I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 11854

The Wider Benefits of Adult Learning: Work-Related Training and Social Capital

Jens Ruhose
Stephan L. Thomsen
Insa Weilage

SEPTEMBER 2018

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 11854

The Wider Benefits of Adult Learning: Work-Related Training and Social Capital

Jens Ruhose
Leibniz Universität Hannover, CESifo and IZA

Stephan L. Thomsen
Leibniz Universität Hannover, ZEW and IZA

Insa Weilage
Leibniz Universität Hannover

SEPTEMBER 2018

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

We propose a regression-adjusted matched difference-in-differences framework to estimate 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. Training 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 Classification: J24, I21, M53

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

Corresponding author:
Jens Ruhose
Leibniz Universität Hannover
Königsworther Platz 1
30167 Hannover
Germany
E-mail: ruhose@wipol.uni-hannover.de

* Previous versions of this paper have been circulated under the title "Wider Benefits from Continuous Work-Related Training". We are grateful to Guido Heineck, Sandra McNally, Jens Mohrenweiser, Ina Rüber, Josef Schrader, Nicole Tieben, Simon Wiederhold, Ludger Woessmann, Oleksandr Zhylyevskyy, and seminar and conference participants at the annual meetings of the EEA (Cologne), MEA/SOLE (Evanston), Verein für Socialpolitik (Vienna), standing field committee on the economics of education of the Verein für Socialpolitik (Bern), the conference of the Centre for Vocational Education Research (London), Society for Empirical Educational Research (Basel), the IZA research seminar (Bonn), Goethe University Frankfurt, Leibniz Universität Hannover, and Leuphana Universität Lüneburg for their most helpful comments and discussions. Financial support by the German Federal Ministry of Education and Research (BMBF) through the project "Nicht-monetäre Erträge der Weiterbildung: zivilgesellschaftliche Partizipation (NEWz)" is gratefully acknowledged.

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 (OECD, 2005, 2013). 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 (OECD, 2017, 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 (Field, 2011).[2] Focusing on the case of Germany, where participation rates are close to the OECD average,[3] this paper makes two key contributions to the literature on adult education. First, we address empirical challenges in the evaluation of wider benefits from training by introducing a flexible econometric framework into the literature, a framework that can be implemented with panel data. 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 (Federal Ministry of Education and Research, 2015, 2017),[4] on measures of civic/political, cultural, and social participation—measures that are related to social capital at the individual level (Putnam, 1993). 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 externalities (see Section 2 for a discussion).

[1]The PIAAC survey shows that 39% of adults participate in non-formal 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" (OECD, 2017, p. 325) and *nonformal learning activities* are "sustained educational activity that does not correspond exactly to the definition of formal education."

[2]For example, Bassanini et al. (2007) and Leuven (2005) provide overview studies on individual labor market outcomes, and Acemoglu and Pischke (1998), Acemoglu and Pischke (1999), De Grip and Sauermann (2012, 2013), and Loewenstein and Spletzer (1999) provide studies on firm performance. Oreopoulos and Salvanes (2011) provide an overview of further non-pecuniary effects of formal education.

[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 (OECD, 2017).

[4]Work-related training is very costly for firms. For example, Seyda and Placke (2017) estimate that the total costs for German firms amount to 33.5 billion euro for the year 2016.

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 outcomes, participation in work-related training activities, and a rich set of socio-economic background variables. To measure domains of social capital and activities (Huang et al., 2009), we use eight non-pecuniary outcome variables that are consistently measured over the study period, including 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. While there is no consensus about the exact definition of social capital, the most appropriate definition for this study refers to the view that social capital represents social connections and interactions, which have (productive) value (Scrivens and Smith, 2013).[5] 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. 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 (Heckman et al., 1997, 1998; Smith and Todd, 2005b), 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 (Hainmueller, 2012).

[5] 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 (Putnam, 1993, 1995, 2002). There also exist other definitions of social capital. For example, Bourdieu (1977) uses his concept of social capital to explain class inequalities, and Coleman (1990) argues that social capital is important for human capital formation because social capital facilitates collective aims.

By calibrating unit weights 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 group 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, the paper carefully assesses the robustness of each step and discusses how changes in the empirical specification affect the results.

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.[6] 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 (Lechner, 1999b; Pischke, 2001; Büchel and Pannenberg, 2004). 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 (De Grip and Sauermann, 2013), further results suggest that these improvements in skills and labor market outcomes are unlikely to explain our findings. We provide suggestive evidence that work-related training opens up networking opportunities, thus leading to higher participation in civic, political, and cultural activities. In that sense, these benefits come as a by-product of activities engaged in for other purposes (Coleman, 1990). Because we are aware that non-experimental data may still conceal correlations of unobserved factors with the treatment and outcome variables that would 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., Balatti and Falk, 2002; Field, 2011; Green et al., 2006; Portes, 1998) and policy makers (e.g., Education Council, 2006; Council of the European Union/European Commission, 2015; OECD, 2005, 2017) that there are wider benefits of adult education, some studies relate participation in CET to well-being, health, job satisfaction, and worries (Balatti and Falk, 2002; Burgard and Görlitz, 2014; Feinstein and Hammond, 2004; Georgellis and Lange, 2007; Jenkins, 2011; Ruhose et al., 2018), social and political attitudes (Balatti and Falk, 2002; Feinstein and Hammond, 2004; Preston and Feinstein, 2004; Ruhose et al., 2018), and measures of social

[6] We also cannot find that trust increases after participation in work-related training (Appendix Section C).

capital such as membership in civic groups, political interest, voting, social networks, and trust (Bynner and Hammond, 2004; Emler and Frazer, 1999; Feinstein and Hammond, 2004; Preston, 2004a,b; Rüber et al., 2018). However, this evidence is almost entirely based on descriptive and qualitative studies, covering only specific questions (Blanden et al., 2010; Desjardins and Schuller, 2011; Field, 2011; OECD, 2010). Many of these studies also do not differentiate by the type of learner, which limits the possibility of identifying causal mechanisms (Field, 2011).

The paper proceeds as follows. Section 2 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 3 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 4 describes the empirical setup and the implementation of the estimator. Section 5 presents the results, discusses the identification assumption, and performs a series of robustness checks. Section 6 discusses potential mechanisms by looking at effect heterogeneity along individual and training characteristics. Section 7 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, Putnam (1993) formulates the concept of *social capital*. His 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.[7] While there is no consensus about the exact definition of social capital, Putnam describes the concept as features of social organizations, such as networks, norms, and trust, that can improve the efficiency of society by facilitating coordination, collaboration, and cooperation. Thus, social capital refers to the idea that social connections and interactions have (productive) value (Scrivens and Smith, 2013). The broadest view of social capital therefore comprises the notion that "it's not *what* you know, but it's *who* you know" (Woolcock, 2001, p. 67) that matters. Another useful operationalization of social capital comes from organizational theory, which acknowledges that social capital has structural, content, and relational dimensions (Widén-Wulff and Ginman, 2004). The structural dimension includes, e.g., the channels and opportunities through which interaction can take place. Examples of this dimension

[7] See, for example, Gradstein and Justman (2002, 2018); Neira et al. (2010); Putnam (1995, 2002); Schneider et al. (2000); Westlund and Adam (2010). Guiso et al. (2011); Helliwell (2001); OECD (2001); Scrivens and Smith (2013); Temple (2001) provide overviews.

are the size of individual networks and the number of social ties. The content dimension describes, among other things, which type of information is exchanged, while the relational dimension characterizes the level of trust, group identification, and the quality of social ties and networks. It is believed that structural social capital is an important prerequisite for the deployment of other dimensions of social capital (Hazleton and Kennan, 2000; Tsai and Ghoshal, 1998). 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 dimensions of social capital (Knack, 2001; Paxton, 2002; Putnam, 1993; Scrivens and Smith, 2013).

High levels of individual social capital may be directly beneficial for workers. For example, recent research shows that employers often use personal networks and referrals to hire new employees,[8] which can be beneficial for the referred worker and the firm (Burks et al., 2015; Schmutte, 2015). By contrast, Bentolila et al. (2010) show that social contacts lead to reduced unemployment duration but at the cost of lower wages due to potential worker-firm mismatch. However, using self-reported sociability and measures of participation in clubs in high school to assess individual social capital, Deming (2017) shows that social capital endowments are perceived to have growing importance in the labor market. The reason is that high-paying jobs require more and more social capital to reduce coordination costs, allowing workers to collaborate more efficiently.

Social capital may provide further economic and social externalities for society (Balatti and Falk, 2002). Since the early work by de Tocqueville (1990), it has been noted that a vigorous associational life is important for a well-functioning democracy (Paxton, 2002). The argument is 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. These activities should then create and foster social ties and networks. It is therefore not surprising that countries all over the world highlight the importance of increasing the social capital of their citizens. For example, the European Union and the OECD promote *active citizenship* as the foundation of an open, democratic, and well-functioning society (Education Council, 2006; Council of the European Union/European Commission, 2015; OECD, 2017; Green et al., 2006). The more people who are actively participating in society, the stronger the quality and quantity of individual networks should be, the more values should be shared by citizens, and the higher levels of trust should be among the population. Social capital and active citizenship may also contribute to social cohesion by reducing the social distance within a society

[8] See, e.g., Calvó-Armengol and Jackson (2004); Dustmann et al. (2016); Topa (2011).

(Gradstein and Justman, 2000, 2002).[9] The literature argues that social cohesion can also provide economic externalities because the absence of a common culture within a population undermines the efficiency of production and exchange (e.g., Alesina et al., 1999; Ashraf and Galor, 2013; Lazear, 1999).

Measuring the level of social capital is demanding because social capital is a multidimensional concept (Hoskins and Mascherini, 2009; Neira et al., 2010). Thus, each study defines (a set of) proxies that are tailored to the objectives of the analysis and also influenced by data availability. In empirical work, social capital at the individual level is often seen as an aggregate of two dimensions: trust in people generally and personal involvement in social activities (Huang et al., 2009). In this study, we follow this literature and examine 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). Directly motivated by the work of Putnam (1995, 2002), these dimensions intend to capture the extent of an individual's associational life and the dimension of structural social capital as an important predictor of the level and quality of social interactions. We also study trust and the number of close friends as measures of relational dimensions of social capital. However, some researchers see the evolution of trust and norms as long-run outcomes of social interactions and networks (Croll, 2004), raising the possiblity that higher participation behavior do not affect relational social capital in the short- and medium-run.

2.2 Social Capital and Work-Related Training

In this section, we discuss theoretical channels through which participation in work-related training may affect social activities and interactions. Our theoretical considerations broadly follow the framework by Feinstein and Hammond (2004), who study the effects of adult education on social capital. We argue that work-related training may affect social capital via at least three channels: (1) economic reasons, (2) the development of abilities and cognitive/non-cognitive skills, (3) positional effects, and (4) peer effects.

Economic reasons. The primary motive for firms to offer work-related training and for employees to participate in training is to increase productivity (De Grip and

[9] While the concept of social cohesion is vague (Council of Europe, 2005), most definitions share the understanding that social cohesion incorporates a set of socially desirable conditions, including equality, equal opportunity, trust, and shared values, as well as active citizenship, civic/political participation and engagement, cultural awareness and expression, and social participation (European Commission, 2001; Education Council, 2006; Council of the European Union/European Commission, 2015; Janmaat and Green, 2013; Hoskins and Mascherini, 2009). This perspective seems questionable when cooperation and coordination are only used to benefit members of the own group (Olson, 1982); this outcome may harm the economic well-being of societies (Knack, 2001) and questions the beneficial role that CET may have for social cohesion within a society (Janmaat and Green, 2013).

Sauermann, 2012, 2013). Those productivity increases may lead to increasing wages and job promotions (Pergamit and Veum, 1999; Melero, 2010). The literature also provides evidence that training reduces the risk of becoming unemployed and increases the probability of finding a job after a layoff (Kluve, 2010). Thus, larger monetary resources may enable more participation in civic/political, cultural, and social activities. The effect can be direct, meaning that individuals have the monetary funds to go to the cinema or opera, meet friends who live far away, or purchase informational material and books about political and social issues. The effect may also be indirect because larger monetary resources give the individual the freedom to spend more time on other activities instead of working. However, given that each hour at work is remunerated with a higher return compared to the situation without training, it is also possible that individuals reduce their outside activities to work more. Job promotions typically also involve working longer hours because responsibilities increase, and the increased work hours may crowd out social activities.

Development of abilities and cognitive/non-cognitive skills. Feinstein and Hammond (2004) emphasize that adult education fosters generic cognitive (e.g., better cognitive skills facilitating self-management and reflection) and personal development (e.g., the development of resilience and grit through learning experiences). Workers may also be able to use these new skills in various contexts (Preston and Hammond, 2002). For example, participating in training about how to organize and manage information at the workplace should also reduce the costs of gathering and processing information for other purposes. Personal development may also increase the awareness of political and societal issues. Successful participation in work-related training may also increase self-confidence and self-esteem (Panitsides, 2013; Tett and Maclachlan, 2007), which can be helpful for other activities as well.

