	t-test		Mean	$\tilde{\Delta}$	t-test	
				coef	pvalue			coef	pvalue
Demographic characteristics									
Age: 25-35	0.41	0.36	9.87	0.048	0.000	0.38	4.45	0.022	0.250
Age: 35-45	0.43	0.44	-3.10	-0.014	0.223	0.43	-0.58	-0.003	0.879
Age: 45-55	0.17	0.20	-8.45	-0.034	0.000	0.18	-4.97	-0.019	0.190
Female	0.42	0.45	-5.90	-0.031	0.019	0.41	1.24	0.006	0.754
Migrant	0.12	0.23	-28.18	-0.098	0.000	0.12	0.18	0.001	0.962
German citizen	0.97	0.87	35.04	0.087	0.000	0.97	-0.69	-0.001	0.842
Married	0.69	0.72	-7.92	-0.033	0.005	0.67	4.15	0.019	0.288
Homeowner	0.50	0.45	10.74	0.051	0.000	0.47	6.28	0.031	0.105
Children	0.52	0.55	-6.42	-0.029	0.021	0.49	4.97	0.025	0.201
East Germany	0.31	0.26	10.70	0.045	0.000	0.30	1.26	0.006	0.756
Self-rated health	0.09	0.05	4.10	0.034	0.141	0.10	-2.02	-0.018	0.591
Attrition from sample	0.32	0.36	-8.77	-0.038	0.000	0.32	-1.15	-0.005	0.761
Education									
Degree: vocational	0.73	0.73	-0.92	-0.004	0.721	0.75	-3.79	-0.017	0.333
Degree: university	0.36	0.16	45.75	0.182	0.000	0.35	1.87	0.009	0.649
School degree: no/basic school	0.17	0.34	-40.70	-0.161	0.000	0.16	2.27	0.008	0.551
School degree: intermediate/other school	0.43	0.45	-5.20	-0.026	0.047	0.44	-3.15	-0.016	0.425
School degree: technical school	0.07	0.04	12.44	0.026	0.000	0.07	-1.29	-0.003	0.748
School degree: academic school track (Abitur)	0.33	0.16	40.74	0.160	0.000	0.32	1.22	0.006	0.764
School degree: no info	0.01	0.01	0.95	0.000	0.868	0.01	4.76	0.005	0.143
Previous work-related training[a]	0.66	0.26	87.29	0.371	0.000	0.65	0.97	0.005	0.789
Labor market characteristics									
Log gross monthly earnings (in 2010 euro)[b]	7.90	7.61	48.18	0.261	0.000	7.90	0.00	0.000	1.000
Log hours worked per week[b]	3.67	3.58	24.03	0.082	0.000	3.67	0.01	0.000	0.999
Earnings tertile: bottom[a]	0.17	0.37	-46.22	-0.184	0.000	0.16	1.05	0.004	0.769
Earnings tertile: middle[a]	0.32	0.34	-5.40	-0.022	0.051	0.32	-1.00	-0.005	0.796
Earnings tertile: top[a]	0.51	0.29	46.98	0.206	0.000	0.51	0.16	0.001	0.968
Entry age	19.91	18.40	61.52	1.409	0.000	19.82	3.24	0.083	0.422
Employment: full-time	0.84	0.78	15.62	0.059	0.000	0.85	-1.62	-0.006	0.671
Employment: part-time	0.14	0.17	-9.01	-0.035	0.000	0.13	1.40	0.005	0.716
Employment: apprenticeship	0.00	0.00	0.80	0.000	0.774	0.00	3.97	0.001	0.157
Employment: marginal/unregular	0.01	0.03	-12.20	-0.015	0.000	0.01	1.21	0.001	0.736
Employment: non-working	0.01	0.02	-8.18	-0.009	0.000	0.01	-0.95	-0.001	0.785
Occupation sample: blue collar worker	0.86	0.54	73.50	0.292	0.000	0.85	1.35	0.005	0.709
Occupation sample: non-blue collar worker	0.14	0.46	-73.50	-0.292	0.000	0.15	-1.35	-0.005	0.709
Civil service	0.41	0.22	41.68	0.174	0.000	0.40	1.18	0.006	0.768
Unemployment experience: 0 years	0.72	0.64	17.35	0.073	0.000	0.72	-0.28	-0.001	0.943
Unemployment experience: 0-2 years	0.25	0.30	-10.21	-0.041	0.000	0.25	0.68	0.003	0.865
Unemployment experience: more than 2 years	0.02	0.06	-18.15	-0.032	0.000	0.02	-1.40	-0.002	0.693
Tenure: 0-2 years	0.20	0.20	-1.91	-0.007	0.464	0.17	7.68	0.030	0.032
Tenure: 2-8 years	0.35	0.36	-3.04	-0.015	0.161	0.37	-5.07	-0.024	0.179
Tenure: 8-15 years	0.25	0.25	1.01	0.007	0.504	0.24	1.98	0.009	0.598
Tenure: more than 15 years	0.20	0.19	4.15	0.014	0.157	0.22	-3.69	-0.015	0.353
Firm size: small firms (<20)	0.14	0.24	-26.64	-0.094	0.000	0.14	-1.08	-0.004	0.771
Firm size: medium firms (20-200)	0.22	0.29	-16.50	-0.066	0.000	0.22	-0.46	-0.002	0.903
Firm size: large firms (>200)	0.61	0.42	38.33	0.172	0.000	0.60	1.35	0.007	0.723
Firm size: no info	0.03	0.04	-6.98	-0.013	0.002	0.03	-0.56	-0.001	0.888
Satisfaction and worries									
Life satisfaction	0.11	0.05	6.48	0.052	0.018	0.13	-2.28	-0.020	0.539
Satisfaction with job situation	0.10	0.03	7.82	0.059	0.006	0.11	-2.11	-0.018	0.568
Worries: economic situation	0.09	0.07	2.24	0.011	0.582	0.08	0.82	0.007	0.816
Worries: own economic situation	-0.22	0.01	-24.48	-0.201	0.000	-0.22	0.12	0.001	0.975
Worries: job	-0.22	-0.01	-22.71	-0.187	0.000	-0.22	0.45	0.004	0.905
Non-pecuniary outcomes (before treatment)									
Civic/political participation score[b]	533	501	29.71	28.945	0.000	533	0.00	-0.004	0.999
Cultural participation score[b]	548	501	49.36	42.865	0.000	548	0.00	0.000	1.000
Social participation score[b]	499	498	1.16	0.748	0.746	499	0.01	0.011	0.998
Interest in politics	0.42	0.05	39.06	0.342	0.000	0.40	2.36	0.022	0.544
Participate in politics	0.18	0.03	14.19	0.146	0.000	0.23	-3.47	-0.042	0.424
Volunteer	0.23	0.00	22.95	0.220	0.000	0.21	2.57	0.028	0.522
Active in artistic/musical activities	0.37	0.04	29.95	0.294	0.000	0.35	1.53	0.017	0.680
Attend classic events	0.30	-0.08	42.44	0.347	0.000	0.30	-0.61	-0.005	0.870
Attend modern events	0.30	0.07	25.28	0.220	0.000	0.31	-1.99	-0.018	0.612
Socialize	0.09	-0.01	9.62	0.083	0.000	0.09	-0.13	-0.001	0.972
Assist	-0.01	-0.01	-0.17	-0.003	0.890	-0.02	0.44	0.004	0.908
Mean/median/P75 absolute $\tilde{\Delta}$ (96 variables)			18.01/9.38/27.40				1.65/1.22/2.27		

Notes: The table shows group means before and after matching for treatment and comparison group for pretreatment period $t-2$. Sample consists of working-age males and females (25-55 years old), working in each of the two pretreatment periods at least in one year in a white collar occupation, a blue collar occupation, or as a public servant. $\tilde{\Delta}$ is the standardized difference in group means. *coef* and *pvalue* are based on a regression of the specific variable on the treatment indicator and evaluation-period fixed effects. Observations are not weighted before matching and by matching weights after matching. Matching also considers ten (plus one for missing) industry dummies, 14 state dummies, and three evaluation period dummies. Variables are not displayed, but included in the average absolute standardized difference calculations. [a]Exact matching on these variables in the propensity score matching stage. [b]Balancing on these variables in the entropy balancing stage.

Table A-6: Baseline Models with Bootstrapped Standard Errors

	(1)	(2)	(3)	(4)
	Panel A: treatment effects by treatment period			
	Earnings	Participation		
		Civic/political	Cultural	Social
Training$_{ie}$ × post$_{t+3}$	0.072	10.624	11.047	–2.646
	(0.021)***	(5.234)**	(4.352)**	(4.868)
	[0.028]***	[6.737]**	[5.997]**	[6.608]
Training$_{ie}$ × post$_{t+2}$	0.040	12.273	10.774	–1.481
	(0.017)**	(4.435)***	(4.018)***	(4.394)
	[0.025]**	[5.650]***	[5.160]***	[5.607]
Training$_{ie}$ × post$_{t+1}$	0.044	4.492	6.496	0.190
	(0.014)***	(4.147)	(3.468)*	(3.637)
	[0.020]***	[5.311]	[4.670]*	[4.885]
Training$_{ie}$ × treat$_{t=0}$	0.039	8.567	3.569	3.440
	(0.011)***	(3.402)**	(3.045)	(3.461)
	[0.016]***	[4.353]**	[3.849]	[4.761]
Training$_{ie}$ × pre$_{t-2}$	0.001	0.053	0.661	0.298
	(0.010)	(3.426)	(3.137)	(2.834)
	[0.014]	[3.857]	[3.361]	[3.603]
Observations	20,695	20,997	20,997	20,997
	Panel B: treatment effects averaged over post-treatment periods			
	Earnings	Participation		
		Civic/political	Cultural	Social
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	0.051	8.605	8.868	–1.434
	(0.015)***	(3.697)**	(3.046)***	(3.579)
	[0.019]***	[4.389]**	[3.780]***	[4.193]
Observations	16,776	17,159	17,159	17,159
Treatment-by-evaluation FE	x	x	x	x
Control variables	x	x	x	x
Individual-by-evaluation FE	x	x	x	x

Notes: The table replicates the baseline models from Tables **??** and **??**. Standard errors, clustered at the individual level, in parentheses. Standard errors, bootstrap with 3,000 replications, in squared brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-7: Work-Related Training and Log Monthly Earnings (in 2010 euro)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log monthly gross earnings (in 2010 euros)							
	Non-matched sample			Matched sample			
$\text{Training}_{ie} \times \text{post}_{t+3}$	0.344***	0.237***	0.074***	0.084***	0.066**	0.072***	0.049***
	(0.020)	(0.019)	(0.014)	(0.031)	(0.027)	(0.021)	(0.016)
$\text{Training}_{ie} \times \text{post}_{t+2}$	0.333***	0.226***	0.058***	0.050**	0.035	0.040**	0.031**
	(0.017)	(0.017)	(0.012)	(0.025)	(0.021)	(0.017)	(0.014)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.338***	0.229***	0.051***	0.049**	0.038*	0.044***	0.031**
	(0.016)	(0.016)	(0.009)	(0.024)	(0.021)	(0.014)	(0.012)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	0.320***	0.215***	0.030***	0.029	0.027	0.039***	0.020**
	(0.015)	(0.014)	(0.007)	(0.021)	(0.018)	(0.011)	(0.009)
$\text{Training}_{ie} \times \text{pre}_{t-1}$	0.297***	0.192***	[baseline]	0.000	–0.003	[baseline]	[baseline]
	(0.014)	(0.014)		(0.019)	(0.017)		
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.261***	0.161***	–0.035***	0.000	–0.004	0.001	0.004
	(0.014)	(0.014)	(0.008)	(0.020)	(0.018)	(0.010)	(0.009)
Treatment-by-evaluation FE	x	x	x	x	x	x	x
Control variables		x	x		x	x	x
Individual-by-evaluation FE			x			x	x
Labor-market control variables							x
R-squared	0.054	0.168	0.835	0.024	0.193	0.797	0.862
Observations	47,789	47,789	47,789	20,695	20,695	20,695	20,596
Mean in $t-1 \cap t-2$	7.630	7.630	7.630	7.933	7.933	7.933	7.933
H_0: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.000	0.091	0.160	0.006	0.023
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.000	0.000	0.063	0.103	0.003	0.015

Notes: The sample is restricted to male and female individuals who are between 25 and 55 years old. In the matched sample, the comparison group is reweighted to match the treatment group by using entropy-balancing adjusted matching weights. $Training_{ie}$ is equal to one if person i in evaluation period e has participated in at least ten hours of work-related training in the last three years and zero if the person has not participated in that period. $Treat_{t=0}$ is equal to one for the averaged three-year treatment period and zero otherwise. $Post_{t+\kappa}$ indicates averaged posttreatment periods $\kappa = \{1,2,3\}$ and $Pre_{t-\kappa}$ indicates averaged pretreatment periods $\kappa = \{1,2\}$. *Treatment-by-evaluation FE* are treatment period by evaluation period fixed effects and *Individual-by-evaluation FE* are individual by evaluation period fixed effects (see Figure **??**). *Control variables:* German citizen, married, homeowner, children, vocational degree, university degree, school degree (four categories), state of residence (14 categories), elections to the national parliament. *Labor-market control variables:* log weekly hours worked, employment status (six categories), occupational status (eight categories), civil service, unemployment experience (three categories), tenure (four categories), industry (ten categories), and firm size (three categories). *Mean in $t-1 \cap t-2$* is computed for the comparison group. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-8: Related Studies

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Article	Estimated return	Training indicator	Time period	Regional coverage	Qualification modules	Specification
Pannenberg (1997)	9%	yes/no	1984-1991	West Germany	1989	Fixed effects models
Lechner (1999b)	9%	yes/no	1990-1994	East Germany	1993	Matching
Pischke (2001)	1% - 3%	training hours	1986-1989	West Germany	1989	Fixed growth model
BÃijchel und Pannenberg (2004)	West: 4% / East: 7%	yes/no	1984-2001	East and West Germany	1989, 1993, 2000	DiD
Muehler, Beckmann, and Schauenberg (2007)	3% - 6%	yes/no	1997-2004	Germany	2000, 2004	Matched DiD
Pannenberg (2008)	3%	yes/no	1984-2002	West Germany	1989, 1993, 2000	DiD
Ruhose, Thomsen, and Weilage (2018)	5%	yes/no	1994-2014	Germany	2000, 2004, 2008	Matched DiD with entropy balancing

Notes: The table shows related studies, which also use the qualification modules of the SOEP to identify the monetary returns from work-related training. DiD = difference-in-differences.

Table A-9: Work-Related Training and Log Hourly Earnings (in 2010 euro)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log hourly earnings (in 2010 euros)							
	Non-matched sample			Matched sample			
$\text{Training}_{ie} \times \text{post}_{t+3}$	0.243***	0.156***	0.062***	0.044*	0.029	0.049***	0.046***
	(0.016)	(0.014)	(0.012)	(0.024)	(0.020)	(0.018)	(0.017)
$\text{Training}_{ie} \times \text{post}_{t+2}$	0.240***	0.152***	0.048***	0.035*	0.020	0.022	0.022
	(0.014)	(0.012)	(0.010)	(0.020)	(0.016)	(0.015)	(0.014)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.243***	0.155***	0.040***	0.034*	0.024	0.027**	0.024*
	(0.013)	(0.012)	(0.009)	(0.019)	(0.016)	(0.013)	(0.013)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	0.216***	0.133***	0.012	0.004	0.004	0.010	0.009
	(0.011)	(0.010)	(0.007)	(0.016)	(0.013)	(0.010)	(0.010)
$\text{Training}_{ie} \times \text{pre}_{t-1}$	0.207***	0.125***	[baseline]	0.000	–0.001	[baseline]	[baseline]
	(0.011)	(0.010)		(0.015)	(0.013)		
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.178***	0.101***	–0.027***	–0.001	–0.002	–0.000	0.002
	(0.011)	(0.010)	(0.007)	(0.015)	(0.013)	(0.010)	(0.010)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x
Control variables		x	x		x	x	x
Individual-by-evaluation period FE			x			x	x
Labor-market control variables							x
R-squared	0.055	0.255	0.755	0.029	0.267	0.743	0.750
Observations	47,512	47,512	47,512	20,596	20,596	20,596	20,596
Control mean in pretreatment periods	2.573	2.573	2.573	2.784	2.784	2.784	2.784
H_0: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.000	0.163	0.285	0.118	0.141
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.000	0.000	0.264	0.411	0.039	0.046

Notes: See Table **??** for sample and variable descriptions. Hourly earnings are constructed by taking monthly earnings and divided them by 4.35 (= 52 weeks/12 months) times actual hours worked per week. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-10: Work-Related Training and Log Hours Worked per Week

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log hours worked per week (in 2010 euros)							
	Non-matched sample			Matched sample			
Training$_{ie}$ × post$_{t+3}$	0.097***	0.078***	0.008	0.032**	0.031**	0.015	0.005
	(0.011)	(0.011)	(0.010)	(0.015)	(0.014)	(0.013)	(0.010)
Training$_{ie}$ × post$_{t+2}$	0.089***	0.070***	0.009	0.017	0.017	0.019*	0.018**
	(0.010)	(0.010)	(0.009)	(0.013)	(0.012)	(0.011)	(0.009)
Training$_{ie}$ × post$_{t+1}$	0.096***	0.075***	0.011	0.017	0.016	0.017*	0.013
	(0.009)	(0.009)	(0.008)	(0.013)	(0.013)	(0.010)	(0.009)
Training$_{ie}$ × treat$_{t=0}$	0.102***	0.080***	0.018***	0.023**	0.022**	0.028***	0.021***
	(0.008)	(0.008)	(0.006)	(0.011)	(0.011)	(0.007)	(0.007)
Training$_{ie}$ × pre$_{t-1}$	0.090***	0.068***	[baseline]	0.000	–0.002	[baseline]	[baseline]
	(0.008)	(0.008)		(0.011)	(0.010)		
Training$_{ie}$ × pre$_{t-2}$	0.082***	0.060***	–0.008	0.000	–0.002	0.001	0.005
	(0.009)	(0.009)	(0.006)	(0.012)	(0.011)	(0.008)	(0.007)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x
Control variables		x	x		x	x	x
Individual-by-evaluation period FE			x			x	x
Labor-market control variables							x
R-squared	0.013	0.060	0.717	0.002	0.046	0.666	0.764
Observations	47,540	47,540	47,540	20,606	20,606	20,606	20,606
Control mean in pretreatment periods	3.587	3.587	3.587	3.679	3.679	3.679	3.679
H_0: post$_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.325	0.327	0.339	0.155	0.118
H_0: post$_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.000	0.522	0.183	0.184	0.293	0.195

Notes: See Table **??** for sample and variable descriptions. Hours worked per week are actual hours worked. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-11: Work-Related Training and Civic/Political Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: civic/political participation score							
	Non-matched sample			Matched sample			
Training$_{ie}$ × post$_{t+3}$	31.469***	21.062***	5.808*	8.295	6.521	10.624**	10.330**
	(3.927)	(3.956)	(3.257)	(6.420)	(6.257)	(5.234)	(5.218)
Training$_{ie}$ × post$_{t+2}$	34.236***	23.442***	6.028**	13.712**	11.735**	12.273***	12.301***
	(3.390)	(3.401)	(2.852)	(5.386)	(5.274)	(4.435)	(4.460)
Training$_{ie}$ × post$_{t+1}$	30.474***	19.106***	1.008	6.670	4.907	4.492	4.493
	(3.148)	(3.196)	(2.309)	(5.182)	(5.133)	(4.147)	(4.155)
Training$_{ie}$ × treat$_{t=0}$	32.104***	21.469***	1.800	9.931**	9.338**	8.567**	8.915***
	(2.904)	(2.926)	(2.080)	(4.657)	(4.529)	(3.402)	(3.402)
Training$_{ie}$ × pre$_{t-1}$	29.506***	19.094***	[baseline]	0.014	–0.610	[baseline]	[baseline]
	(2.878)	(2.945)		(5.026)	(4.872)		
Training$_{ie}$ × pre$_{t-2}$	29.017***	18.966***	–0.301	–0.030	–1.020	0.053	0.147
	(2.812)	(2.823)	(2.070)	(4.854)	(4.738)	(3.426)	(3.422)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x
Control variables		x	x		x	x	x
Individual-by-evaluation period FE			x			x	x
Labor-market control variables							x
R-squared	0.019	0.062	0.660	0.002	0.046	0.677	0.678
Observations	49,100	49,100	49,100	20,997	20,997	20,997	20,997
Control mean in pretreatment periods	502	502	502	533	533	533	533
H_0: post$_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.070	0.027	0.051	0.018	0.018
H_0: post$_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.000	0.101	0.055	0.100	0.037	0.039

Notes: See Table **??** for sample and variable descriptions. The participation score is standardized to have mean 500 and standard deviation 100 in the pretreatment control group for each evaluation period. *Labor-market control variables* additionally include log monthly earnings and log weekly hours worked. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-12: Work-Related Training and Cultural Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: cultural participation score							
	Not matched			Matched			
Training$_{ie}$ × post$_{t+3}$	38.705***	20.230***	0.836	10.688**	9.445**	11.047**	10.945**
	(3.023)	(2.871)	(2.650)	(4.430)	(4.231)	(4.352)	(4.352)
Training$_{ie}$ × post$_{t+2}$	45.074***	25.910***	6.124***	9.039**	8.525**	10.774***	10.449***
	(2.611)	(2.460)	(2.362)	(3.821)	(3.592)	(4.018)	(4.022)
Training$_{ie}$ × post$_{t+1}$	40.918***	20.817***	–0.182	6.089*	5.566	6.496*	5.597
	(2.457)	(2.323)	(2.039)	(3.648)	(3.505)	(3.468)	(3.421)
Training$_{ie}$ × treat$_{t=0}$	43.273***	23.120***	0.140	3.491	3.572	3.569	2.667
	(2.279)	(2.141)	(1.844)	(3.383)	(3.155)	(3.045)	(3.051)
Training$_{ie}$ × pre$_{t-1}$	43.080***	22.872***	[baseline]	–0.153	0.094	[baseline]	[baseline]
	(2.334)	(2.180)		(3.405)	(3.149)		
Training$_{ie}$ × pre$_{t-2}$	42.926***	23.133***	–0.542	–0.052	1.071	0.661	0.710
	(2.328)	(2.180)	(1.902)	(3.310)	(3.058)	(3.137)	(3.118)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x
Control variables		x	x		x	x	x
Individual-by-evaluation period FE			x			x	x
Labor-market control variables							x
R-squared	0.041	0.173	0.650	0.006	0.111	0.601	0.605
Observations	49,100	49,100	49,100	20,997	20,997	20,997	20,997
Control mean in pretreatment periods	502	502	502	549	549	549	549
H_0: post$_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.008	0.057	0.055	0.023	0.033
H_0: post$_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.000	0.016	0.063	0.074	0.031	0.038