Positional effects. Work-related training may affect an individual's (perceived and actual) social status (Blanden et al., 2009, 2010). For example, increased income levels and job promotions have the potential to change both one's network and the recognition that one receives from family members, relatives, friends, and neighbors. New networks and social ties open up new opportunities to participate more in existing and new social activities. For example, job promotions change the work environment and introduce the worker to a new set of colleagues with perhaps very different interests in social activities. The new position may also pressure the worker to attend cultural events or join a particular political party. However, promotions into higher positions can be associated with social isolation if the individual is not able to adapt to the new social environment.

Peer effects. Participation in training also intensifies contact with other colleagues and creates an opportunity to connect with individuals who one would not otherwise have seen or interacted with (Balatti et al., 2006; Preston and Hammond, 2002). This contact creates opportunities for social networking with similar-minded and engaged persons, potentially leading to higher participation in civic/political, cultural, and social activities. Those new or existing relationships may easily spill over into private life (Fujiwara, 2012). Peers may further 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, potential 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. However, as work-related training can have positive and negative effects, it is an empirical question whether there are net gains or losses from participation in work-related training. In addition, it could also be that participation in one social activity may crowd out other activities.

Coleman (1990, p. 312) argues 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. The theoretical discussion shows that increasing social capital is likely a second-order concern for people participating in work-related training. 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. 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%). They also took courses in science, IT, and technology (23%). Those are 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. Furthermore, 7% of respondents use work-related training to invest in language-, culture-, and politics-oriented courses. It is also unlikely that employers who initiate most work-related training (Federal Ministry of Education and Research, 2017) are primarily concerned about the social capital of their employees. 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%).

3 Data

3.1 Basic Data Setup

We use data from the SOEP (German Socio-Economic Panel Study), one of the world's largest and longest panel studies (Wagner et al., 2007). Representative of the German population, the SOEP has been used for a broad variety of research questions. Started in 1984, the study conducts more than 20,000 individual interviews annually in over 10,000 households in Germany. The respondents provide information about a wide range of topics, including their demographic situation, educational attainment, and labor market outcomes. Also included is information about participation in work-related training, information about non-pecuniary and pecuniary outcomes, and a very rich set of background information to control for selection into training participation.

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 years*.[10] 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 1 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 (and includes appropriate fixed effects).

Insert Figure 1 here

We define seven treatment periods: three pretreatment periods, one treatment period, and three posttreatment periods. Because information about outcome variables is not equally distributed across the years, we define two years for each treatment period (three years for the period that contains the information on work-related training). Whenever possible, we average the available information within each treatment period, which should reduce measurement error.[11] 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. The two years before the treatment period form pretreatment period $t-1$, years three and four before

[10] 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.

[11] Averaging takes place only in seven treatment periods because we average only when we have information on non-pecuniary outcomes (see Figure 1).

[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 A-1). Because this reporting behavior may indicate recall bias, we do not use variation about the timing of the course start.

the treatment period form pretreatment period $t-2$, and years five and six before the treatment period form pretreatment period $t-3$. In the analysis, we use pretreatment periods $t-1$ and $t-2$ to compare participants to non-participants prior to the training activity. The pretreatment period $t-3$ is used for identification checks. The two years after the treatment period form the posttreatment period $t+1$, years three and four after the treatment period form the posttreatment period $t+2$, and years five and six after the treatment period form the posttreatment period $t+3$. We restrict the sample to individuals with observations in pretreatment periods $t-1$ and $t-2$ and at least one observation in either the treatment period $t=0$ or one of the first two posttreatment periods. This restriction ensures a minimal degree of panel stability.

We further restrict the estimation sample to individuals who are between 25 and 55 years old and with (potential) labor market entry before pretreatment period $t-2$.[13] 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).

3.2 Measures of Social Capital

Our measures of 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. The variable is measured on a 4-point scale from 1 [not at all], 2 [not so strongly], 3 [strongly], to 4 [very strongly]. *Participate in politics* asks whether the person participates in local politics. The variable is measured on a 3-point scale from 1 [never], 2 [rarely], to 3 [often]. 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 variable is measured on a 4-point scale from 1 [never], 2 [rarely], 3 [every month], to 4 [every week]. 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

[13] We define the (potential) labor market entry year by adding years of schooling (incl. apprenticeships and possible university education) plus six years to the birth year.

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. The variables are measured on a 4-point scale from 1 [never], 2 [rarely], 3 [every month], to 4 [every week]. 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. Both variables are measured on a 4-point scale from 1 [never], 2 [rarely], 3 [every month], to 4 [every week].

The eight non-pecuniary outcome variables are related to each other (see correlation matrix in Appendix Table A-1). To identify underlying concepts, to avoid ad-hoc definitions of how to aggregate the information and to increase the statistical discrimination between the outcome dimensions, we use a principal component analysis (PCA). To calculate the factor rotations, we restrict the sample to the pretreatment periods $t-1$ and $t-2$ and to individuals in the group of non-participants who answered all eight questions. The resulting PCA indicates three principal components, which confirm the assignment of the eight variables to the three participation domains.[14]

Using the rotations from the PCA, we construct three non-pecuniary outcome scores for each individual. 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. To obtain a sense of the information content of these measures, Figure 2 plots average scores by educational degree. The figure shows that civic/political participation and cultural participation are highest for individuals with a university degree, second highest for vocational degree holders, and lowest for individuals with no educational degree. This finding is in line with 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 (OECD, 2016). However, the reverse is true for social participation. This pattern may be explained by different time-use behaviors of high-skilled versus low-skilled individuals.[15]

Insert Figure 2 here

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

[14] 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 A-2 shows the rotations of the PCA.

[15] The pattern of results is reiterated when looking at non-pecuniary outcome scores along the distribution of earnings (see Appendix Figure A-2). There we find that the levels of the outcome scores are rather similar until the 60th percentile. For higher percentiles, we observe increasing civic/political and cultural participation and decreasing social participation.

Figure 1). 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 B 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 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 1, 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. Figure 3 shows the distribution of the cumulative duration of the three training courses. The density plot indicates a bunching of short courses with fewer than ten hours of training. 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.[17] The ten-hour restriction reduces the incidence of training to 27% (28% in 2000, 25% in 2004, 27% in 2008). 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 specific evaluation period. This treatment specification could lead to a case in which individuals can be in the treatment

[16]The total number of courses could be larger. Appendix Figures A-3(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]Appendix Figure A-3(c) shows the distribution of the sum of reported course hours for the restricted sample, and Appendix Figure A-3(d) provides the CDF for the unrestricted sample.

group in one evaluation period but in the comparison group in another treatment period. In the empirical analysis, we therefore condition on previous training participation.

Insert Figure 3 here

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) control group (before matching).

SOEP does not have direct information about whether the employer or the employee induced the training. However, information from the adult education survey for 2014 shows that in 61% of all trainings, the firm directly orders participation in work-related training (Federal Ministry of Education and Research, 2015, p. 49). In addition, the employee's supervisor suggests participation in an additional 16% of trainings. Thus, only 23% of participation in work-related training is entirely at the discretion of the employee. 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 and those that are due to the motivation of the employee. We 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. This distinction shows that 84% report employer-induced courses and 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 A-4 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

[18]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.

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 (Lynch, 1992; Arulampalam and Booth, 1997; Leuven and Oosterbeek, 1999; Bassanini et al., 2007). Moreover, the literature has identified differences in training participation according to age; that is, younger workers are more likely to participate (Oosterbeek, 1996, 1998). More recently, Caliendo et al. (2016) 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 (Oosterbeek, 1996; Lynch and Black, 1998; Grund and Martin, 2012).

Table 1 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 1 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 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 Ashenfelter (1978), Ashenfelter and Card (1985) and LaLonde (1986), economists have been interested in the labor market effects of training programs.[21]

[19]See, e.g., (Arulampalam et al., 2004; Bassanini et al., 2007; Grund and Martin, 2012; Yendell, 2013) for overviews.

[20]To make the variable scales comparable, we z-standardize variables according to Kling et al. (2007). 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 $t-2$.

[21]There are at least three strands of literature: The first strand of the literature studies the effects of work-related training activities (LaLonde, 1986; Blundell et al., 1999; Lechner, 1999a; Lynch, 1992; Goux and Maurin, 2000; Pischke, 2001; Frazis and Loewenstein, 2005; Leuven and Oosterbeek, 2008). The second strand of the literature focuses on adults who return to upper-secondary schooling or college (Leigh and Gill, 1997; Stenberg, 2011; Stenberg et al., 2012), often after displacement (Jacobson et al., 2005; Stenberg and Westerlund, 2008). And the third strand of the literature looks at the effects of

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. Heckman et al. (1997, 1998) and Dehejia and Wahba (2002) proposed matching estimators to construct counterfactual comparison groups. Smith and Todd (2005b) 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 (Heckman et al., 1997, 1998; Todd, 2008). The estimator is described in Equation (1). 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 (2) 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 outcome of the control group in the absence of treatment (indicated by subscript 0). Hence, the estimator identifies a causal effect if there are 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

training for unemployed individuals, including the effectiveness of active labor market policies (Card et al., 2010; Hujer et al., 2006; Kluve, 2010; McCall et al., 2016). See Leuven (2005) and Bassanini et al. (2007) for overviews and De Grip and Sauermann (2013) for a current overview of the main takeaways from the literature.

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 (Caliendo and Kopeinig, 2008).

4.2 Implementation

We implement this 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 1 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, Imbens (2015) and Imbens and Rubin (2015) 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 A-3 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 described before on the trimmed sample and compute propensity scores and odds ratios for further analysis.

[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 (Frölich, 2007; Zanutto, 2006).

[23] For the treatment group, Appendix Figures A-5 and A-6 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.

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 (3) 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 Heckman et al. (1997).[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 (Leuven and Sianesi, 2003). 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, Smith and Todd (2005a) and Heckman and Todd (2009) 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]

[24]Matching is implemented by using the `psmatch2` command in Stata (Leuven and Sianesi, 2003).

[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 (Smith and Todd, 2005b; Heckman and Todd, 2009).

[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.

because there is a strong presumption that many workers take up training to improve their 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. Taken together, we make sure that the comparison takes place between individuals in the same tertile of the earnings distribution, in the same evaluation period, with the same broader occupational background, and who have received training before.

Fourth step: Entropy balancing. We use entropy balancing to overhaul the conventional matching weights (Hainmueller, 2012; Hainmueller and Xu, 2013).[29] This nonparametric procedure refines the matching weights from the previous steps such that they exactly satisfy prespecified balancing constraints that are imposed on the sample moments of the covariate distribution. At the same time, entropy balancing keeps the weights as close as possible to the conventional matching weights to prevent loss of information. 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 participation (97 vs. 115), cultural participation (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

[29] We implement entropy balancing by using the `ebalance` command in Stata (Hainmueller and Xu, 2013).

analysis to estimate the following model:

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

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 (Caliendo and Kopeinig, 2008; Stuart, 2010), we also provide bootstrapped standard errors (see Appendix Table A-12). 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 2 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 2 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 (5), 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 $S^2_{X,c,k}$) (Rosenbaum and Rubin, 1985; Imbens, 2015). Caliendo and Kopeinig (2008) suggest that one should regard matching as unsuccessful when the normalized difference in means exceeds 5%. Columns (3) and (7) of Table 2 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 (Caliendo and Kopeinig, 2008). 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 (Heckman et al., 1997, 1998; Caliendo and Kopeinig, 2008).

5.2 Establishing the Model: Work-Related Training and Earnings

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 4 shows the results from the regression analysis using log monthly earnings.[30] The top left panel in Figure 4 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 (Pischke, 2001; Heckman et al., 2018). 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 A-6, Column (6)). On average, we find earnings gains of 5.1% after participation in training (regression not shown). This effect is in line with the literature studying the earnings effects of work-related training in Germany (Lechner, 1999b; Pischke, 2001; Büchel and Pannenberg, 2004).

Insert Figure 4 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 A-6, 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.[31]

[30] Appendix Table A-6 shows the corresponding regression results. Appendix Figure A-5 plots average log monthly earnings by treatment period.

[31] Appendix Tables A-7 and A-8 show that training participation increases both weekly hours worked (on average: 0.033 (0.012), significant at the 1% level) and hourly earnings (on average: 0.017 (0.009), significant at the 10% level).