Notes: See Table **??** for sample and variable descriptions. The participation score is standardized to have mean 500 and standard deviation 100 in the pretreatment control group for each evaluation period. *Labor-market control variables* additionally include log monthly earnings and log weekly hours worked. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-13: Work-Related Training and Social Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: social participation score							
	Unmatched sample			Matched sample			
$\text{Training}_{ie} \times \text{post}_{t+3}$	–2.314	2.723	–3.488	–3.038	–3.348	–2.646	–2.506
	(3.098)	(3.095)	(3.061)	(4.508)	(4.487)	(4.868)	(4.842)
$\text{Training}_{ie} \times \text{post}_{t+2}$	–1.958	3.492	–1.536	–3.781	–3.593	–1.481	–0.929
	(2.732)	(2.736)	(2.640)	(3.974)	(3.936)	(4.394)	(4.422)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.714	6.479***	1.671	–0.628	–0.272	0.190	0.466
	(2.523)	(2.507)	(2.344)	(3.582)	(3.500)	(3.637)	(3.630)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	1.391	7.526***	1.068	4.339	4.725	3.440	3.374
	(2.413)	(2.381)	(2.297)	(3.435)	(3.364)	(3.461)	(3.459)
$\text{Training}_{ie} \times \text{pre}_{t-1}$	0.516	6.502***	[baseline]	0.206	0.398	[baseline]	[baseline]
	(2.288)	(2.282)		(3.386)	(3.295)		
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.714	6.926***	0.228	0.116	0.801	0.298	0.619
	(2.312)	(2.297)	(1.720)	(3.496)	(3.425)	(2.834)	(2.830)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x
Control variables		x	x		x	x	x
Individual-by-evaluation period FE			x			x	x
Labor-market control variables							x
R-squared	0.001	0.034	0.536	0.003	0.035	0.537	0.539
Observations	49,100	49,100	49,100	20,997	20,997	20,997	20,997
Control mean in pretreatment periods	500	500	500	501	501	501	501
H_0: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.445	0.029	0.335	0.549	0.543	0.886	0.921
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.575	0.062	0.273	0.743	0.721	0.925	0.925

Notes: See Table **??** for sample and variable descriptions. The participation score is standardized to have mean 500 and standard deviation 100 in the pretreatment control group for each evaluation period. *Labor-market control variables* additionally include log monthly earnings and log weekly hours worked. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-14: Treatment Effects in Subdimensions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: treatment effects by treatment period								
	Interest in politics	Participate in politics	Volunteer	Active	Attend classic events	Attend modern events	Socialize	Assist
$\text{Training}_{ie} \times \text{post}_{t+3}$	0.042	0.134**	0.054	0.083	0.093**	0.066	0.015	–0.053
	(0.039)	(0.062)	(0.056)	(0.057)	(0.045)	(0.048)	(0.049)	(0.050)
$\text{Training}_{ie} \times \text{post}_{t+2}$	0.026	0.090*	0.073	0.115**	0.141***	0.021	–0.023	0.007
	(0.034)	(0.052)	(0.047)	(0.051)	(0.042)	(0.045)	(0.045)	(0.044)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.012	0.027	0.047	0.047	0.058	0.041	–0.001	–0.003
	(0.033)	(0.048)	(0.044)	(0.043)	(0.039)	(0.037)	(0.039)	(0.041)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	0.008	0.106***	0.026	0.031	0.090**	–0.041	0.043	0.035
	(0.029)	(0.041)	(0.036)	(0.041)	(0.036)	(0.033)	(0.037)	(0.039)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	–0.016	–0.004	0.013	–0.004	0.029	–0.009	0.003	0.001
	(0.029)	(0.043)	(0.035)	(0.036)	(0.038)	(0.034)	(0.029)	(0.029)
R-squared	0.707	0.565	0.622	0.533	0.514	0.474	0.528	0.459
Observations	21,330	21,316	21,323	21,292	21,337	21,319	21,292	21,306
H_0: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.755	0.202	0.288	0.083	0.003	0.536	0.775	0.967
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.716	0.123	0.477	0.169	0.009	0.490	0.751	0.509
Panel B: treatment effects averaged over post-treatment periods								
	Interest in politics	Participate in politics	Volunteer	Active	Attend classic events	Attend modern events	Socialize	Assist
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	0.031	0.080*	0.049	0.081**	0.084***	0.046	–0.011	–0.014
	(0.026)	(0.043)	(0.040)	(0.039)	(0.029)	(0.033)	(0.038)	(0.037)
R-squared	0.693	0.545	0.598	0.523	0.496	0.450	0.528	0.473
Observations	17,305	17,292	17,300	17,290	17,313	17,302	17,405	17,417
Treatment-by-evaluation FE	x	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x	x
Individual-by-evaluation FE	x	x	x	x	x	x	x	x
Mean in $t-1 \cap t-2$	0.3726	0.2041	0.2507	0.2838	0.4296	0.2684	0.1011	–0.0023

Notes: The participation scores are standardized to have mean 0 and standard deviation 1 in the pretreatment comparison group for each evaluation period. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-15: Earnings, Social Capital, and Work-Related Training: Extension to $t-3$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log earnings	Participation					
		Civic/political		Cultural		Social	
Training$_{ie}$ × post$_{t+3}$	0.062***	11.242**	11.243**	11.047**	10.944**	–2.100	–1.945
	(0.021)	(5.208)	(5.185)	(4.317)	(4.313)	(4.776)	(4.747)
Training$_{ie}$ × post$_{t+2}$	0.039**	12.667***	12.932***	10.848***	10.460***	–0.908	–0.421
	(0.017)	(4.389)	(4.407)	(3.973)	(3.972)	(4.323)	(4.339)
Training$_{ie}$ × post$_{t+1}$	0.042***	4.590	4.884	6.703*	5.836*	0.349	0.607
	(0.014)	(4.092)	(4.091)	(3.429)	(3.385)	(3.577)	(3.563)
Training$_{ie}$ × treat$_{t=0}$	0.038***	8.760***	9.146***	3.619	2.733	3.491	3.488
	(0.011)	(3.356)	(3.354)	(3.008)	(3.011)	(3.410)	(3.399)
Training$_{ie}$ × pre$_{t-2}$	0.001	–0.011	0.100	0.770	0.813	0.223	0.466
	(0.010)	(3.370)	(3.365)	(3.088)	(3.076)	(2.786)	(2.785)
Training$_{ie}$ × pre$_{t-3}$	–0.007	5.112	5.028	1.421	1.318	0.293	0.581
	(0.015)	(4.045)	(4.025)	(3.358)	(3.339)	(3.832)	(3.829)
Treatment-by-evaluation FE	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x
Individual-by-evaluation FE	x	x	x	x	x	x	x
Labor-market control variables			x		x		x
R-squared	0.781	0.663	0.665	0.600	0.604	0.511	0.513
Observations	23,779	24,174	24,174	24,174	24,174	24,174	24,174
H_0: post$_{t+1,t+2} = 0$ (pvalue)	0.009	0.012	0.011	0.020	0.029	0.933	0.950
H_0: post$_{t+1,t+2,t+3} = 0$ (pvalue)	0.009	0.026	0.024	0.027	0.035	0.954	0.950
H_0: pre$_{t-2,t-3} = 0$ (pvalue)	0.822	0.349	0.368	0.914	0.922	0.995	0.981

Notes: The table replicates regressions from Appendix Table **??**, Column (6) and Table **??**, extending the time periods to $t-3$. *Control variables:* German citizen, married, homeowner, children, vocational degree, university degree, school degree (four categories), state of residence (14 categories), elections to the national parliament. *Labor-market control variables:* log monthly earnings, missing earnings dummy, log weekly hours worked, missing hours worked dummy, employment status (six categories), occupational status (eight categories), civil service, unemployment experience (three categories), tenure (four categories)), industry (ten categories)), and firm size (three categories). All regressions contain dummy variables for outcome scores that are based on imputed *socialize*, *assist*, and *active* values. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-16: Heterogeneity by Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Gender		University education		Blue collar worker		Family status		Wage distribution				
	Female	Male	Yes	No	Yes	No	Childless single	Married / single + child	Above median	Below median	Bottom tertile	Middle tertile	Top tertile
Panel A: civic/political participation													
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	16.378***	4.962	17.436**	0.757	–6.321	10.172**	23.994*	5.235	9.086**	6.821	3.328	10.650	6.878
	(5.498)	(5.477)	(6.885)	(4.625)	(11.498)	(4.148)	(12.957)	(4.293)	(4.472)	(6.676)	(11.973)	(6.554)	(5.404)
R-squared	0.594	0.686	0.681	0.640	0.599	0.661	0.563	0.664	0.682	0.604	0.590	0.607	0.695
Panel B: cultural participation													
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	11.236**	6.006	9.113	9.420**	16.892**	8.232**	18.197**	5.347*	9.930***	7.450	7.021	9.502*	10.889**
	(4.549)	(4.218)	(6.072)	(3.689)	(7.870)	(3.370)	(7.949)	(3.226)	(3.727)	(5.039)	(7.130)	(5.265)	(4.393)
R-squared	0.591	0.583	0.582	0.561	0.548	0.580	0.612	0.570	0.583	0.589	0.608	0.581	0.587
Panel C: social participation													
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	0.035	–2.654	–1.392	–0.772	1.999	–1.319	1.298	–1.577	–4.104	–0.775	–17.561*	–2.060	0.387
	(5.711)	(4.787)	(6.747)	(4.408)	(11.154)	(3.890)	(8.701)	(4.095)	(4.411)	(6.245)	(10.125)	(7.058)	(5.012)
R-squared	0.526	0.551	0.564	0.528	0.573	0.533	0.552	0.534	0.553	0.514	0.512	0.508	0.570
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x	x	x	x	x	x	x
Individual-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	7,369	9,790	5,860	11,299	2,786	14,373	4,229	12,930	11,243	5,916	3,155	5,648	8,356
Mean absolute $\tilde{\Delta}$	3.88	3.02	3.62	2.38	7.33	1.92	6.27	2.13	2.32	4.01	6.84	3.87	3.05
Median absolute $\tilde{\Delta}$	3.22	2.59	2.62	1.78	6.44	1.33	5.46	2.09	1.92	3.07	6.60	2.79	2.66
P75 absolute $\tilde{\Delta}$	5.71	4.34	5.76	3.28	10.33	3.16	10.00	3.13	3.59	5.08	10.91	5.29	4.74