5.3 Wider Benefits of Work-Related Training

We now turn to the effects of participating in work-related training on our measures of social capital. In Figure 5, 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. While there is a small (insignificant) increase in treatment period $t = 0$, we do not find any substantial treatment effects for social participation. This non-effect can also be interpreted such that increases in the other domains do not crowd out social participation.[33]

Insert Figure 5 here

For effect sizes, we look at the regression results in Table 3. 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). Again, for social participation, we do not see any noteworthy changes in the participation score. In Panel B of Table 3, we calculate averaged treatment effects by comparing the averaged effect of the three posttreatment periods to the averaged effect in the two pretreatment periods. We do not consider the effect in the treatment period because this effect is a mixture of treated and not-yet-treated effects. 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). The effect on social participation is close to zero (Column (5)).

Insert Table 3 here

In Appendix Table A-13, we show regressions on 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 Appendix Sections C and D, we provide evidence for the effects on two further measures of social capital, trust and the number of close friends. We show that both concepts are strongly linked to each of our three participation measures, but we do not

[32]The detailed regression results can be found in Appendix Tables A-9 to A-11, Columns (1), (3), (4), and (6). Appendix Figure A-6 plots treatment-period averages of the non-pecuniary outcome scores and Appendix Figure A-7 depicts the same plots for the eight subdimensions.

[33]Obviously, it could well be the case that the increased activities crowd out other activities that we do not analyze or observe.

find that participation in work-related training affects trust or the number of close friends, respectively. However, data convergence 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. It could also be that changes in these variables manifest only after repeated and long-lasting interactions.

5.4 Identification

The most important identifying assumption is the *common trend assumption* (see Section 4.1). To assess the plausibility of this assumption, we restrict the sample to the pretreatment periods $t-1$, $t-2$, and $t-3$ and try to predict the outcome in period $t-3$ with participation in work-related training in treatment period $t=0$. Running the model in Equation 6, 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.

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

Table 4 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 4 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.

Insert Table 4 here

[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 4, top right panel) but no pretreatment trends for the non-pecuniary outcomes (Figure 5, top right panels).

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. Controlling explicitly for labor market characteristics shuts down the labor-market-driven selection channel. In Columns (2), (4), and (6) of Table 3, we 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. 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 5 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 5 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

[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 4.2 is used. To analyze balancing quality, the bottom of Table 5 reports average normalized differences for different points in the normalized differences distribution.

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 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.

5.5 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 (Appendix Table A-14). 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 Appendix Table A-15). 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 (Appendix Table A-16).

5.6 Robustness Checks

Table 6 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 (Appendix Table A-17 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 Heckman et al. (1997) and Smith and Todd (2005b) argue for the use of kernel matching, we also apply 5-to-1 nearest-neighbor matching and report results in Column (4).[37] While coefficients are slightly smaller, we still find statistically and economically significant effects from participation in work-related training.

Insert Table 6 here

In the remaining columns of Table 6, 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

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

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 1 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.

6 Mechanism

In Section 2, we laid out several mechanisms that may explain a connection between participation in work-related training and our non-pecuniary outcomes. In this section, we discuss and present suggestive evidence that participation in work-related training affects social capital at the individual level by opening up opportunities for social networking rather than by increasing monetary resources, inducing shifts in job positions, or improving skills and abilities. Thus, it seems that work-related training fosters the structural dimension of social capital by creating more opportunities to form social interactions because of reduced networking costs, which may provide beneficial long-run effects on the relational dimension of social capital (i.e., better social networks and increasing levels of trust).

Previously, we have already discussed that controlling for endogenous labor market characteristics does not change the results (see Section 5.4). While this is helpful for identification, it also suggests 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. We can also rule out a strong impact of training-related changes in ability and skills—at least as long as they are associated with changes in earnings. This interpretation is supported by similar non-pecuniary returns to treatments with and without high monetary returns (see Section 5.4).

Figure 6 shows the results of several sample splits used to learn more about the origins of the average effect. In each subsample, we refine the baseline matching weights using entropy balancing that requires exact matching on the outcome variables (log monthly earnings, log weekly hours worked, three participation scores), separately for pretreatment periods $t-1$ and $t-2$. We start by analyzing effect heterogeneity by individual characteristics of the participant (Figure 6(a)). The most striking effect heterogeneity is that by gender. The results show that the effects are much stronger for females than for males. This may be explained by the findings of Moore (1990) and Umberson et al. (1996), who argue that females seek to be socially connected to a higher degree than men, which makes it plausible that women take up networking opportunities to a larger degree than men. Of course, this may also indicate a selection pattern of women into trainings that are more likely to lead to social interactions. Important heterogeneity also arises depending on whether the individual has a university degree or not. For individuals without a degree, there are no returns to civic/political participation, whereas high-skilled individuals have a return that is more than twice as large as the baseline effect. This suggests a positive interaction between high levels of civic-mindedness and interests in politics and work-related training. Interestingly, the effect on cultural participation is similar for both groups. To some extent, these findings are mirrored by the fact that results are slightly larger for individuals 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 $t-2$). In the last sample split, we find that the largest effect for cultural participation is found among blue-collar workers compared to non-blue-collar workers (i.e., public servants and white-collar workers). Because the effect on civic/political participation is negative for blue collar workers, it seems that there is a tradeoff between cultural activities and civic/political activities in this occupation group. This tradeoff is not observed for non-blue-collar workers.

Insert Figure 6 here

We also analyze subsamples according to training characteristics. This includes training intensity, whether the training participant has participated in some training activity before, whether the training is firm-specific, whether the training is employer-induced, and according to the size of the firm. Although some notable differences exist, effects do not vary strongly between the different subsamples, and any interpretation of the differences between two samples should be treated with caution because of large standard errors. In general, however, the treatment effects tend to be stronger with a longer training intensity, which seems plausible because people get to know each other better.[38] Splitting the sample by whether the individual has participated in training before, we also find slightly stronger effects than in the baseline case. However, the difference is small, indicating that non-pecuniary returns from training participation are increasing at a decreasing rate.

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

In further analysis, the results are not different between trainings teaching firm-specific and general skills.[39] We also find that non-employer-induced training increases social activities more than employer-induced training. Both analyses suggest that the effect is not driven by productivity-enhancing skills. Finally, 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.

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 selection 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 participation, cultural participation, 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.

[39]To categorize courses based on whether they are firm-specific or not, we use the 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 Caliendo et al. (2016), we use the most recent course to categorize whether training is firm-specific or not.

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.

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 dimensions of social capital, potentially yielding beneficial externalities for societies (over and above direct training effects) over 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 (see also Janmaat and Green, 2013; van Ingen and van der Meer, 2011).

References

Acemoglu, D. and Pischke, J.-S. (1998). Why Do Firms Train? Theory and Evidence. *Quarterly Journal of Economics*, 113(1):79–119.

Acemoglu, D. and Pischke, J.-S. (1999). Beyond Becker: Training in Imperfect Labour Markets. *Economic Journal*, 109(453):112–142.

Alesina, A., Baqir, R., and Easterly, W. (1999). Public Goods and Ethnic Divisions. *Quarterly Journal of Economics*, 114(4):1243–1284.

Arulampalam, W. and Booth, A. L. (1997). Who Gets Over the Training Hurdle? A Study of the Training Experiences of Young Men and Women in Britain. *Journal of Population Economics*, 10(2):197–217.

Arulampalam, W., Bryan, M. L., and Booth, A. L. (2004). Training in Europe. *Journal of the European Economic Association*, 2(2-3):346–360.

Ashenfelter, O. C. (1978). Estimating the Effect of Training Programs on Earnings. *Review of Economics and Statistics*, 60(1):47–57.

Ashenfelter, O. C. and Card, D. (1985). Using Longitudinal Structure of Earnings to Estimate the Effect of Training Programs. *Review of Economics and Statistics*, 67(4):648–660.

Ashraf, Q. and Galor, O. (2013). The "Out of Africa" Hypothesis, Human Genetic Diversity, and Comparative Economic Development. *American Economic Review*, 103(1):1–46.

Balatti, J., Black, S., and Falk, I. (2006). Reframing Adult Literacy and Numeracy Course Outcomes: A Social Capital Perspective. National Centre for Vocational Education Research (NCVER).

Balatti, J. and Falk, I. (2002). Socioeconomic Contributions of Adult Learning to Community: A Social Capital Perspective. *Adult Educaton Quarterly*, 52(4):281–298.

Bassanini, A., Booth, A., Brunello, G., De Paola, M., and Leuven, E. (2007). Workplace Training in Europe. In Brunello, G., Pietro Garibaldi, and Wasmer, E., editors, *Education and Training in Europe*. Oxford University Press.

Bentolila, S., Michelacci, C., and Suarez, J. (2010). Social Contacts and Occupational Choice. *Economica*, 77(305):20–45.

Blanden, J., Buscha, F., Sturgis, P., and Urwin, P. (2010). Measuring the Returns to Lifelong Learning. Centre for the Economics of Education Discussion Paper No. 110.

Blanden, J., Sturgis, P., Buscha, F., and Urwin, P. (2009). The Effect of Lifelong Learning on Intra-Generational Social Mobility: Evidence from Longitudinal Data in the United Kingdom.

Blundell, R., Dearden, L., Meghir, C., and Sianesi, B. (1999). Human Capital Investment: The Returns from Education and Training to the Individual, the Firm and the Economy. *Financial Studies*, 20(1):1–23.

Bourdieu, P. (1977). Cultural Reproduction and Social Reproduction. In Karabel, J. and Halsey, A. H., editors, *Power and Ideology in Education*, pages 487–511. Oxford University Press.

Büchel, F. and Pannenberg, M. (2004). Berufliche Weiterbildung in West- und Ostdeutschland: Teilnehmer, Struktur und individueller Ertrag. *Journal for Labour Market Research*, 37(2):73–126.

Burgard, C. and Görlitz, K. (2014). Continuous Training, Job Satisfaction and Gender: An Empirical Analysis using German Panel Data. *Evidence-based HRM: a Global Forum for Empirical Scholarship*, 2(2):126–144.

Burks, S. V., Cowgill, B., Hoffman, M., and Housman, M. (2015). The Value of Hiring through Employee Referrals. *Quarterly Journal of Economics*, 130(2):805–839.

Bynner, J. and Hammond, C. (2004). The Benefits of Adult Learning: Quantitative Insights. In Schuller, T., Preston, J., Hammond, C., and Brassett-Grundy, A., editors, *The Benefits of Learning: The Impact of Education on Health, Family Life and Social Capital*, chapter 9, pages 161–178. Routledge Chapman Hall.

Caliendo, M., Cobb-Clark, D. A., Seitz, H., and Uhlendorff, A. (2016). Locus of Control and Investment in Training. IZA Working Paper No. 10406.

Caliendo, M. and Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, 22(1):31–72.

Calvó-Armengol, A. and Jackson, M. O. (2004). The Effects of Social Networks on Employment and Inequality. *American Economic Review*, 94(3):426–454.

Card, D., Kluve, J., and Weber, A. (2010). Active Labour Market Policy Evaluations: A Meta-Analysis. *Economic Journal*, 120(1976):452–477.

Coleman, J. S. (1990). *Foundations of Social Theory*. Harvard University Press.

Council of Europe (2005). Methodological Guide to the Concerted Development of Social Cohesion Indicators. `https://www.coe.int/t/dg3/socialpolicies/socialcohesiondev/source/GUIDE_en.pdf`.

Council of the European Union/European Commission (2015). 2015 Joint Report of the Council and the Commission on the implementation of the strategic framework for European cooperation in education and training (ET 2020): New priorities for European cooperation in education and training. `http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52015XG1215(02)&from=EN`.

Croll, P. (2004). Families, Social Capital and Educational Outcomes. *British Journal of Educational Studies*, 52(4):390–416.

De Grip, A. and Sauermann, J. (2012). The Effects of Training on Own and Co-Worker Productivity: Evidence from a Field Experiment. *Economic Journal*, 122(560):376–399.

De Grip, A. and Sauermann, J. (2013). The Effect of Training on Productivity: The Transfer of On-the-Job Training from the Perspective of Economics. *Educational Research Review*, 8:28–36.

de Tocqueville, A. ([1835, 1840] 1990). *Democracy in America. Reprint.* Vintage.

Dehejia, R. H. and Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics*, 84(1):151–161.

Deming, D. J. (2017). The Growing Importance of Social Skills in the Labor Market. *Quarterly Journal of Economics*, 132(4):1593–1640.

Desjardins, R. and Schuller, T. (2011). Wider Benefits of Adult Education. In Rubenson, K., editor, *International Encyclopedia of Adult Learning and Education*, pages 294–298. Elsevier.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-Based Job Search Networks. *Review of Economic Studies*, 83(2):514–546.

Education Council (2006). Recommendation of the European Parliament and the Council of 18 December 2006 on Key Competencies for Lifelong Learning. Brussels: Official Journal of the European Union, 30.12.2006. http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32006H0962.

Emler, N. and Frazer, E. (1999). Politics: The Education Effect. *Oxford Review of Education*, 25(1-2):251–273.

European Commission (2001). Making a European Area of Lifelong Learning a Reality. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2001:0678:FIN:EN:PDF.

Federal Ministry of Education and Research (2015). Weiterbildungsverhalten in Deutschland 2014. Ergebnisse des Adult Education Survey. https://www.bmbf.de/pub/Weiterbildungsverhalten_in_Deutschland_2014.pdf.

Federal Ministry of Education and Research (2017). Weiterbildungsverhalten in Deutschland 2016. Ergebnisse des Adult Education Survey. https://www.bmbf.de/pub/Weiterbildungsverhalten_in_Deutschland_2016.pdf.

Feinstein, L. and Hammond, C. (2004). The Contribution of Adult Learning to Health and Social Capital. *Oxford Review of Education*, 30(2):199–221.

Field, J. (2011). Researching the Benefits of Learning: The Persuasive Power of Longitudinal Studies. *London Review of Education*, 9(3):283–292.

Frazis, H. and Loewenstein, M. A. (2005). Reexamining the Returns to Training: Functional Form, Magnitude, and Interpretation. *Journal of Human Resources*, 40(2):453–476.

Frölich, M. (2007). Propensity Score Matching without Conditional Independence Assumption - With an Application to the Gender Wage Gap in the United Kingdom. *Econometrics Journal*, 10(2):359–407.

Fujiwara, D. (2012). Valuing the Impact of Adult Learning: An Analysis of the Effect of Adult Learning on Different Domains in Life. *National Institute for Adult Continuing Education*.

Georgellis, Y. and Lange, T. (2007). Participation in Continuous, On-The-Job Training and the Impact on Job Satisfaction: Longitudinal Evidence from the German Labour Market. *International Journal of Human Resource Management*, 18(6):969–985.

Goux, D. and Maurin, E. (2000). Returns to Firm-Provided Training: Evidence from French Worker-Firm Matched Data. *Labour Economics*, 7(1):1–19.

Gradstein, M. and Justman, M. (2000). Human Capital, Social Capital, and Public Schooling. *European Economic Review*, 44(4-6):879–890.

Gradstein, M. and Justman, M. (2002). Education, Social Cohesion, and Economic Growth. *American Economic Review*, 92(4):1192–1204.

Gradstein, M. and Justman, M. (2018). Diversity and Growth. IZA Working Paper No. 11553.

Green, A., Preston, J., and Janmaat, J. G. (2006). *Education, Equality and Social Cohesion: A Comparative Analysis*. Palgrave Macmillan.

Grund, C. and Martin, J. (2012). Determinants of Further Training – Evidence for Germany. *International Journal of Human Resource Management*, 23(17):3536–3558.

Guiso, L., Sapienza, P., and Zingales, L. (2011). Civic Capital as the Missing Link. In Benhabib, J., Bisin, A., and Jackson, M. O., editors, *Handbook of Social Economics*, volume 1A, chapter 10, pages 417–480. Elsevier B.V.

Hainmueller, J. (2012). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis*, 20(1):25–46.

Hainmueller, J. and Xu, Y. (2013). ebalance: A Stata Package for Entropy Balancing. *Journal of Statistical Software*, 54(7):1–18.

Hazleton, V. and Kennan, W. (2000). Social Capital: Reconceptualizing the Bottom Line. *Corporate Communications*, 5(2):81–86.

Heckman, J. J., Humphries, J. E., and Veramendi, G. (2018). The Non-Market Benefits of Education and Ability. *Journal of Human Capital*, forthcoming.

Heckman, J. J., Ichimura, H., Smith, J., and Todd, P. (1998). Characterizing Selection Bias Using Experimental Data. *Econometrica*, 66(5):1017–1098.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies*, 64(4):605–654.

Heckman, J. J. and Todd, P. E. (2009). A Note on Adapting Propensity Score Matching and Selection Models to Choice Based Samples. *Econometrics Journal*, 12(S1):230–234.

Helliwell, J. F. (2001). *The Contribution of Human and Social Capital to Sustained Economic Growth and Well-Being*. OECD and Human Resources Development Canada.

Hoskins, B. L. and Mascherini, M. (2009). Measuring Active Citizenship through the Development of a Composite Indicator. *Social Indicators Research*, 90(3):459–488.

Huang, J., Maassen van den Brink, H., and Groot, W. (2009). A Meta-Analysis of the Effect of Education on Social Capital. *Economics of Education Review*, 28(4):454–464.

Hujer, R., Thomsen, S. L., and Zeiss, C. (2006). The Effects of Vocational Training Programmes on the Duration of Unemployment in Eastern Germany. *Allgemeines Statistisches Archiv*, 90(2):299–321.

Imbens, G. W. (2015). Matching Methods in Practice: Three Examples. *Journal of Human Resources*, 50(2):373–419.

Imbens, G. W. and Rubin, D. B. (2015). *Causal Inference in Statistics, Social, and Biomedical Sciences*. Cambridge University Press.

Jacobson, L. S., LaLonde, R., and Sullivan, D. G. (2005). Estimating the Returns to Community College Schooling for Displaced Workers. *Journal of Econometrics*, 125(1-2):271–304.

Janmaat, J. G. and Green, A. (2013). Skills Inequality, Adult Learning and Social Cohesion in the United Kingdom. *British Journal of Educational Studies*, 61(1):7–24.

Jenkins, A. (2011). Participation in Learning and Wellbeing Among Older Adults. *International Journal of Lifelong Education*, 30(3):403–420.

Kling, J. R., Liebman, J. B., and Katz, L. F. (2007). Experimental Analysis of Neighborhood Effects. *Econometrica*, 75(1):83–119.

Kluve, J. (2010). The Effectiveness of European Active Labor Market Programs. *Labour Economics*, 17(6):904–918.

Knack, S. (2001). Trust, Associational Life, and Economic Performance. In Helliwell, J. F., editor, *The Contribution of Human and Social Capital to Sustained Economic Growth and Well-Being*, chapter 9, pages 172–202. OECD and Human Resources Development Canada.

LaLonde, R. J. (1986). Evaluating the Econometric Evaluations of Training Programs with Experimental Data. *American Economic Review*, 76(4):604–620.

Lazear, E. P. (1999). Culture and Language. *Journal of Political Economy*, 107(S6):S95–S126.

Lechner, M. (1999a). Earnings and Employment Effects of Continuous Off-the-Job Training in East Germany after Unification. *Journal of Business & Economic Statistics*, 17(1):74–90.

Lechner, M. (1999b). The Effects of Enterprise-Related Training in East Germany on Individual Employment and Earnings. *Annales d'Économie et de Statistique*, 55/56:97–128.

Leigh, D. E. and Gill, A. M. (1997). Labor Market Returns to Community Colleges: Evidence for Returning Adults. *Journal of Human Resources*, 32(2):334–353.

Leuven, E. (2005). The Economics of Private Sector Training: A Survey of the Literature. *Journal of Economic Surveys*, 19(1):91–111.

Leuven, E. and Oosterbeek, H. (1999). The Demand and Supply of Work-Related Training: Evidence from Four Countries. *Research in Labor Economics*, 18:303–330.

Leuven, E. and Oosterbeek, H. (2008). An Alternative Approach of Estimate the Wage Returns to Private-Sector Training. *Journal of Applied Econometrics*, 23(4):423–434.

Leuven, E. and Sianesi, B. (2003). psmatch2. STATA Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. `https://ideas.repec.org/c/boc/bocode/s432001.html`.

Loewenstein, M. A. and Spletzer, J. R. (1999). General and Specific Training: Evidence and Implications. *Journal of Human Resources*, 34(4):710–733.

Lynch, L. M. (1992). Private-Sector Training and the Earnings of Young Workers. *American Economic Review*, 82(1):299–312.

Lynch, L. M. and Black, S. E. (1998). Beyond the Incidence of Employer-Provided Training. *Industrial and Labor Relations Review*, 52(1):64–81.

McCall, B., Smith, J., and Wunsch, C. (2016). Government-Sponsored Vocational Education for Adults. In Hanushek, E. A., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, chapter 9, pages 479–652. Elsevier B.V., 5 edition.

Melero, E. (2010). Training and Promotion: Allocation of Skills or Incentives? *Industrial Relations*, 49(4):640–667.

Moore, G. (1990). Structural Determinants of Men's and Women's Personal Networks. *American Sociological Review*, 55(5):726–735.

Neira, I., Portela, M., and Vieira, E. (2010). Social Capital and Growth in European Regions. *Regional and Sectoral Economic Studies*, 10(2):19–28.

OECD (2001). The Well-Being of Nations: The Role of Human and Social Capital. OECD Publishing, `http://www.oecd.org/site/worldforum/33703702.pdf`.

OECD (2005). Promoting Adult Learning. Education and Training Policy, OECD Publishing, `https://doi.org/10.1787/9789264010932-en`.

OECD (2010). Improving Health and Social Cohesion through Education. Educational Research and Innovation, OECD Publishing, `https://doi.org/10.1787/9789264086319-en`.

OECD (2013). OECD Skills Outlook 2013: First Results from the Survey of Adult Skills. OECD Publishing, `http://dx.doi.org/10.1787/9789264204256-en`.

OECD (2016). Skills Matter: Further Results from the Survey of Adult Skills. OECD Publishing, `http://www.oecd.org/skills/skills-matter-9789264258051-en.htm`.

OECD (2017). Education at a Glance 2017: OECD Indicators. OECD Publishing, `http://dx.doi.org/10.1787/eag-2017-en`.

Olson, M. (1982). *The Rise and Decline of Nations: Economic Growth, Stagflation, and Social Rigidities*. Yale University Press.

Oosterbeek, H. (1996). A Decomposition of Training Probabilities. *Applied Economics*, 28(7):799–805.

Oosterbeek, H. (1998). Unravelling Supply and Demand Factors in Work-Related Training. *Oxford Economic Papers*, 50(2):266–283.

Oreopoulos, P. and Salvanes, K. G. (2011). Priceless: The Nonpecuniary Benefits of Schooling. *Journal of Economic Perspectives*, 25(1):159–184.

Panitsides, E. (2013). Researching Returns Emanating from Participation in Adult Education Courses: A Quantitative Approach. *International Journal of Lifelong Education*, 32(5):600–619.

Paxton, P. (2002). Social Capital and Democracy. *American Sociological Review*, 67(2):254–277.

Pergamit, M. R. and Veum, J. R. (1999). What is a Promotion? *Industrial and Labor Relations Review*, 52(4):581–601.

Pischke, J.-S. (2001). Continuous Training in Germany. *Journal of Population Economics*, 14(3):523–548.

Portes, A. (1998). Social Capital: Its Origins and Applications in Modern Sociology. *Annual Review of Sociology*, 24(1):1–24.

Preston, J. (2004a). A Continuous Effort of Sociability: Learning and Social Capital in Adult Life. In Schuller, T., Preston, J., Hammond, C., and Brassett-Grundy, A., editors, *The Benefits of Learning: The Impact of Education on Health, Family Life and Social Capital*, chapter 7, pages 119–136. Routledge Chapman Hall.

Preston, J. (2004b). Lifelong Learning and Civic Participation: Inclusion, Exclusion, and Community. In Schuller, T., Preston, J., Hammond, C., and Brassett-Grundy, A., editors, *The Benefits of Learning: The Impact of Education on Health, Family Life and Social Capital*, chapter 8, pages 137–158. Routledge Chapman Hall.

Preston, J. and Feinstein, L. (2004). Adult Education and Attitude Change. Wider Benefits of Learning Research Report No. 11.

Preston, J. and Hammond, C. (2002). *The Wider Benefits of Further Education: Practitioner Views [Wider Benefits of Learning Research Report No. 1]*, volume 1. Centre for Research on the Wider Benefits of Learning, Institute of Education, University of London.

Putnam, R. D. (1993). *Making Democracy Work*. Princeton University Press.

Putnam, R. D. (1995). Bowling Alone: America's Declining Social Capital. *Journal of Democracy*, 6(1):65–78.

Putnam, R. D. (2002). Soziales Kapital in der Bundesrepublik Deutschland und in den USA. In Enquete-Kommission "Zukunft des Bürgerschaftlichen Engagements" Deutscher Bundestag, editor, *Bürgerschaftliches Engagement und Zivilgesellschaft*, pages 257–271. VS Verlag für Sozialwissenschaften, Wiesbaden.

Rüber, I. E., Rees, S.-L., and Schmidt-Hertha, B. (2018). Lifelong Learning - Lifelong Returns? A New Theoretical Framework for the Analysis of Civic Returns on Adult Learning. *International Review of Education*, forthcoming.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician*, 39(1):33–38.