Notes: The table shows baseline regressions on sample splits, with the column header indicating the sample. Table **??** provides description of samples; especially for *position in wage distribution* and *blue collar worker*. *Family status* is assessed in period $t-1$ and is based on the two variables *married* and *children*. In the category *childless single*, the respondent is not married and has no child under the age of 16. All other respondents are assigned to the category *married / single + child*. Regressions compare the average treatment effect from the period $t+1$, $t+2$, and $t+3$ to the pretreatment periods $t-1$ and $t-2$. The variable post$_{t+1,t+2,t+3}$ is equal to one if post$_{t+1}$, post$_{t+2}$, or post$_{t+3}$ are equal to one and zero otherwise; period $t=0$ is not considered. The comparison group is reweighted to match the treatment group by using entropy-balancing adjusted matching weights. Baseline weights are refined by entropy balancing (covariates: log monthly earnings, log hours worked, and the three non-pecuniary outcomes in periods $t-1$ and $t-2$) in the subsamples. Table **??** provides treatment period-specific results and Table **??** provides further description on sample construction and variable definitions. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-17: Treatment Period-Specific Heterogeneity by Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Gender		University education		Blue collar worker		Family status		Wage distribution				
	Female	Male	Yes	No	Yes	No	Childless single	Married / single + child	Above median	Below median	Bottom tertile	Middle tertile	Top tertile
						Panel A: civic/political participation							
Training$_{ie}$ × post$_{t+3}$	21.110***	3.964	17.063*	5.926	–17.262	14.225**	22.581*	6.422	11.004*	11.011	12.715	16.240*	5.223
	(7.990)	(7.215)	(9.940)	(6.425)	(14.578)	(5.744)	(13.697)	(6.164)	(6.441)	(9.858)	(16.890)	(8.620)	(7.903)
Training$_{ie}$ × post$_{t+2}$	21.800***	6.831	26.170***	3.925	8.740	12.419**	21.565	9.104*	12.031**	9.515	6.699	12.974*	10.009
	(6.698)	(6.298)	(8.167)	(5.443)	(12.900)	(4.946)	(16.219)	(5.180)	(5.494)	(8.134)	(13.924)	(7.687)	(6.610)
Training$_{ie}$ × post$_{t+1}$	8.055	3.825	9.297	–2.805	–7.703	5.452	22.235*	1.827	5.426	2.942	–2.876	4.939	4.450
	(6.431)	(5.872)	(7.510)	(5.296)	(11.670)	(4.677)	(12.524)	(4.731)	(4.905)	(8.000)	(13.037)	(8.320)	(5.887)
Training$_{ie}$ × treat$_{t=0}$	8.565*	9.120*	12.316*	5.833	4.590	9.331**	20.346**	7.399*	10.953***	2.548	2.543	11.611*	8.647*
	(5.134)	(5.059)	(6.378)	(4.373)	(9.587)	(3.796)	(9.111)	(4.013)	(4.132)	(6.074)	(9.791)	(6.130)	(4.956)
Training$_{ie}$ × pre$_{t-2}$	–0.061	–0.517	0.054	0.173	1.714	0.098	0.237	0.051	0.285	0.153	0.405	1.266	–0.214
	(5.267)	(4.623)	(5.938)	(4.120)	(13.724)	(3.860)	(9.213)	(3.990)	(4.153)	(6.327)	(9.725)	(6.376)	(4.923)
						Panel B: cultural participation							
Training$_{ie}$ × post$_{t+3}$	13.379**	8.879	13.685	9.538*	21.929**	10.275**	15.589	8.207*	11.910**	9.917	3.759	9.341	12.129*
	(6.262)	(6.230)	(8.466)	(5.136)	(10.985)	(4.858)	(11.696)	(4.823)	(5.586)	(7.390)	(10.217)	(7.363)	(6.515)
Training$_{ie}$ × post$_{t+2}$	13.787**	8.855	3.735	14.177***	9.241	10.969**	20.575**	6.676	10.617**	11.429*	15.598	9.821	11.649**
	(5.776)	(5.701)	(7.430)	(4.805)	(10.717)	(4.495)	(9.052)	(4.262)	(4.884)	(6.214)	(9.612)	(7.426)	(5.649)
Training$_{ie}$ × post$_{t+1}$	8.527	2.669	11.374	5.592	22.302**	5.101	15.373	2.957	7.909*	4.797	6.410	8.607	9.282*
	(5.219)	(4.924)	(7.265)	(4.061)	(10.132)	(3.881)	(10.742)	(3.751)	(4.423)	(5.677)	(9.053)	(5.833)	(5.166)
Training$_{ie}$ × treat$_{t=0}$	4.454	2.510	0.837	3.747	13.692	2.962	6.712	2.788	5.323	2.212	–2.374	6.600	4.307
	(4.641)	(4.281)	(5.743)	(3.590)	(12.451)	(3.359)	(7.812)	(3.331)	(3.796)	(5.172)	(7.932)	(5.153)	(4.565)
Training$_{ie}$ × pre$_{t-2}$	0.719	0.610	0.056	0.500	1.216	0.662	–0.181	0.341	0.579	0.659	0.487	0.243	0.401
	(4.707)	(4.284)	(6.182)	(3.687)	(9.274)	(3.485)	(8.601)	(3.367)	(3.935)	(5.201)	(7.498)	(5.071)	(4.659)
						Panel C: social participation							
Training$_{ie}$ × post$_{t+3}$	–8.134	2.406	–5.968	1.790	11.569	–3.610	–0.186	–2.156	–7.915	2.465	–28.961**	2.308	–3.502
	(8.098)	(6.499)	(8.896)	(5.685)	(12.986)	(5.322)	(11.491)	(5.773)	(6.270)	(8.637)	(14.743)	(9.019)	(6.895)
Training$_{ie}$ × post$_{t+2}$	1.674	–5.387	0.480	–2.122	–1.125	–1.285	2.773	–1.245	–2.952	–4.591	–11.773	–5.380	1.398
	(6.840)	(5.717)	(8.199)	(5.367)	(12.350)	(4.760)	(10.676)	(4.888)	(5.322)	(7.795)	(10.649)	(8.613)	(6.171)
Training$_{ie}$ × post$_{t+1}$	3.744	–1.602	0.786	–0.310	1.803	0.368	0.211	–0.587	–2.075	1.471	–11.085	–0.088	2.084
	(5.540)	(4.946)	(6.902)	(4.603)	(12.054)	(3.938)	(8.132)	(4.180)	(4.575)	(6.573)	(9.880)	(7.342)	(5.115)
Training$_{ie}$ × treat$_{t=0}$	5.548	2.576	3.798	4.283	11.751	3.251	–0.184	3.460	2.707	1.220	–8.413	3.601	3.749
	(5.357)	(4.874)	(6.463)	(4.314)	(12.745)	(3.826)	(7.713)	(4.014)	(4.344)	(6.465)	(8.945)	(7.110)	(4.996)
Training$_{ie}$ × pre$_{t-2}$	0.132	0.321	0.449	–0.189	–0.952	0.314	–0.306	0.018	0.266	–0.375	0.796	0.027	0.148
	(4.080)	(4.031)	(4.431)	(3.654)	(7.113)	(3.071)	(6.305)	(3.268)	(3.357)	(5.739)	(8.408)	(5.225)	(3.673)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x	x	x	x	x	x	x
Individual-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	9,014	11,983	7,192	13,805	3,390	17,607	5,164	15,833	13,784	7,213	3,846	6,883	10,268
Mean absolute $\tilde{\Delta}$	3.88	3.02	3.62	2.38	7.33	1.92	6.27	2.13	2.32	4.01	6.84	3.87	3.05
Median absolute $\tilde{\Delta}$	3.22	2.59	2.62	1.78	6.44	1.33	5.46	2.09	1.92	3.07	6.60	2.79	2.66
P75 absolute $\tilde{\Delta}$	5.71	4.34	5.76	3.28	10.33	3.16	10.00	3.13	3.59	5.08	10.91	5.29	4.74

Notes: The table shows treatment period-specific baseline regressions on sample splits, with the column header indicating the sample. Table **??** provides further information. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-18: Training-Induced Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Training hours		Training courses		Previous training		Firm-specific training		Employer-induced		Firm size		Paid off in job		Distance learning	
	Above median	Below median	> 3	≤ 3	Yes	No	Yes	No	Yes	No	Large	Small/ medium	Yes	Only little / no	Yes	No
	Panel A: civic/political participation															
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	9.030**	8.321**	10.962**	6.771*	9.349**	6.371	8.998**	8.263**	7.584**	11.296*	6.893	13.233**	8.465*	8.810**	4.122	9.151**
	(4.316)	(4.187)	(5.261)	(3.813)	(4.185)	(4.488)	(4.506)	(4.101)	(3.793)	(6.677)	(4.438)	(6.436)	(4.893)	(3.889)	(7.547)	(3.760)
R-squared	0.642	0.671	0.652	0.659	0.670	0.625	0.672	0.650	0.664	0.618	0.666	0.658	0.660	0.653	0.693	0.652
	Panel B: cultural participation															
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	10.043***	7.607**	10.347**	7.575**	9.627***	7.076*	9.747***	8.510**	8.683***	9.805*	8.628**	8.836*	10.079**	8.170**	2.545	9.420***
	(3.563)	(3.386)	(4.115)	(3.182)	(3.394)	(3.831)	(3.430)	(3.499)	(3.111)	(5.249)	(3.809)	(4.977)	(3.999)	(3.180)	(6.062)	(3.081)
R-squared	0.597	0.567	0.577	0.585	0.581	0.584	0.573	0.586	0.580	0.606	0.585	0.586	0.574	0.586	0.566	0.586
	Panel C: social participation															
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	–2.551	–0.231	–2.091	–0.983	–2.260	–0.265	–4.518	0.406	–1.102	–3.190	–2.586	–0.691	–0.657	–2.014	3.929	–1.853
	(4.057)	(4.199)	(4.537)	(3.904)	(3.931)	(4.607)	(4.330)	(3.966)	(3.678)	(6.657)	(4.519)	(6.184)	(4.519)	(3.830)	(7.275)	(3.633)
R-squared	0.527	0.549	0.561	0.525	0.541	0.532	0.540	0.537	0.549	0.471	0.559	0.527	0.535	0.537	0.536	0.539
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Individual-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	11,834	11,678	10,230	13,282	13,436	10,076	10,246	13,209	15,698	7,792	10,366	6,394	10,557	12,923	7,328	16,184
Mean absolute $\tilde{\Delta}$	2.50	1.99	3.50	2.04	3.52	5.01	3.23	2.47	1.80	7.08	2.74	4.09	2.61	1.84	7.35	1.57
Median absolute $\tilde{\Delta}$	2.02	1.57	3.02	1.81	2.29	3.07	2.31	1.87	1.38	4.88	2.08	2.62	2.09	1.23	6.13	1.19
P75 absolute $\tilde{\Delta}$	3.82	2.78	4.86	2.96	4.13	4.59	4.39	3.28	2.67	10.98	4.10	6.80	4.00	2.70	10.08	2.38