Ruhose, J., Thomsen, S. L., and Weilage, I. (2018). Work-Related Training and Subjective Well-Being: Estimating the Effect of Training Participation on Satisfaction, Worries, and Health in Germany. Mimeo.

Schmutte, I. M. (2015). Job Referral Networks and the Determination of Earnings in Local Labor Markets. *Journal of Labor Economics*, 33(1):1–32.

Schneider, G., Plümper, T., and Baumann, S. (2000). Bringing Putnam to the European Regions: On the Relevance of Social Capital for Economic Growth. *European Urban and Regional Studies*, 7(4):307–317.

Scrivens, K. and Smith, C. (2013). Four Interpretations of Social Capital: An Agenda for Measurement. OECD Statistics Working Papers, 2013/06, OECD Publishing, Paris.

Seyda, S. and Placke, B. (2017). Die neunte IW-Weiterbildungserhebung. *Vierteljahresschrift zur empirischen Wirtschaftsforschung*, 44(4):1–19.

Smith, J. and Todd, P. E. (2005a). Rejoinder. *Journal of Econometrics*, 125(1-2):365–375.

Smith, J. A. and Todd, P. E. (2005b). Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators? *Journal of Econometrics*, 125(1-2):305–353.

Stenberg, A. (2011). Using Longitudinal Data to Evaluate Publicly Provided Formal Education for Low Skilled. *Economics of Education Review*, 30(6):1262–1280.

Stenberg, A., de Luna, X., and Westerlund, O. (2012). Can Adult Education Delay Retirement from the Labour Market? *Journal of Population Economics*, 25(2):677–696.

Stenberg, A. and Westerlund, O. (2008). Does Comprehensive Education Work for the Long-Term Unemployed? *Labour Economics*, 15(1):54–67.

Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. *Statistical Science*, 25(1):1–21.

Temple, J. (2001). Growth Effects of Education and Social Capital in the OECD Countries. *OECD Economic Studies*, 33(2):57–101.

Tett, L. and Maclachlan, K. (2007). Adult Literacy and Numeracy, Social Capital, Learner Identities and Self-Confidence. *Studies in the Education of Adults*, 39(2):150–167.

Todd, P. E. (2008). Evaluating Social Programs with Endogenous Program Placement and Selection of the Treated. In Schultz, T. P. and Strauss, J. A., editors, *Handbook of Development Economics*, chapter 60, pages 3847–3894. Elsevier B.V., 4 edition.

Topa, G. (2011). Labor Markets and Referrals. In Benhabib, J., Bisin, A., and Jackson, M. O., editors, *Handbook of Social Economics*, volume 1B, chapter 22, pages 1193–1221. Elsevier B.V.

Tsai, W. and Ghoshal, S. (1998). Social Capital and Value Creation: The Role of Intrafirm Networks. *Academy of Management Journal*, 41(4):464–476.

Umberson, D., Chen, M. D., House, J. S., Hopkins, K., and Slaten, E. (1996). The Effect of Social Relationships on Psychological Well-Being: Are Men and Women Really so Different? *American Sociological Review*, 61(5):837–857.

van Ingen, E. and van der Meer, T. (2011). Welfare State Expenditure and Inequalities in Voluntary Association Participation. *Journal of European Social Policy*, 21(4):302–322.

Wagner, G. G., Frick, J. R., and Schupp, J. (2007). The German Socio-Economic Panel Study (SOEP) – Scope, Evolution, and Enhancements. *Schmollers Jahrbuch*, 127(1):139–169.

Westlund, H. and Adam, F. (2010). Social Capital and Economic Performance: A Meta-Analysis of 65 Studies. *European Planning Studies*, 18(6):893–919.

Widén-Wulff, G. and Ginman, M. (2004). Explaining Knowledge Sharing in Organizations Through the Dimensions of Social Capital. *Journal of Information Science*, 30(5):448–458.

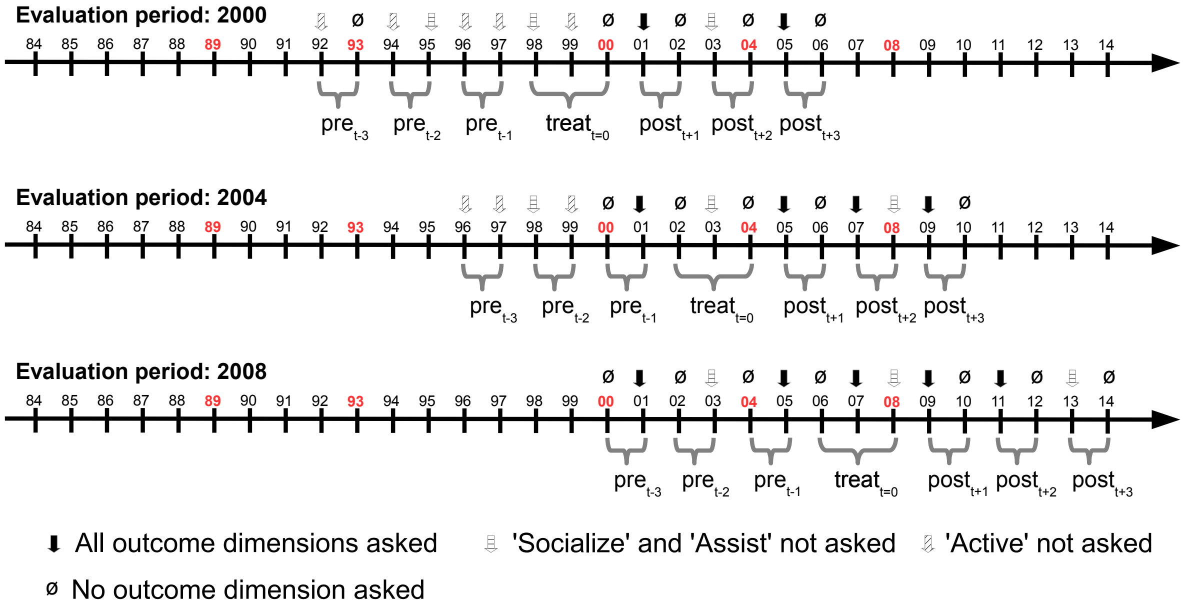
Woolcock, M. (2001). The Place of Social Capital in Understanding Social and Economic Outcomes. In Helliwell, J. F., editor, *The Contribution of Human and Social Capital to Sustained Economic Growth and Well-Being*, chapter 5, pages 65–88. OECD and Human Resources Development Canada.

Yendell, A. (2013). Participation in Continuing Vocational Training in Germany between 1989 and 2008. *Journal of Applied Social Science Studies*, 133(2):169–184.

Zanutto, E. L. (2006). A Comparison of Propensity Score and Linear Regression Analysis of Complex Survey Data. *Journal of Data Science*, 4:67–91.

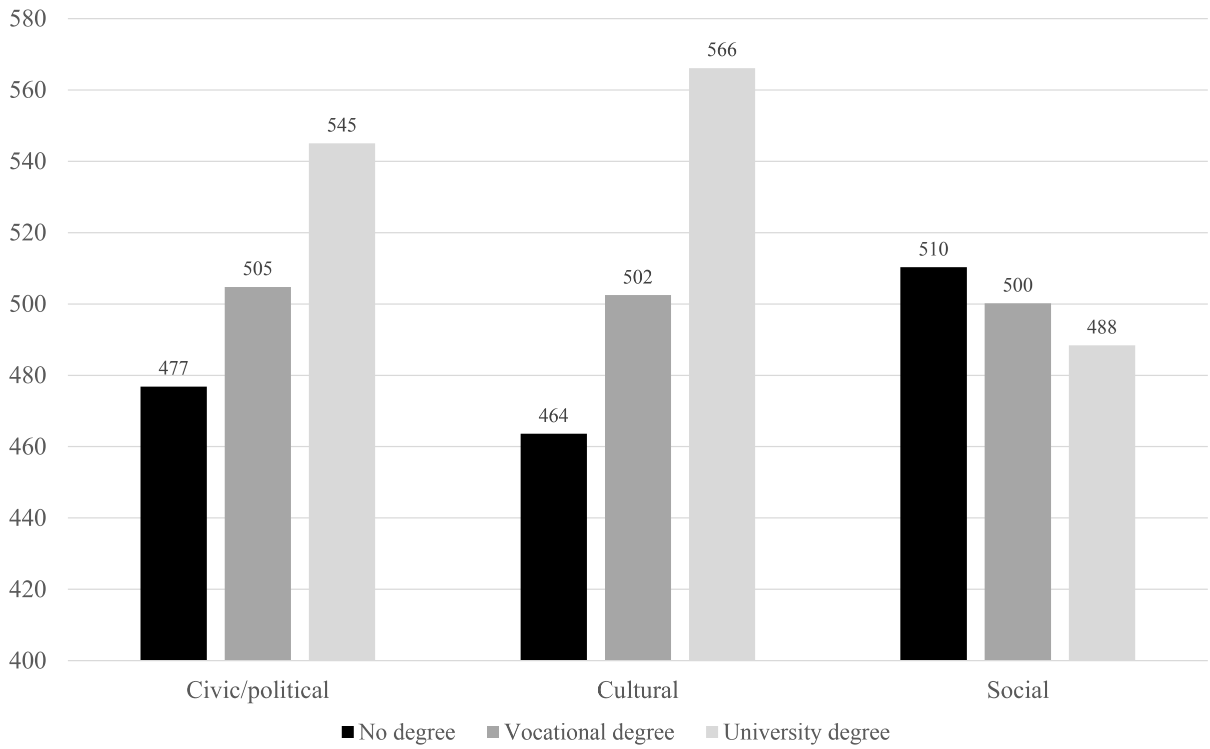
Figures and Tables

Figure 1: Description of Treatment and Evaluation Periods



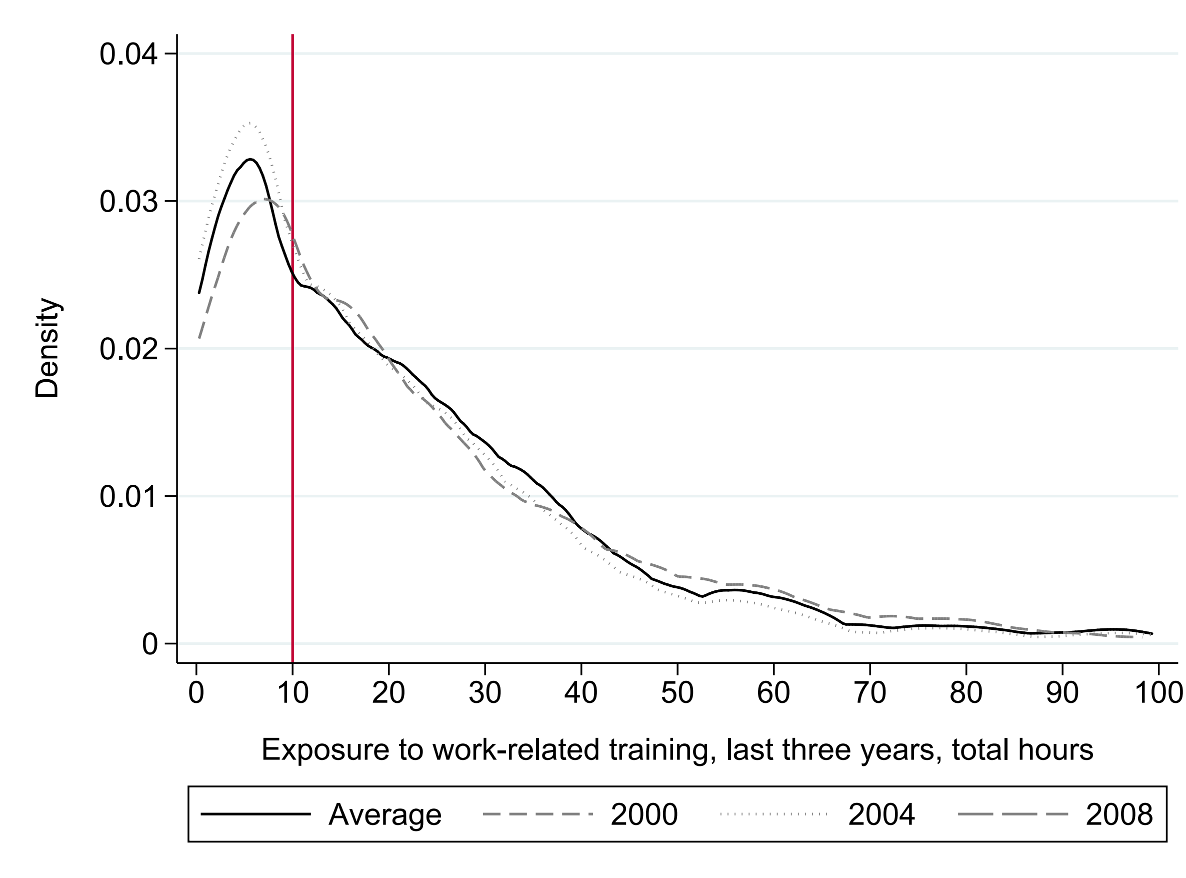
Notes: The figure describes the evaluation periods. Years marked in red indicate survey years with qualification survey modules in the GSOEP. We evaluate the years 2000, 2004, and 2008. Treatment periods are centered around most reported treatment years, which in all cases is the year prior to the survey. 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: Non-Pecuniary Outcome Scores by Educational Degree