Notes: The table shows baseline regressions on sample splits, with the column header indicating the sample. *Training hours* splits treatment group at median training hours (33 hours). *Previous training* splits treatment group by whether the respondent has already received training in the past. *Firm-specific training* splits treatment group by whether the respondent has received firm-specific or general training. To categorize the nature of courses, we use information received in response to the following question: *"To what extent could you use the newly acquired skills if you got a new job in a different company?"*. Response categories "for the most part" and "completely" are categorized as general training, while "not at all" and "only to a limited extend" are categorized as specific training. Following **?**, we use the most recent course to categorize whether training is firm-specific or not. *Employer-induced* splits treatment group by whether the respondent has taken mainly employer-induced training, i.e., the majority of courses took place during work-time, were financed by the employer, or were organized and hosted by the employer. *Paid off in job* splits treatment group by whether the participant reports that the majority of the last three courses substantially paid off in the job versus the respondent did not experience that the training yields a (substantial) payoff in the job or is not yet sure about the payoff. *Distance learning* splits the treatment group by whether the participant has attended at least one distance learning training course (among the last three reported courses). Regressions compare the average treatment effect from the period $t+1$, $t+2$, and $t+3$ to the pretreatment periods $t-1$ and $t-2$. The variable post$_{t+1,t+2,t+3}$ is equal to one if post$_{t+1}$, post$_{t+2}$, or post$_{t+3}$ are equal to one and zero otherwise; period $t=0$ is not considered. The comparison group is reweighted to match the treatment group by using entropy-balancing adjusted matching weights. Baseline weights are refined by entropy balancing (covariates: log monthly earnings, log hours worked, and the three non-pecuniary outcomes in periods $t-1$ and $t-2$) in the subsamples. Table **??** provides treatment period-specific results and Table **??** provides further description on sample construction and variable definitions. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A-19: Treatment Period-Specific Training-Induced Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Training hours		Training courses		Previous training		Firm-specific training		Employer-induced		Firm size		Paid off in job		Distance learning	
	Above median	Below median	> 3	≤ 3	Yes	No	Yes	No	Yes	No	Large	Small/ medium	Yes	Only little / no	Yes	No
Panel A: civic/political participation																
Training$_{ie}$ × post$_{t+3}$	11.248*	10.377*	14.303*	8.151	10.076*	10.785*	8.871	11.352**	10.000*	9.773	10.277	16.117*	12.488*	9.326*	7.538	11.131**
	(5.871)	(6.234)	(7.433)	(5.310)	(5.946)	(6.367)	(6.424)	(5.730)	(5.374)	(9.356)	(6.512)	(9.097)	(6.866)	(5.481)	(11.666)	(5.243)
Training$_{ie}$ × post$_{t+2}$	12.601**	12.025**	14.451**	10.943**	13.216***	9.857*	11.307**	12.868***	11.652**	12.908	11.204**	16.765**	12.044**	12.819***	5.428	13.108***
	(5.291)	(5.108)	(6.271)	(4.631)	(5.071)	(5.552)	(5.473)	(4.942)	(4.538)	(8.427)	(5.546)	(7.787)	(5.993)	(4.710)	(9.446)	(4.515)
Training$_{ie}$ × post$_{t+1}$	4.721	4.185	6.466	2.537	6.047	1.191	7.248	2.942	3.009	11.204	0.386	8.903	3.485	5.015	2.434	4.692
	(4.866)	(4.698)	(5.744)	(4.323)	(4.702)	(5.212)	(5.143)	(4.541)	(4.271)	(7.186)	(5.096)	(6.685)	(5.485)	(4.331)	(8.925)	(4.193)
Training$_{ie}$ × treat$_{t=0}$	9.979**	7.312*	11.160**	7.336**	10.412***	6.069	10.028**	7.838**	7.376**	15.897**	5.663	10.658*	9.785**	8.035**	9.671	8.543**
	(3.919)	(3.955)	(4.866)	(3.511)	(3.973)	(4.128)	(4.222)	(3.736)	(3.477)	(6.569)	(4.449)	(5.753)	(4.583)	(3.541)	(8.224)	(3.409)
Training$_{ie}$ × pre$_{t-2}$	0.121	–0.167	0.176	–0.055	0.113	0.264	–0.042	0.164	0.144	0.447	–0.003	–0.512	0.299	–0.192	0.106	0.088
	(3.943)	(4.013)	(4.669)	(3.599)	(3.870)	(4.193)	(4.216)	(3.745)	(3.499)	(6.369)	(4.681)	(5.653)	(4.462)	(3.633)	(6.747)	(3.490)
Panel B: cultural participation																
Training$_{ie}$ × post$_{t+3}$	11.987**	10.015**	15.681***	8.389*	13.101***	7.099	15.216***	8.875*	11.167**	10.010	6.585	16.036**	13.508**	9.552**	4.148	11.556***
	(4.976)	(5.027)	(5.912)	(4.532)	(4.782)	(5.636)	(5.331)	(4.745)	(4.505)	(7.675)	(5.751)	(7.440)	(5.503)	(4.666)	(8.752)	(4.401)
Training$_{ie}$ × post$_{t+2}$	11.042**	10.569**	12.888**	9.200**	12.713***	7.100	10.208**	11.334**	10.458**	13.483**	11.126**	6.656	13.492***	9.057**	–4.651	12.204***
	(4.745)	(4.433)	(5.332)	(4.200)	(4.374)	(5.161)	(4.618)	(4.575)	(4.111)	(6.840)	(5.295)	(6.558)	(5.228)	(4.214)	(8.001)	(4.061)
Training$_{ie}$ × post$_{t+1}$	8.313**	4.532	6.228	6.090*	5.812	7.263	7.357*	6.095	6.055*	8.378	5.932	8.022	6.487	6.474*	9.330	6.173*
	(3.995)	(3.938)	(4.856)	(3.637)	(3.815)	(4.511)	(4.018)	(3.954)	(3.566)	(5.926)	(4.530)	(5.387)	(4.649)	(3.664)	(6.723)	(3.511)
Training$_{ie}$ × treat$_{t=0}$	1.705	5.398	5.358	3.079	4.234	2.830	1.294	5.200	3.458	4.454	3.363	0.338	6.723*	1.997	3.960	3.639
	(3.473)	(3.489)	(4.157)	(3.218)	(3.320)	(3.907)	(3.694)	(3.380)	(3.164)	(5.041)	(4.166)	(4.781)	(3.968)	(3.233)	(6.548)	(3.077)
Training$_{ie}$ × pre$_{t-2}$	0.334	1.002	1.081	0.632	1.004	0.260	0.889	0.515	0.512	1.495	–0.295	0.673	0.804	0.635	1.163	0.594
	(3.505)	(3.656)	(4.042)	(3.298)	(3.504)	(3.858)	(3.874)	(3.423)	(3.253)	(5.155)	(4.409)	(4.926)	(3.994)	(3.335)	(6.636)	(3.170)
Panel C: social participation																
Training$_{ie}$ × post$_{t+3}$	–4.327	–0.869	–3.728	–1.805	–2.698	–2.732	–6.670	–0.248	–2.813	–1.301	–8.302	5.026	–1.672	–3.210	5.292	–3.182
	(5.488)	(5.620)	(6.158)	(5.220)	(5.366)	(6.077)	(5.762)	(5.315)	(5.004)	(8.760)	(6.410)	(8.283)	(5.923)	(5.266)	(9.398)	(4.939)
Training$_{ie}$ × post$_{t+2}$	–2.454	–0.400	–2.427	–0.902	–3.132	0.605	–7.911	1.989	–0.541	–7.835	–3.095	–2.650	0.853	–3.130	0.392	–1.515
	(5.005)	(5.108)	(5.415)	(4.789)	(4.866)	(5.488)	(5.252)	(4.859)	(4.501)	(8.319)	(5.517)	(7.197)	(5.530)	(4.684)	(8.684)	(4.453)
Training$_{ie}$ × post$_{t+1}$	–1.573	1.994	0.719	0.197	0.039	0.088	–0.327	0.636	0.481	–1.137	0.024	–0.578	0.339	0.132	6.214	–0.343
	(4.174)	(4.314)	(4.536)	(4.079)	(3.926)	(5.037)	(4.494)	(4.036)	(3.750)	(6.950)	(4.670)	(6.070)	(4.636)	(3.975)	(7.338)	(3.722)
Training$_{ie}$ × treat$_{t=0}$	2.130	4.591	8.903*	0.720	3.835	2.663	3.249	4.098	3.292	5.052	3.998	3.220	3.197	3.815	8.647	3.054
	(3.980)	(4.124)	(4.656)	(3.834)	(3.792)	(4.671)	(4.341)	(3.811)	(3.597)	(6.677)	(4.538)	(5.641)	(4.506)	(3.819)	(6.857)	(3.554)
Training$_{ie}$ × pre$_{t-2}$	0.006	0.582	0.609	0.266	0.392	0.015	0.397	0.114	0.274	–0.029	–0.164	0.290	0.543	0.173	–0.098	0.350
	(3.302)	(3.143)	(3.542)	(3.117)	(2.962)	(3.926)	(3.436)	(3.067)	(2.916)	(4.746)	(3.670)	(4.433)	(3.371)	(3.154)	(5.615)	(2.857)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Individual-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	14,470	14,300	12,517	16,253	16,434	12,336	12,540	16,160	19,208	9,535	12,683	7,827	12,918	15,812	8,959	19,811
Mean absolute $\tilde{\Delta}$	2.50	1.99	3.50	2.04	3.52	5.01	3.23	2.47	1.80	7.08	2.74	4.09	2.61	1.84	7.35	1.57
Median absolute $\tilde{\Delta}$	2.02	1.57	3.02	1.81	2.29	3.07	2.31	1.87	1.38	4.88	2.08	2.62	2.09	1.23	6.13	1.19
P75 absolute $\tilde{\Delta}$	3.82	2.78	4.86	2.96	4.13	4.59	4.39	3.28	2.67	10.98	4.10	6.80	4.00	2.70	10.08	2.38

Notes: The table shows treatment period-specific baseline regressions on sample splits, with the column header indicating the sample. Table **??** provides further information. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

B Imputation of Missing Information to Compute Outcome Scores

The construction of outcome scores with the principal component analysis require valid information for each question for each individual. We cannot compute PCA scores when one variable is not asked or not answered by the individual. Figure **??** shows the coverage of years and questions. It shows that the survey does not ask questions on *socialize*, *assist*, and *active in artistic/musical activities* in some years. Table **??** indicates the years that are missing and the years that are used for the imputation. In general, we are using the information from the closest survey year. Imputation takes only place within either pretreatment, treatment, or posttreatment period, respectively.

Table B-1: Imputation Years

Socialize / assist			Active		
Evaluation period	Year		Evaluation period	Year	
	Missing	Imputed		Missing	Imputed
2000	1995	1994	2000	1992	1995
2000	1998	1999	2000	1994	1995
2000	2003	2001	2000	1996	1995
2004	1998	1999	2000	1997	1995
2004	2003	2005	2000	1999	1998
2004	2008	2007	2004	1996	1995
2008	2003	2005	2004	1997	1995
2008	2008	2007	2004	1999	1998
2008	2013	2011			

Notes: The table indicates the survey years with missing information on socialize, assist, and active (see also Figure **??**). Information are imputed by the years indicated.

C Entropy Balancing

In this section, we describe briefly the main points of the entropy balancing method formulated by **?**. Please note that this exposition is only to inform the interested reader about the most important features. The overview is likely to be incomplete and captures only the very basic idea. We refer the reader to **?** for a much better and more extensive treatment of the matter.

Entropy balancing can be considered a generalization of the conventional propensity score matching. The conventional matching approach is to estimate a logit or probit regression to predict the treatment assignment and then use the propensity scores from that regression to compute unit weights such that the estimated weights equalizes the covariate distributions between treatment and comparison group. Balancing checks are required to check whether the weights successfully achieve this goal. By contrast, entropy balancing tackles this equalization problem from the reverse and estimates the weights directly from the imposed balancing constraints. The method also allows us to impose restrictions on higher moments of the covariate distribution and not only on the mean as it is usually the case with conventional matching. With entropy balancing, there is no further need for balancing checks because the weights equalize the differences in the prespecified covariate distributions by construction.

In most applications, we are interested in estimating the average treatment effect on the treated (ATT), which can be expressed as $\tau = E[Y(1)|D=1] - E[Y(0)|D=1]$. In the simplest possible case, the counterfactual mean for a population may be estimated by

$$E[Y\widehat{(0)|D}=1] = \frac{\sum_{\{i|D=0\}} Y_i \; \omega_i}{\sum_{\{i|D=0\}} \omega_i}, \tag{7}$$

where ω_i is an individual-specific weight chosen by the following reweighting scheme:

$$\min_{\omega_i} H(\omega) = \sum_{\{i|D=0\}} h(\omega_i) \tag{8}$$

subject to balance and normalizing constraints

$$\sum_{\{i|D=0\}} \omega_i \; c_{ri}(X_i) = m_r \text{ with } r \in 1, \ldots, R \text{ and} \tag{9}$$

$$\sum_{\{i|D=0\}} \omega_i = 1 \text{ and} \tag{10}$$

$$\omega_i \geq 0 \text{ for all } i \text{ such that } D = 0, \tag{11}$$

where $h(\cdot)$ is a distance metric (discussed in detail in **?**, p. 31) and $c_{ri}(X_i) = m_r$ describes a set of R balance constraints imposed by the researcher on the covariate moments of the reweighted comparison group. We further impose that all weights add up to one (Eq. (**??**)) and that all weights are nonnegative (Eq. (**??**)).

To fit the entropy balancing weights in practice, we need to minimize the loss function $H(\omega)$ subject to the balance and normalization constraints given in equations (**??**) to (**??**). Using the Lagrange multiplier, we obtain the primal optimization problem:

$$\begin{aligned}\min_{W,\lambda_0,Z} L^p = &\sum_{\{i|D=0\}} \omega_i \log\left(\frac{\omega_i}{q_i}\right) + \sum_{r=1}^{R} \lambda_r \left(\sum_{\{i|D=0\}} \omega_i c_{ri}(X_i) - m_r\right) \\ &+ (\lambda_0 - 1)\left(\sum_{\{i|D=0\}} \omega_i - 1\right),\end{aligned} \tag{12}$$

where $Z = \{\lambda_1, \ldots, \lambda_R\}'$ is a vector of Lagrange multipliers for the balance constraints and $\lambda_0 - 1$ is the Lagrange multiplier for the normalization constraints. Given that the loss function is (strictly) convex and duality holds (see **?**, p. 32 for details), the first order condition for each weight is attained by

$$\omega_i^* = \frac{q_i \exp\left(-\sum_{r=1}^{R} \lambda_r c_{ri}(X_i)\right)}{\sum_{\{i|D=0\}} q_i \exp\left(-\sum_{r=1}^{R} \lambda_r c_{ri}(X_i)\right)}. \tag{13}$$

The expression makes clear that the weights can be estimated as a log-linear function of the covariates specified in the moment conditions.[39] Plugging this expression back into L^p eliminates the constraints and leads to an unrestricted dual problem given by

$$\min_{Z} L^d = \log\left(\sum_{\{i|D=0\}} q_i \exp\Big(-\sum_{r=1}^{R} \lambda_r c_{ri}(X_i)\Big)\right) + \sum_{r=1}^{R} \lambda_r m_r. \tag{14}$$

The solution to the dual problem Z^* solves the primal problem and the weights W^* can be recovered via equation (**??**). This dual problem is much more tractable because it is unconstrained and the dimensionality is reduced to a system of nonlinear equations in the R Lagrange multipliers. Moreover, if a solution exists, it will be unique since L^d is strictly convex. **?** applies a Levenberg-Marquardt scheme to find a solution to this optimization problem. The resulting iterative algorithm is globally convergent if the problem is feasible and the solution is usually obtained within seconds even in moderately large data sets.

[39]Evidently, the inequality bounds $\omega_i \geq 0$ are inactive and can be safely ignored.

D Attrition and Robustness

D.1 Attrition

Because non-pecuniary returns increase over time, one may worry that selective sample attrition is responsible for this finding. For example, assuming that the treatment had no effect, we would observe the same pattern of results if either the worse-performing individuals in the treatment group or the better-performing individuals in the comparison group were to drop out over time. In general, attrition in period $t+1$ is only approximately 4% on average (Table **??**). However, attrition increases up to 40% in the non-matched comparison group in period $t+3$. Attrition in the treatment group is 5.4 percentage-points lower (significant difference at the one percent level). However, attrition in the matched comparison group (32% in $t+3$) was not significantly different from attrition in the treatment group. We also measure to what extent individuals who drop out of the sample are different compared to individuals who remain in the sample measured in pretreatment (periods $t-1$ and $t-2$) outcomes. The results from a regression of the outcome variable on the training indicator interacted with an indicator that is one if the individual drops out from the sample in later periods and zero otherwise indicates that treated individuals who drop out are relatively *more positively* selected compared to drop-outs in the comparison group (see Table **??**). However, after weighting with matching weights, the interaction is small and statistically not significant. Finally, estimating the baseline model on a balanced sample (balanced for non-pecuniary outcomes) does not imply that compositional changes in either group affect the results (Table **??**).

D.2 Robustness Checks

Table **??** shows that the results are qualitatively and quantitatively robust to a variety of changes in the empirical model specification. To keep the results tractable, we concentrate on changes in averaged treatment effects when we change model assumptions (Table **??** shows treatment period-specific robustness results). In Columns (2) to (4), we vary different steps of the baseline matching approach. Column (2) reports regression results when we further refine the baseline matching weights by adjusting them for differential trends in the outcome variables (log monthly earnings, log hours worked per week, three non-pecuniary outcomes) by previous work-related training, university degree, vocational degree, gender, and occupation sample. We again use entropy balancing to overhaul the baseline matching weights. This specification change addresses differential pretreatment trends in those groups. As expected, the change has no effect on the estimates because we have already seen that individuals are not self-selected on the average pretreatment trend. Trimming the propensity scores may lead to an overestimation of the training effects because we mainly drop individuals in the comparison group with low propensity scores. Thus, in Column (3), we report results from specification without trimming the sample in the data processing stage. The estimates indicate that trimming does not strongly affect the results. The choice of the matching procedure may also affect the construction of the comparison group. While **?** and **?** argue for the use of kernel matching, we also apply 5-to-1 nearest-neighbor matching and report results in Column (4).[40] While coefficients are slightly smaller, we still find statistically and economically significant effects from participation in work-related training.

In the remaining columns of Table **??**, we evaluate the performance of using the different matching procedures separately. In Column (5), we use conventional kernel matching weights without refinement by entropy balancing. Using these weights to construct the comparison group also performs well in eliminating pretreatment normalized differences between the treatment and comparison groups (see last three rows in Column (5)). In Columns (6) and (7), we use entropy balancing without previous adjustment through the propensity score matching stage. We use all conditioning variables from Table **??** for the construction of the balancing weights (Column (6)) and with additional refinement of these weights by taking differential trends in the outcome variables (log monthly earnings, log hours worked per week, three non-pecuniary outcomes) by previous work-related training, university degree, vocational degree, gender, and occupation sample into account (Column (7)). This procedure has the advantage of allowing us to retain all individuals for the analysis, which increases statistical precision. The results show significant positive non-pecuniary returns to work-related training with effect sizes closer to the non-trimmed sample in Column (3). However, this specification also means that we keep individuals with very low participation probabilities for identification (even though they enter with low weights). Specifically, in the evaluation of work-related training, this is a questionable specification choice because individuals with low participation probabilities are not very likely to ever participate in work-related training.

[40]Using 1-to-1 nearest-neighbor matching yields very similar results (not shown).

Table D-1: Attrition from Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Period	Matched sample			Non-matched sample		
	Average attrition	Attrition in comparison group	Difference to treatment group	Average	Attrition in comparison group	Difference to treatment group
	%	%	%-points	%	%	%-points
$t+3$	0.321	0.322	–0.004	0.389	0.404	–0.054***
			(0.018)			(0.011)
$t+2$	0.177	0.170	–0.016	0.209	0.218	–0.033***
			(0.014)			(0.009)
$t+1$	0.034	0.041	–0.015**	0.039	0.044	–0.014***
			(0.007)			(0.004)

Notes: Differences and standard errors are obtained from an OLS regression (including jointly all treatment periods) of the attrition dummy on the treatment-specific treatment indicator. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table D-2: Attrition and Pretreatment Outcomes

	(1)	(2)	(3)	(4)
Panel A: non-matched sample				
	Earnings	Civic/political	Cultural	Social
$\text{Training}_{ie} \times \text{attrition}_i$	0.058**	10.834**	14.355***	–0.567
	(0.027)	(5.243)	(4.077)	(4.123)
Attrition_i	0.019	4.117*	–11.623***	–14.053***
	(0.017)	(2.336)	(2.273)	(2.221)
Training_{ie}	0.290***	27.534***	38.292***	0.575
	(0.016)	(3.208)	(2.583)	(2.497)
R-squared	0.051	0.020	0.045	0.006
Observations	18,672	18,610	18,610	18,610
Panel B: matched sample				
	Earnings	Civic/political	Cultural	Social
$\text{Training}_{ie} \times \text{attrition}_i$	–0.027	4.931	3.986	4.732
	(0.039)	(9.469)	(6.140)	(6.348)
Attrition_i	0.088***	11.043	–0.769	–20.227***
	(0.033)	(8.081)	(5.174)	(5.308)
Training_{ie}	0.024	3.375	0.543	0.557
	(0.023)	(5.572)	(3.735)	(3.635)
R-squared	0.025	0.005	0.003	0.011
Observations	7,961	7,880	7,880	7,880
Treatment-by-evaluation FE	x	x	x	x

Notes: The table shows regression to evaluate the characteristics of individuals who drop out of the sample in later periods. $Attrition_i$ is equal to one if individual i drops out in periods $t+1$, $t+2$, or $t+3$, and zero otherwise. The sample is restricted to periods $t-1$ and $t-2$. Individuals in Panel B are weighted by matching weights. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table D-3: Balanced Panel