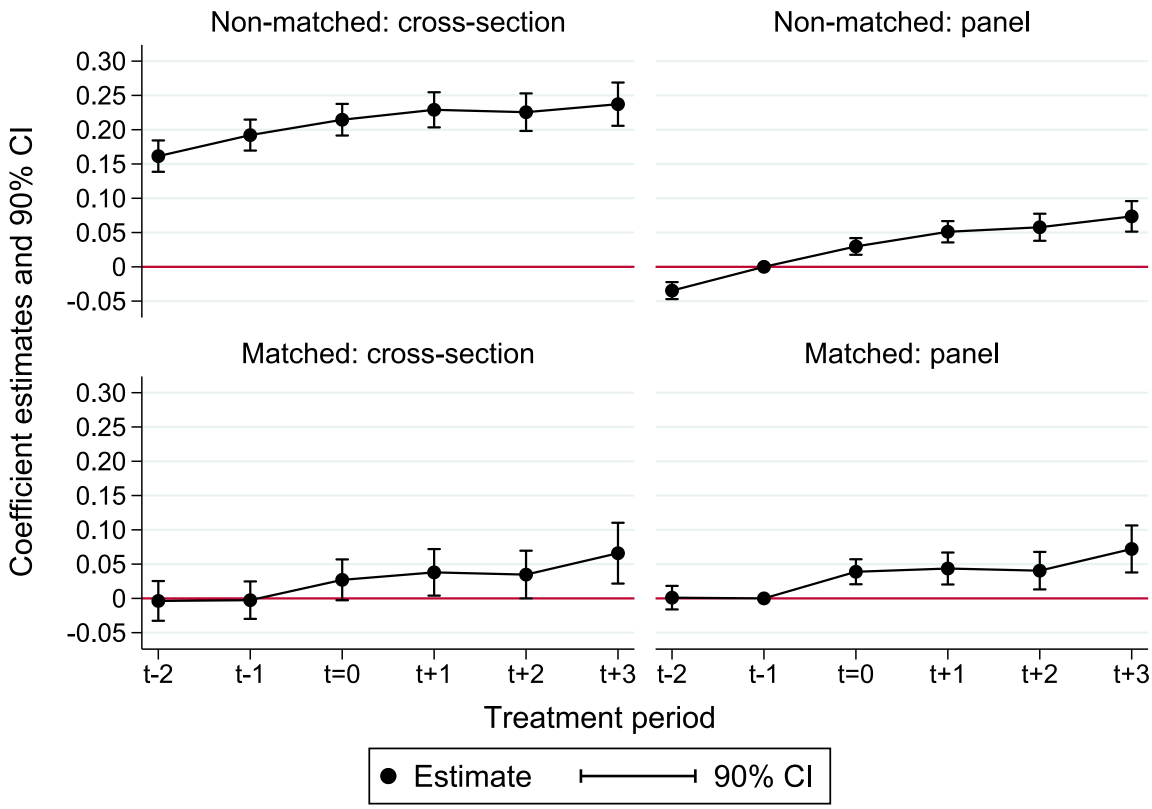
Notes: The figure shows average values of the three non-pecuniary outcome variables by educational degree of the individual. Averages are calculated over all available individual observations in all evaluation periods. Number of observations: no degree: $8,299$; vocational degree: $43,719$; university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

Figure 3: Distribution of Course Hours



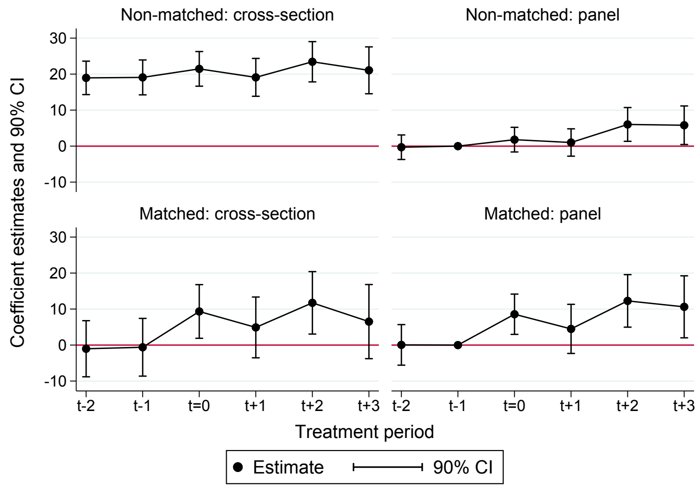
Notes: The figure shows the distribution of individual training course hours. Individual training course hours are calculated as the sum of the three reported training courses. The distribution is based on the sample in the pretreatment period $t-1$. For illustrative purpose, the distribution is capped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

Figure 4: Estimation Results for Log Monthly Earnings

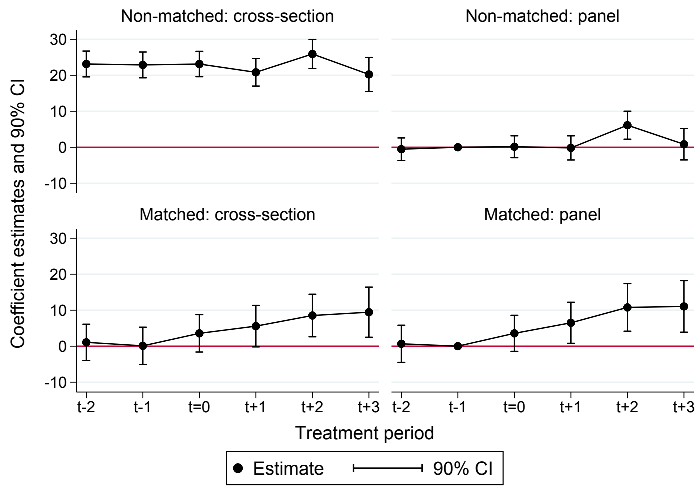


Notes: The figure displays coefficients and 90% confidence intervals for different regression models. Explanations are provided in the text. Regressions results can be found in Appendix Table A-6, Columns (1), (3), (4), and (6).

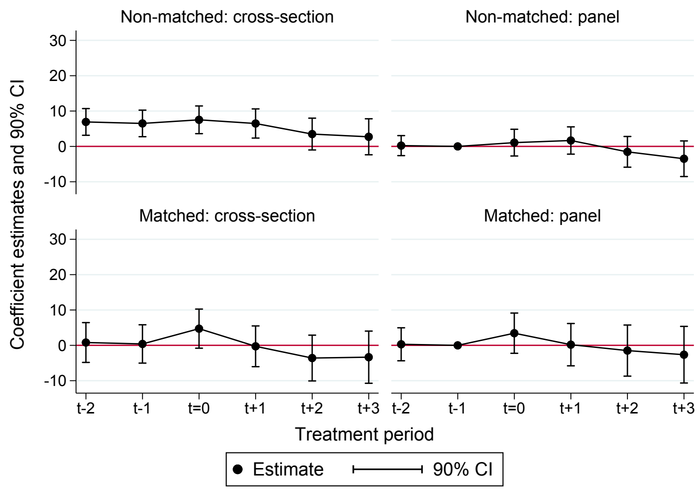
Figure 5: Estimation Results for Social Capital



(a) Civic/political participation



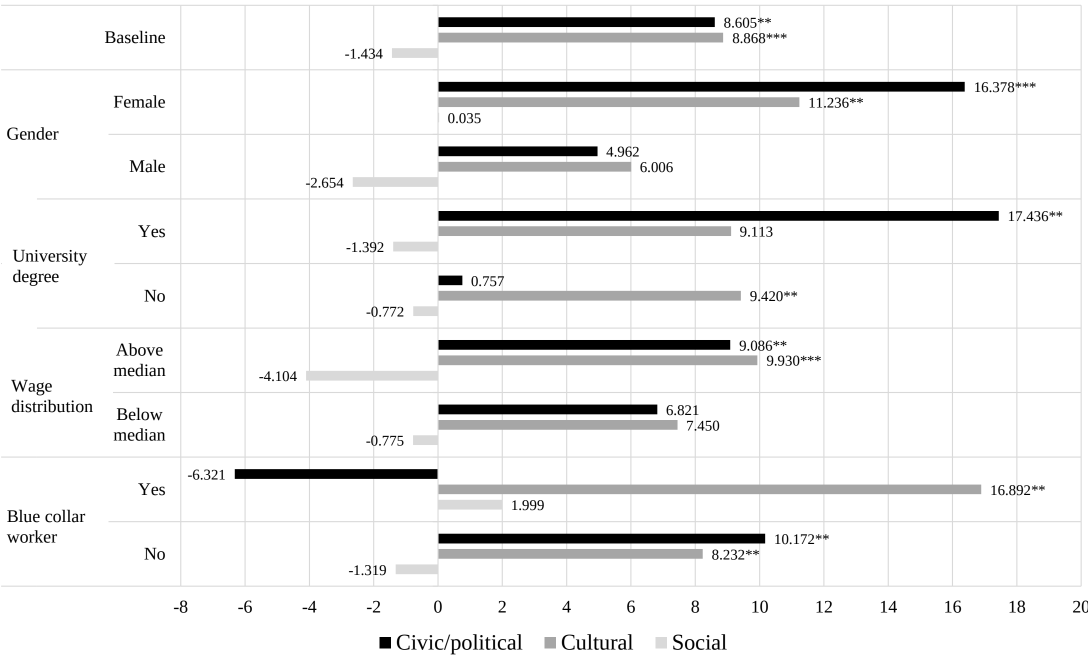
(b) Cultural participation



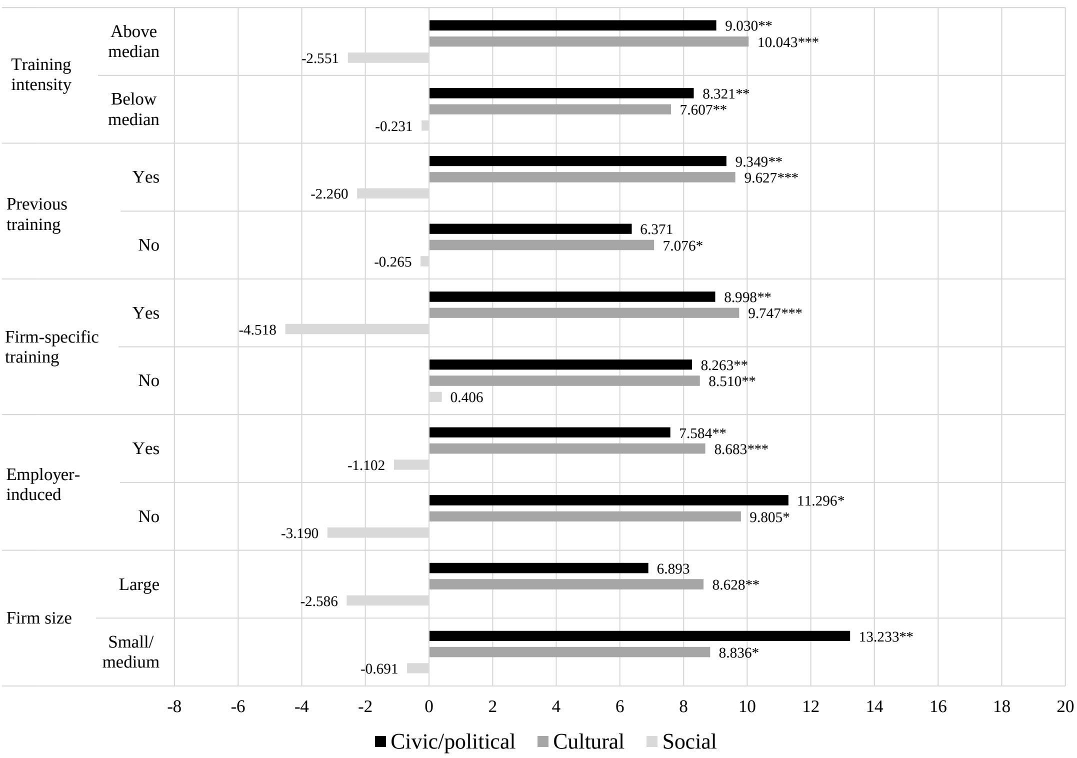
(c) Social participation

Notes: The figure displays coefficients and 90% confidence intervals for different regression models. Explanations are provided in the text. Regressions results can be found in Appendix Tables A-9 to A-11, Columns (1), (3), (4), and (6).