	(1)	(2)	(3)	(4)
	Panel A: treatment effects by treatment period			
	Earnings	Civic/political	Cultural	Social
Training$_{ie}$ × post$_{t+3}$	0.082***	10.952*	10.657**	–2.926
	(0.023)	(5.828)	(4.875)	(5.444)
Training$_{ie}$ × post$_{t+2}$	0.051***	11.052**	10.653**	–0.877
	(0.019)	(5.631)	(4.750)	(5.067)
Training$_{ie}$ × post$_{t+1}$	0.054***	7.530	6.088	–0.227
	(0.020)	(5.462)	(4.445)	(4.732)
Training$_{ie}$ × treat$_{t=0}$	0.045***	6.657	4.563	0.152
	(0.016)	(4.370)	(3.993)	(4.615)
Training$_{ie}$ × pre$_{t-2}$	0.000	–0.440	1.351	0.179
	(0.015)	(4.588)	(3.933)	(3.840)
R-squared	0.782	0.665	0.596	0.513
Observations	13,354	13,848	13,848	13,848
H_0: post$_{t+1,t+2} = 0$ (pvalue)	0.009	0.144	0.080	0.980
H_0: post$_{t+1,t+2,t+3} = 0$ (pvalue)	0.004	0.223	0.111	0.942
	Panel B: treatment effects averaged over post-treatment periods			
	Earnings	Civic/political	Cultural	Social
Training$_{ie}$ × post$_{t+1,t+2,t+3}$	0.059***	10.073**	8.507**	–1.328
	(0.019)	(4.462)	(3.597)	(4.353)
R-squared	0.771	0.646	0.581	0.511
Observations	11,115	11,540	11,540	11,540
Treatment-by-evaluation FE	x	x	x	x
Control variables	x	x	x	x
Individual-by-evaluation FE	x	x	x	x
Mean absolute $\tilde{\Delta}$	2.55	2.55	2.55	2.55
Median absolute $\tilde{\Delta}$	2.29	2.29	2.29	2.29
P75 absolute $\tilde{\Delta}$	3.16	3.16	3.16	3.16

Notes: The table shows estimates of the baseline model on a balanced sample (defined by non-pecuniary outcomes). Baseline weights are refined by entropy balancing (covariates: log monthly earnings, log hours worked, and the three non-pecuniary outcomes in periods $t-1$ and $t-2$). Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table D-4: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline (PSM with refinement by EB)				PSM	EB	
	Baseline	Trends	No trimming	NN		Baseline	Trends
			Panel A: civic/political participation				
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.605**	8.139**	7.593**	6.608**	9.380**	6.612**	6.599**
	(3.697)	(3.749)	(3.364)	(3.026)	(3.755)	(2.762)	(2.768)
R-squared	0.657	0.660	0.676	0.672	0.650	0.674	0.673
			Panel B: cultural participation				
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.868***	9.603***	7.976***	6.721***	8.615***	7.202***	7.524***
	(3.046)	(3.080)	(2.777)	(2.455)	(3.140)	(2.401)	(2.383)
R-squared	0.583	0.581	0.592	0.582	0.582	0.592	0.593
			Panel C: social participation				
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	–1.434	–1.153	1.174	–0.997	–2.571	1.675	1.954
	(3.579)	(3.661)	(3.448)	(2.921)	(3.598)	(2.788)	(2.781)
R-squared	0.538	0.539	0.541	0.543	0.540	0.546	0.547
Treatment-by-evaluation FE	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x
Individual-by-evaluation FE	x	x	x	x	x	x	x
Observations	17,159	17,159	18,256	25,486	17,159	40,035	40,035
Mean absolute $\tilde{\Delta}$	1.49	1.66	1.77	1.15	1.45	0.34	0.79
Median absolute $\tilde{\Delta}$	1.14	1.27	1.39	0.90	1.13	0.10	0.65
P75 absolute $\tilde{\Delta}$	1.96	2.13	2.27	1.83	2.11	0.43	1.10

Notes: The table shows averaged treatment effects under different model specifications. The variable $\text{post}_{t+1,t+2,t+3}$ is equal to one if post_{t+1}, post_{t+2}, or post_{t+3} are equal to one and zero otherwise; period $t = 0$ is not considered. Column (2): use entropy balancing to further refine the baseline weights (used in Column (1)) by adjusting for trends in the outcome variables (log monthly earnings, log hours worked per week, three non-pecuniary outcome scores) by previous work-related training, university degree, vocational degree, gender, and occupation sample. Column (3): sample is not trimmed after calculating the propensity scores. Column (4): use 5-to-1 nearest-neighbor matching instead of kernel matching. Column (5): use matching weights from propensity score matching without further refinement. Column (6): use only entropy balancing on same covariates as in the baseline model (Column (1)). Column (6): use only entropy balancing on same covariates as in Column (1) with further refinement of the weights by adjusting for trends in the outcome variables (log monthly earnings, log hours worked per week, three non-pecuniary outcome scores) by previous work-related training, university degree, vocational degree, gender, and occupation sample. Appendix Table **??** provides treatment period-specific results. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table D-5: Treatment Period-Specific Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline (EB+PSM)				PSM	EB	
	Baseline	Trends	No trimming	NN		Baseline	Trends
Panel A: civic/political participation							
$\text{Training}_{ie} \times \text{post}_{t+3}$	10.624**	11.908**	10.104**	8.774**	13.546**	9.688**	9.504**
	(5.234)	(5.171)	(4.711)	(4.181)	(5.323)	(4.017)	(3.939)
$\text{Training}_{ie} \times \text{post}_{t+2}$	12.273***	11.725***	10.497**	9.711***	13.431***	8.781**	8.520**
	(4.435)	(4.488)	(4.328)	(3.753)	(4.482)	(3.632)	(3.550)
$\text{Training}_{ie} \times \text{post}_{t+1}$	4.492	3.260	3.311	2.850	5.058	2.775	2.856
	(4.147)	(4.185)	(3.752)	(3.372)	(4.307)	(3.055)	(3.042)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	8.567**	8.668**	4.184	5.207*	9.274***	4.880*	4.991*
	(3.402)	(3.450)	(3.144)	(2.780)	(3.395)	(2.697)	(2.707)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.053	0.081	0.069	–0.034	1.431	0.099	0.130
	(3.426)	(3.476)	(3.195)	(2.751)	(3.454)	(2.675)	(2.632)
Panel B: cultural participation							
$\text{Training}_{ie} \times \text{post}_{t+3}$	11.047**	11.759***	8.504*	6.846*	11.681***	7.610**	7.812**
	(4.352)	(4.343)	(4.404)	(3.633)	(4.366)	(3.560)	(3.506)
$\text{Training}_{ie} \times \text{post}_{t+2}$	10.774***	12.200***	8.371**	10.099***	11.257***	9.767***	10.168***
	(4.018)	(4.078)	(3.798)	(3.224)	(4.138)	(3.150)	(3.118)
$\text{Training}_{ie} \times \text{post}_{t+1}$	6.496*	6.491*	6.869**	3.864	6.248*	4.901*	5.164*
	(3.468)	(3.490)	(3.134)	(2.753)	(3.451)	(2.659)	(2.670)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	3.569	3.649	1.267	1.665	3.975	1.678	1.182
	(3.045)	(3.058)	(2.928)	(2.423)	(3.040)	(2.355)	(2.351)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.661	0.587	0.145	0.089	1.384	–0.068	–0.080
	(3.137)	(3.184)	(2.916)	(2.513)	(3.142)	(2.393)	(2.398)
Panel C: social participation							
$\text{Training}_{ie} \times \text{post}_{t+3}$	–2.646	–3.465	–2.454	–4.469	–3.595	–0.798	–0.603
	(4.868)	(4.964)	(4.613)	(3.951)	(4.862)	(3.835)	(3.764)
$\text{Training}_{ie} \times \text{post}_{t+2}$	–1.481	–0.877	0.080	–1.187	–3.154	1.462	1.997
	(4.394)	(4.526)	(4.279)	(3.556)	(4.430)	(3.306)	(3.284)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.190	0.741	4.694	1.616	–1.138	4.467	4.568
	(3.637)	(3.736)	(3.648)	(3.055)	(3.655)	(2.930)	(2.930)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	3.440	2.944	4.364	2.258	2.278	5.261*	5.010*
	(3.461)	(3.479)	(3.467)	(2.895)	(3.484)	(2.818)	(2.791)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.298	0.217	0.261	0.163	–0.472	0.163	0.162
	(2.834)	(2.823)	(2.660)	(2.211)	(2.790)	(2.151)	(2.132)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x
Control variables	x	x	x	x	x	x	x
Individual-by-evaluation period FE	x	x	x	x	x	x	x
Observations	20,997	20,997	22,338	31,203	20,997	49,086	49,086
Mean absolute $\tilde{\Delta}$	1.84	1.92	1.88	1.55	1.93	1.11	1.66
Median absolute $\tilde{\Delta}$	1.48	1.49	1.35	1.12	1.60	0.78	0.95

Notes: See Tables **??** and **??** for sample and variable descriptions. The participation scores are standardized to have mean 500 and standard deviation 100 in the pretreatment control group for each evaluation period. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

E Trust and Non-Pecuniary Outcomes

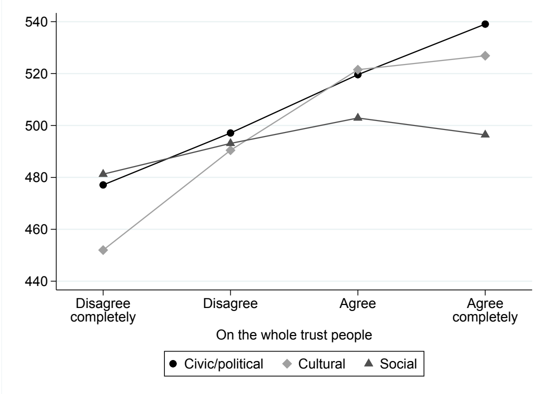
In many applications, trust is an important dimension of social capital. The SOEP provides information on trust in the years 2003, 2008, and 2013. The question asks to what extent people can agree or disagree with the statement that people can be trusted. The variable is measured on a 4-point scale from 1 [disagree completely], 2 [disagree], 3 [agree slightly], to 4 [agree completely].

Figure **??** shows average participation scores by level of trust. The measures are averaged over all available years (2003, 2008, and 2013). In Figure **??**(a), the plot shows the raw correlation in the data. Correlation coefficients are equal to $r = 0.13$ between trust and civic/political participation, $r = 0.18$ between trust and cultural participation, and $r = 0.05$ between trust and social participation. In Figure **??**(b), the plot shows the same correlation after adjusting participation scores for gender, age, migrant status, log monthly earnings, university degree, vocational degree, and evaluation period-by-survey year fixed effects. Correlation coefficients are equal to $r = 0.11$ between trust and conditional civic/political participation, $r = 0.14$ between trust and conditional cultural participation, and $r = 0.07$ between trust and conditional social participation. All correlation coefficients are significantly different from zero at the one percent level.

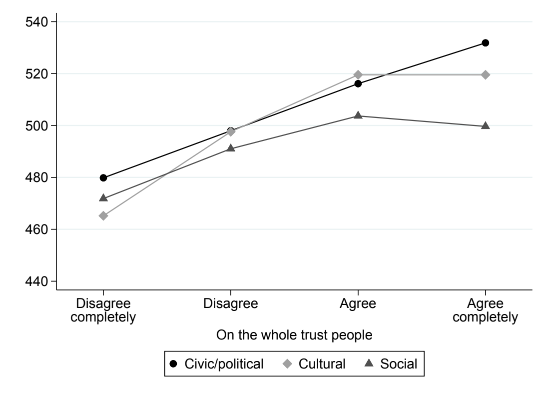
Table **??** shows linear probability regressions of trust on non-pecuniary outcomes. The dependent variable is a dummy that is one if the individual agrees or strongly agrees that general people can be trusted and zero if the individual disagrees or strongly disagrees. The dummy is used because the majority of individuals choose either *agree* and *disagree* (92%) instead of *strongly agree* and *strongly disagree*. The results show that there is a strong positive correlation between all participation domains and trust. This relationship holds after controlling for a set of covariates.

Finally, Table **??** shows the effect of participating in work-related training on trust. While we do find positive coefficients in the cross-sectional regression on the non-matched sample (Column (1)), this effect disappears completely in either the individual fixed effects regressions or on the matched sample.

Figure E-1: Relationship between Levels of Trust and Social Activities



(a) Unconditional



(b) Conditional

Notes: The figures show average participation scores by level of trust. Measures averaged over all available years (2003, 2008, and 2013). Figure **??**(a) plots the raw values. Figure **??**(b) plots the values after adjusting participation scores for gender, age, migrant status, log monthly earnings, university degree, vocational degree, and evaluation period-by-survey year fixed effects.

Table E-1: Trust and Social Activities

	(1)	(2)	(3)	(4)	(5)
Dependent variable: trust in general people (yes/no)					
Civic/political participation $\times 100^{-1}$	0.034***	0.029***	0.045***		
	(0.004)	(0.004)	(0.004)		
Cultural participation $\times 100^{-1}$	0.069***	0.055***		0.067***	
	(0.005)	(0.005)		(0.005)	
Social participation $\times 100^{-1}$	0.015***	0.023***			0.035***
	(0.005)	(0.005)			(0.005)
Female		0.037***	0.047***	0.028**	0.040***
		(0.011)	(0.011)	(0.011)	(0.011)
Age		0.001	–0.000	0.001	0.001*
		(0.001)	(0.001)	(0.001)	(0.001)
Migrant		–0.011	–0.019	–0.013	–0.034**
		(0.013)	(0.013)	(0.013)	(0.013)
Log monthly earnings		0.027***	0.035***	0.025***	0.039***
		(0.008)	(0.008)	(0.008)	(0.008)
University degree		0.086***	0.109***	0.087***	0.132***
		(0.014)	(0.014)	(0.014)	(0.014)
Vocational degree		–0.009	–0.004	–0.009	–0.001
		(0.013)	(0.013)	(0.013)	(0.013)
Treatment-by-evaluation FE	x	x	x	x	x
R-squared	0.036	0.045	0.032	0.039	0.027
Observations	13,297	13,297	13,297	13,297	13,297

Notes: The table shows regression models of trust in general people. The dependent variable is a dummy that is one if the individual agrees or strongly agrees that general people can be trusted and zero if the individual disagrees or strongly disagrees. On average, 63% of individuals report that people can be trusted. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table E-2: Trust and Work-Related Training

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: trust in general people (yes/no)						
	Non-matched sample			Matched sample		
Training$_{ie}$ $\times$ post$_{t+3}$	0.056**	0.012	0.012	–0.001	–0.013	0.013
	(0.022)	(0.022)	(0.035)	(0.037)	(0.036)	(0.052)
Training$_{ie}$ $\times$ post$_{t+2}$	0.043***	–0.004	0.016	–0.049*	–0.051*	–0.001
	(0.017)	(0.016)	(0.050)	(0.027)	(0.026)	(0.081)
Training$_{ie}$ $\times$ treat$_{t=0}$	0.046***	–0.001	0.014	–0.013	–0.015	0.012
	(0.013)	(0.013)	(0.027)	(0.023)	(0.023)	(0.047)
Training$_{ie}$ $\times$ pre$_{t-2}$	0.038**	–0.006	[baseline]	–0.008	–0.012	[baseline]
	(0.016)	(0.016)		(0.028)	(0.027)	
Treatment-by-evaluation FE	x	x	x	x	x	x
Control variables		x	x		x	x
Individual-by-evaluation FE			x			x
R-squared	0.003	0.039	0.370	0.001	0.036	0.430
Observations	18,870	18,870	18,870	6,824	6,824	6,824
Mean in $t-2$	0.614	0.614	0.614	0.672	0.672	0.672
H_0: post$_{t+2,t+3} = 0$ (pvalue)	0.002	0.832	0.916	0.176	0.146	0.967

Notes: The table shows regression models of trust in general people. The dependent variable is a dummy that is one if the individual agrees or strongly agrees that general people can be trusted and zero if the individual disagrees or strongly disagrees. There is no information for treatment period $t-1$ and $t+1$. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

F Number of Close Friends and Non-Pecuniary Outcomes

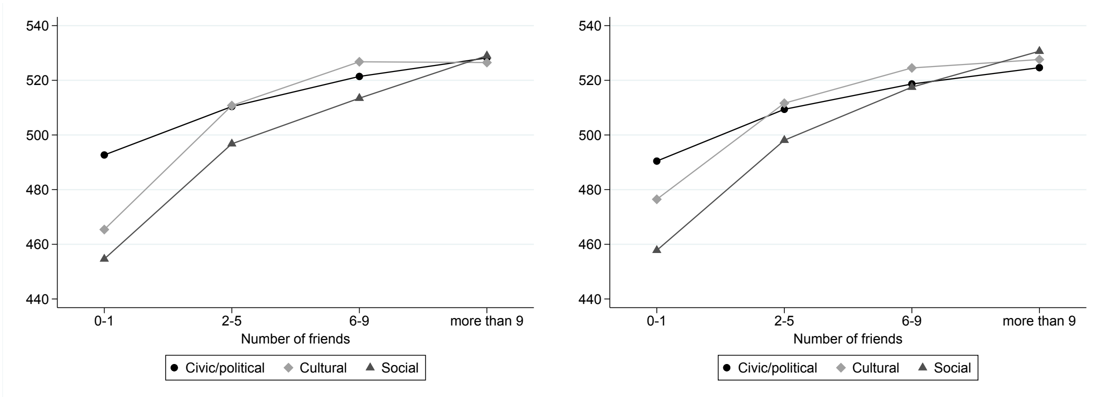
In this section, we study the number of close friends as a proxy for the quality indicator of social ties. The SOEP provides information on the number of close friends in the years 2003, 2008, 2011, and 2013. The question asks the respondent to report the number of close friends. The average (median) number of friends in our sample is equal to 4.4 (4), which indicates that the question is not about the size of the network, but more about a specific aspect of the quality of the network.

Figure **??** shows average participation scores by the number of friends. The measures are averaged over all available years (2003, 2008, 2011, and 2013). In Figure **??**(a), the plot shows the raw correlation in the data. Correlation coefficients are equal to $r = 0.07$ between number of friends and civic/political participation, $r = 0.12$ between number of friends and cultural participation, and $r = 0.17$ between number of friends and social participation. In Figure **??**(b), the plot shows the same correlation after adjusting participation scores for gender, age, migrant status, log monthly earnings, university degree, vocational degree, and evaluation period-by-survey year fixed effects. Correlation coefficients are equal to $r = 0.07$ between number of friends and conditional civic/political participation, $r = 0.11$ between number of friends and conditional cultural participation, and $r = 0.17$ between number of friends and conditional social participation. All correlation coefficients are significantly different from zero at the one percent level.

Table **??** shows the results of linear probability models of the log number of close friends on non-pecuniary outcomes. The results show that there is a strong positive correlation between all participation domains and the number of close friends. This relationship holds after controlling for a set of covariates.

Finally, Table **??** shows the effect of participating in work-related training on the log number of close friends. While we do find positive coefficients in the cross-sectional regression on the non-matched sample (Column (1)), this effect disappears completely in either the individual fixed effects regressions or on the matched sample.

Figure F-1: Relationship between Number of Close Friends and Social Activities



(a) Unconditional (b) Conditional

Notes: The figures show average participation scores by the number of friends. Measures averaged over all available years (2003, 2008, 2011, and 2013). Figure **??**(a) plots the raw values. Figure **??**(b) plots the values after adjusting participation scores for gender, age, migrant status, log monthly earnings, university degree, vocational degree, and evaluation period-by-survey year fixed effects.

Table F-1: Number of Close Friends and Social Activities

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log number of close friends					
Civic/political participation $\times 100^{-1}$	0.021***	0.019***	0.047***		
	(0.006)	(0.006)	(0.006)		
Cultural participation $\times 100^{-1}$	0.074***	0.068***		0.090***	
	(0.007)	(0.007)		(0.007)	
Social participation $\times 100^{-1}$	0.101***	0.104***			0.116***
	(0.007)	(0.007)			(0.007)
Female		0.003	0.010	–0.011	0.010
		(0.015)	(0.015)	(0.015)	(0.015)
Age		–0.000	–0.003***	–0.002*	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Migrant		–0.030*	–0.035*	–0.024	–0.053***
		(0.018)	(0.019)	(0.019)	(0.018)
Log monthly earnings		–0.002	0.005	–0.009	0.011
		(0.011)	(0.011)	(0.011)	(0.011)
University degree		0.042**	0.056***	0.021	0.092***
		(0.019)	(0.020)	(0.020)	(0.019)
Vocational degree		0.004	0.005	–0.002	0.012
		(0.018)	(0.019)	(0.018)	(0.018)
Treatment-by-evaluation FE	x	x	x	x	x
R-squared	0.049	0.050	0.013	0.025	0.038
Observations	15,460	15,460	15,460	15,460	15,460

Notes: The table shows regression models of log number of close friends. The sample excludes individuals with zero friends, which is the case for 5.5% of the people. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table F-2: Number of Close Friends and Work-Related Training

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log number of close friends						
	Non-matched sample			Matched sample		
Training$_{ie}$ $\times$ post$_{t+3}$	0.052*	0.034	–0.010	0.013	0.010	–0.001
	(0.028)	(0.028)	(0.040)	(0.047)	(0.046)	(0.059)
Training$_{ie}$ $\times$ post$_{t+2}$	0.041**	0.021	0.022	0.034	0.033	0.030
	(0.018)	(0.018)	(0.038)	(0.027)	(0.026)	(0.058)
Training$_{ie}$ $\times$ treat$_{t=0}$	0.067***	0.043**	0.018	0.027	0.022	0.011
	(0.017)	(0.018)	(0.030)	(0.028)	(0.028)	(0.051)
Training$_{ie}$ $\times$ pre$_{t-2}$	0.060***	0.036	[baseline]	0.010	0.004	[baseline]
	(0.022)	(0.022)		(0.036)	(0.035)	
Treatment-by-evaluation FE	x	x	x	x	x	x
Control variables		x	x		x	x
Individual-by-evaluation FE			x			x
R-squared	0.006	0.014	0.457	0.005	0.016	0.480
Observations	20,395	20,395	20,395	7,454	7,454	7,454
Mean in $t-2$	4.696	4.696	4.696	4.694	4.694	4.694
H_0: post$_{t+2,t+3} = 0$ (pvalue)	0.033	0.351	0.636	0.448	0.444	0.808

Notes: The table shows regression models of log number of close friends. The sample excludes individuals with zero friends, which is the case for 5.5% of the people. There is no information for treatment period $t-1$ and $t+1$. Standard errors, clustered at the individual level, in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.