Figure 6: Heterogeneity of Treatment Effects



(a) Individual characteristics



(b) 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. 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 A-18 and A-20 provide regression results. Appendix Tables A-19 and A-21 provide 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 - 4 very much)
Participate in politics[b] ($t-1$; $t-2$)	4 categories (1 not at all - 4 very much)
Volunteer[b] ($t-1$; $t-2$)	4 categories (1 never - 4 every week)
Active in artistic/musical activities[b] ($t-1$; $t-2$)	4 categories (1 never - 4 every week)
Attend classic events[b] ($t-1$; $t-2$)	4 categories (1 never - 4 every week)
Attend modern events[b] ($t-1$; $t-2$)	4 categories (1 never - 4 every week)
Socialize[b] ($t-1$; $t-2$)	4 categories (1 never - 4 every week)
Assist[b] ($t-1$; $t-2$)	4 categories (1 never - 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 Kling et al., 2007). 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

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	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 A-4 and A-5 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 1). *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								
$\text{Training}_{ie} \times \text{pre}_{t-3}$	–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								
$\text{Training}_{ie} \times \text{pre}_{t-3}$	–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 3 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.

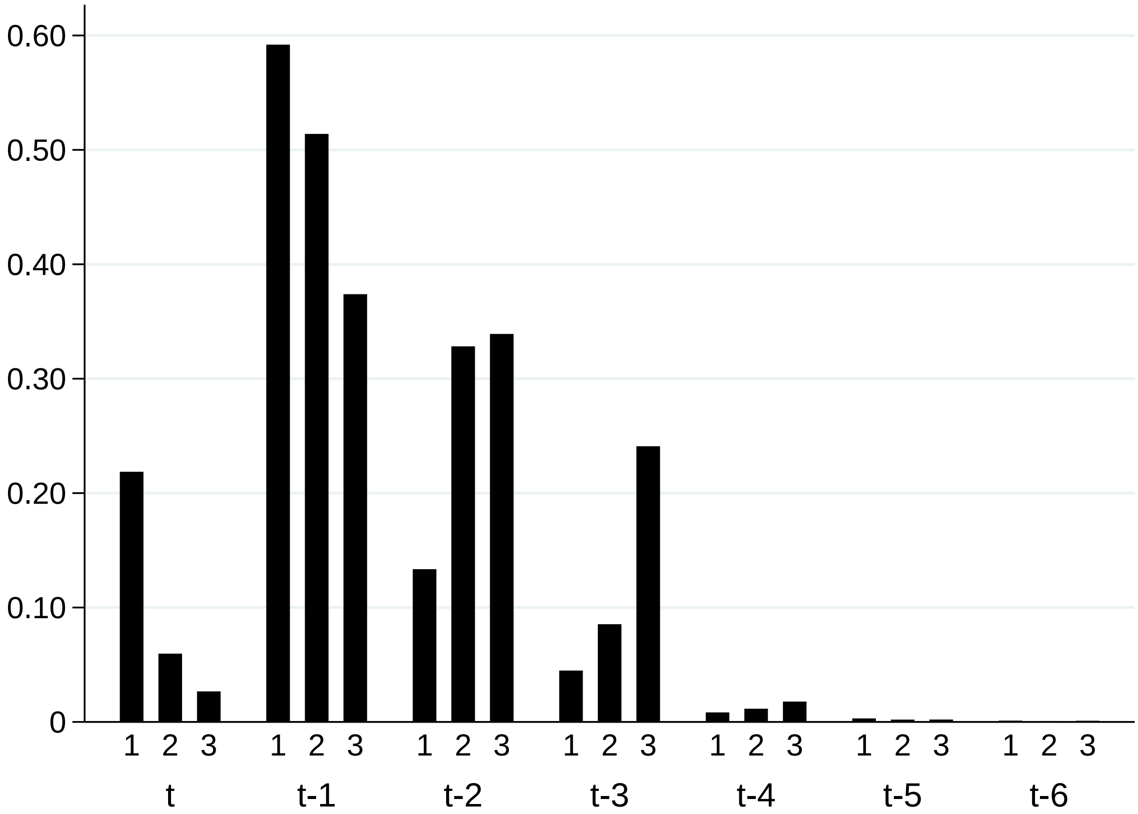
Table 6: Robustness Checks

	(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 A-17 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.

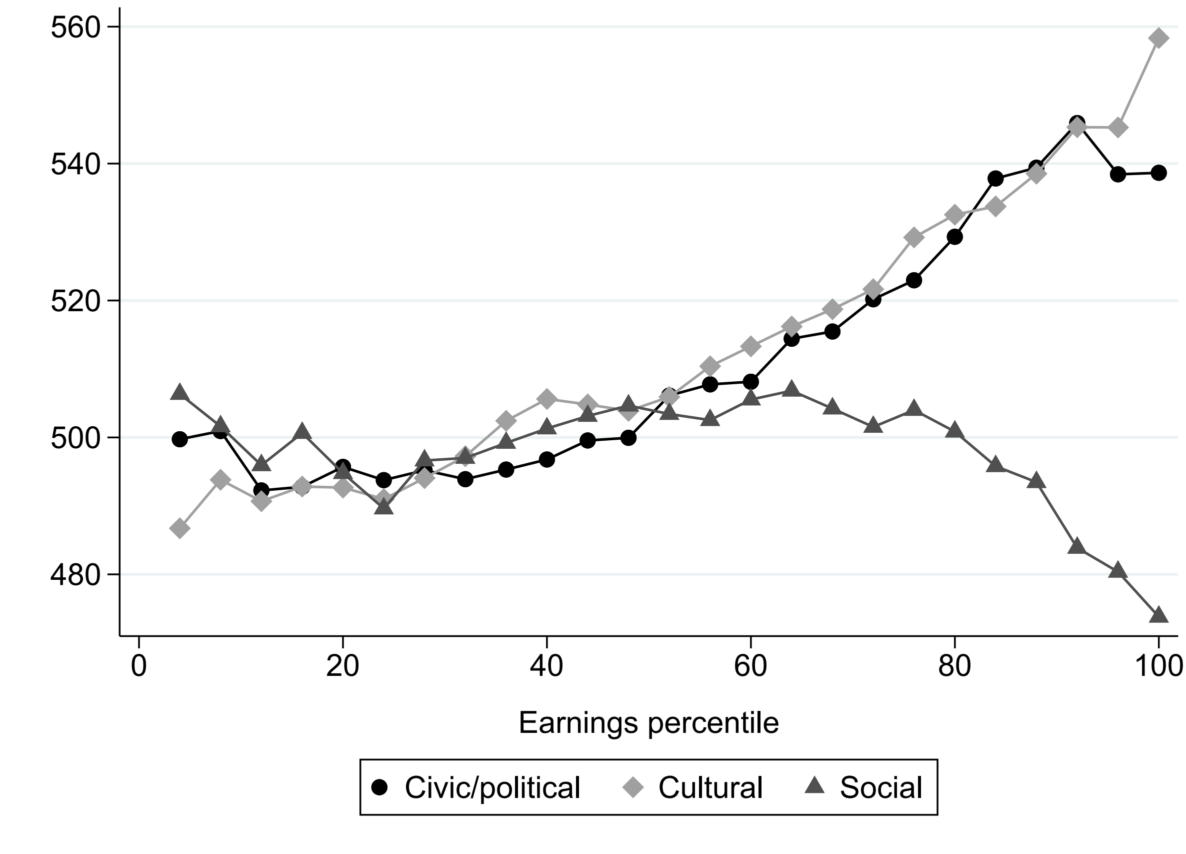
A Appendix Figures and Tables

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



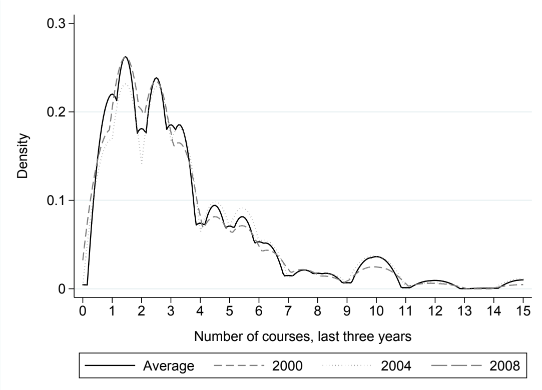
Notes: The figure shows the distribution of start years (relative to the qualification survey) for the last three courses of the individual.

Figure A-2: Non-Pecuniary Outcome Scores by Position in the Monthly Earnings Distribution

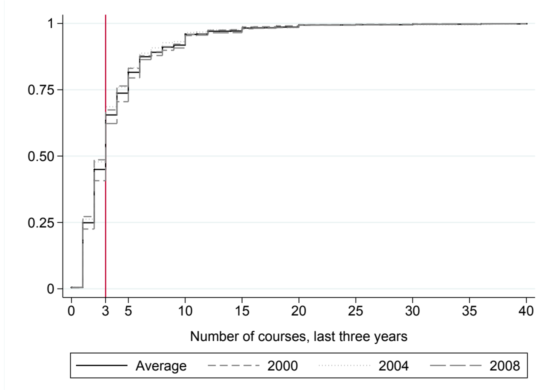


Notes: The figure shows average values of the three non-pecuniary outcome variables by position of the individual in the monthly earnings distribution. Earnings are in 2010 euro.

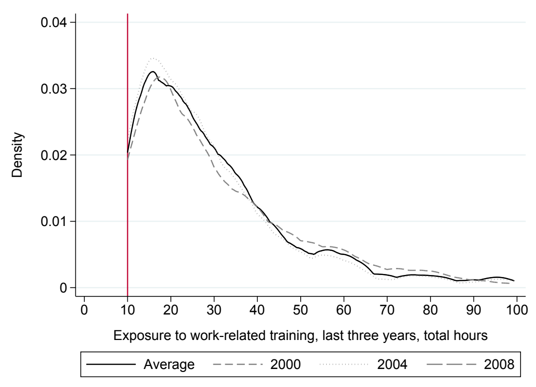
Figure A-3: Distribution of Courses and Course Hours



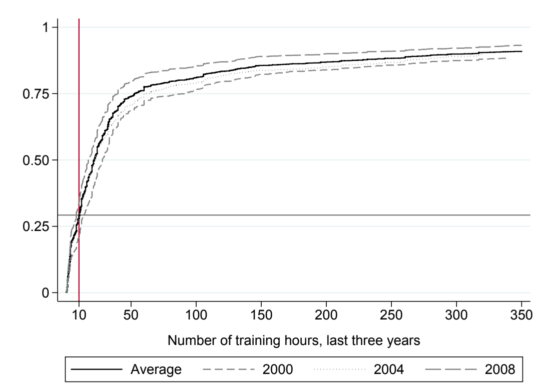
(a) Number of courses (pdf)



(b) Number of courses (cdf)



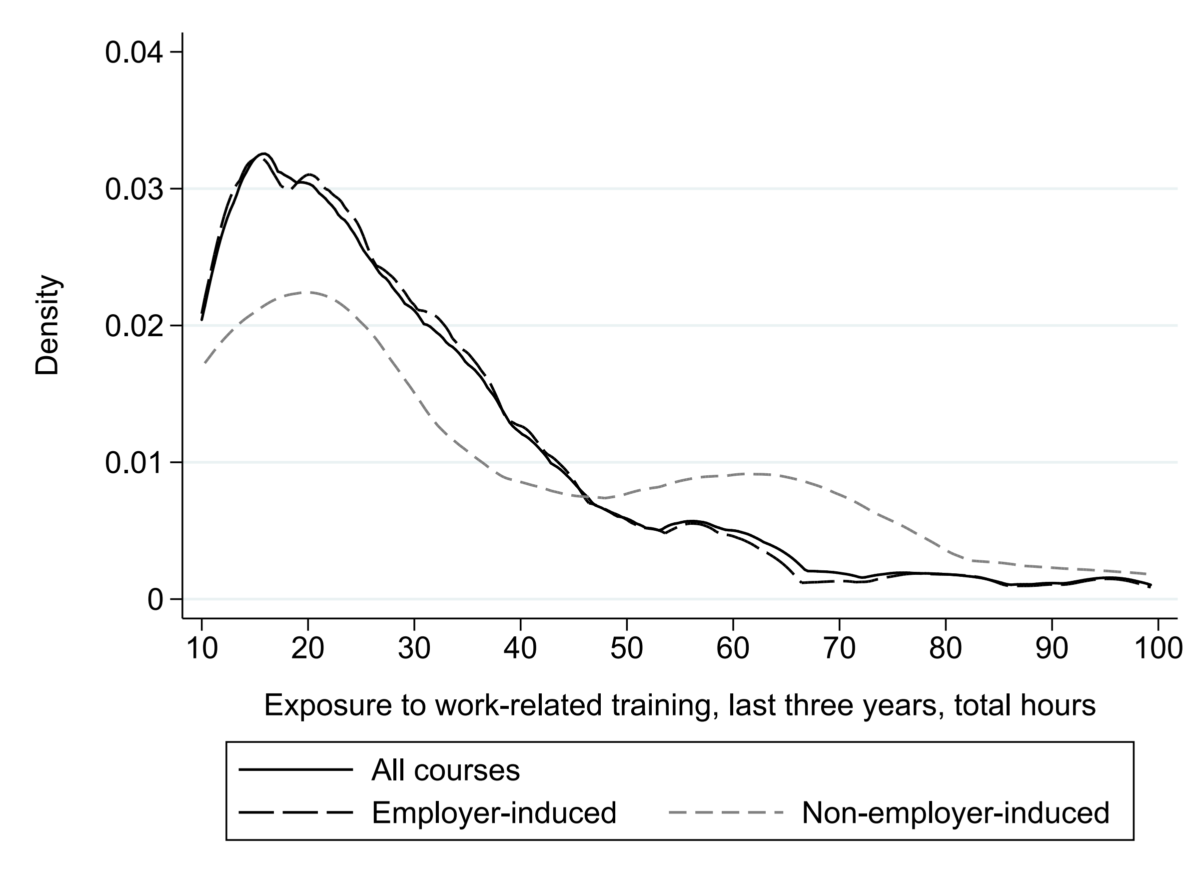
(c) Number of course hours (pdf)



(d) Number of course hours (cdf)

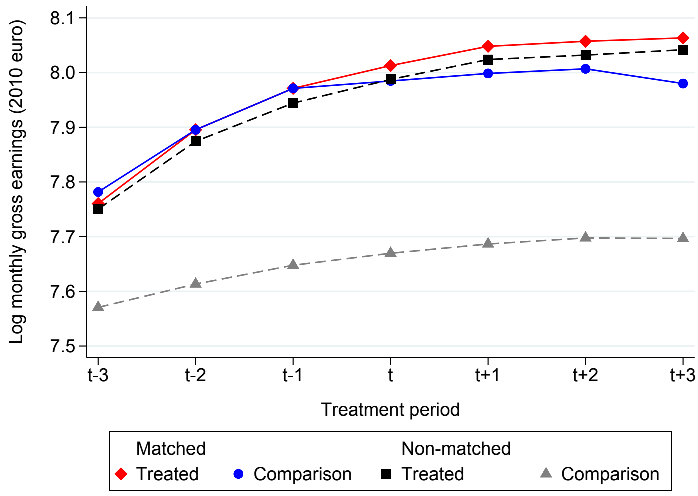
Notes: The figures show the distribution of courses and course hours. Distributions are based on the sample in the pretreatment period $t-1$. For illustrative purpose, distributions are capped at the last value displayed. For number of courses in Figures A-3(a) and A-3(b), the mean is equal to 3.9, the median is equal to 3, and the largest value is equal to 99. Figure A-3(c) shows the distribution of course hours after restricting the sample to individuals with at least 10 hours of training. Figure A-3(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-4: Distribution of Employer- and Non-Employer-Induced Course Hours

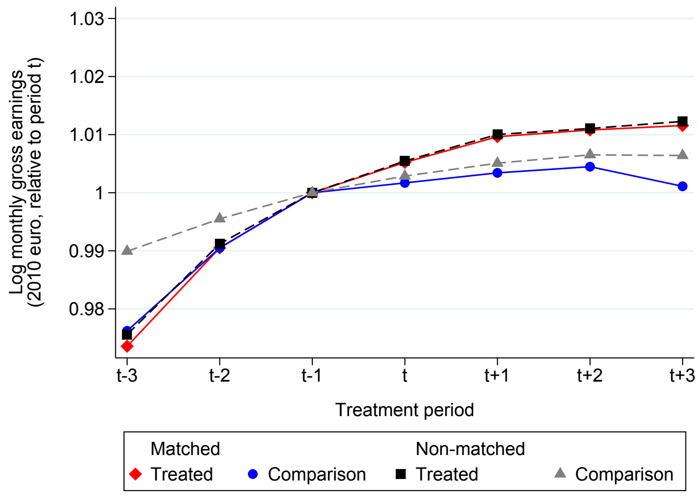


Notes: The figure shows the distribution of individual training course hours. Individual training course hours are calculated as the sum of the three reported training courses. The distribution is based on the sample in the pretreatment period $t-1$. For illustrative purpose, the distribution is capped 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-5: Descriptive Relationship between Work-Related Training and Earnings



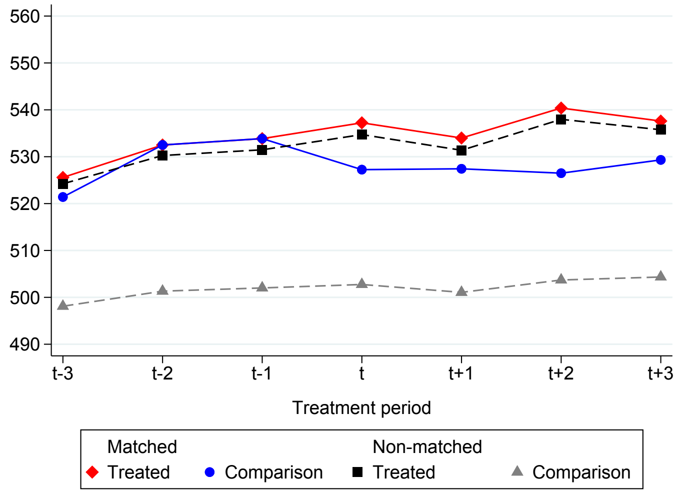
(a) Log monthly earnings



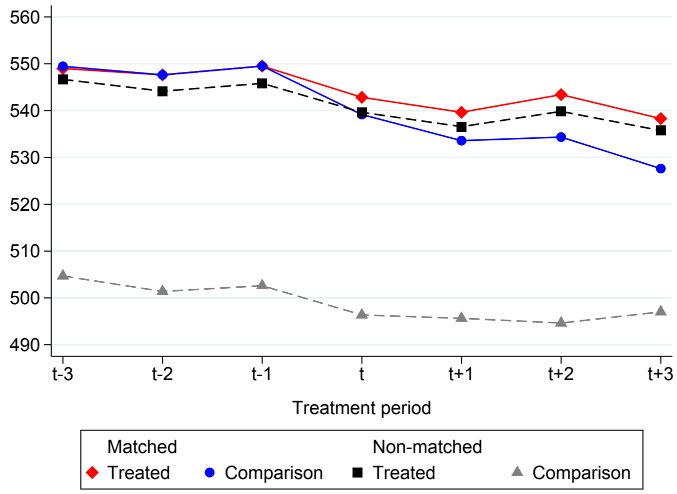
(b) Log monthly earnings relative to pretreatment period $t-1$

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.

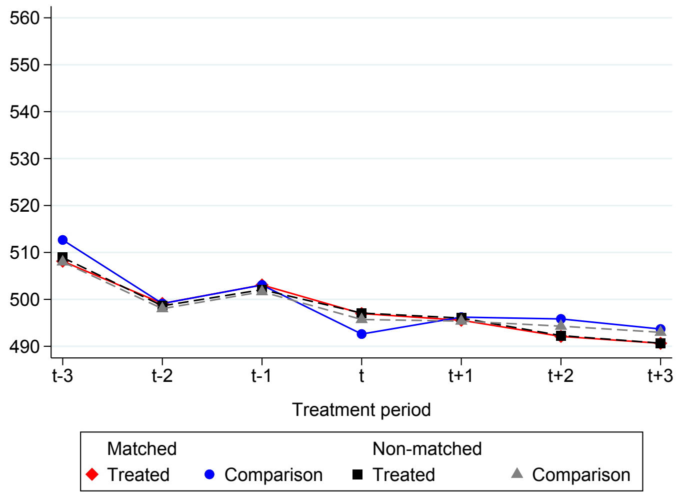
Figure A-6: Descriptive Relationship between Work-Related Training and Participation Domains



(a) Civic/political participation



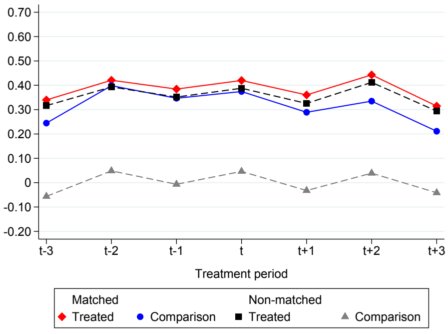
(b) Cultural participation



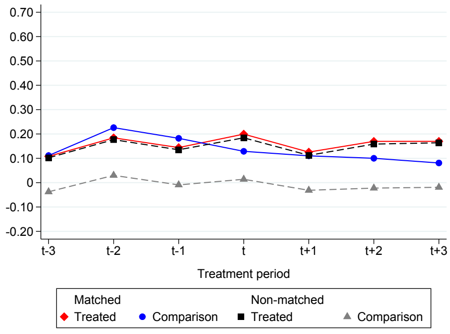
(c) Social participation

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

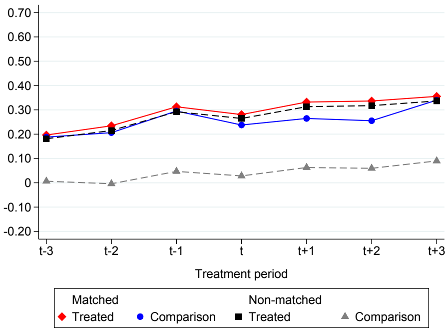
Figure A-7: Treatment-Period Averages of Subdimensions



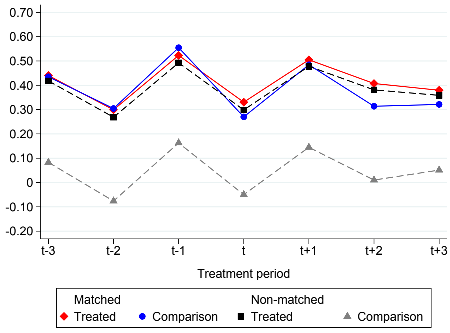
(a) Interest in politics



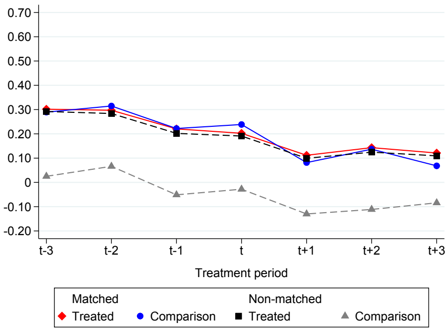
(b) Participate in politics



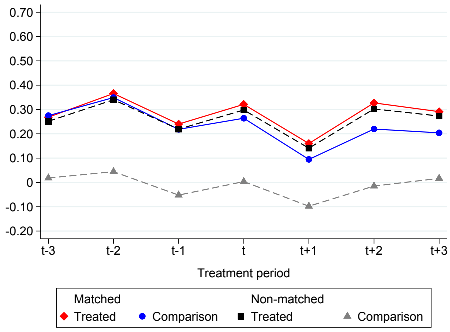
(c) Volunteer



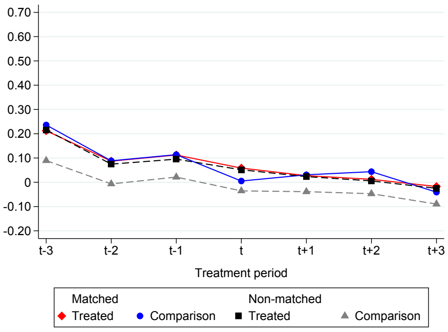
(d) Attend cultural events



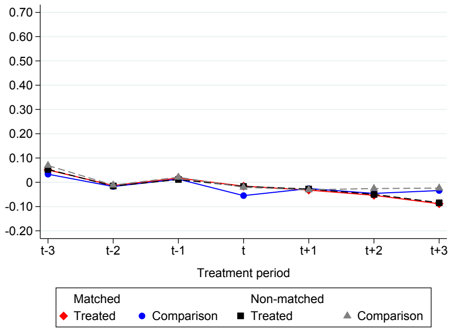
(e) Attend modern events



(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: Rotated Components

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 rotations 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: 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			
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × pre$_{t-1}$	0.297***	0.192***	[baseline]	0.000	–0.003	[baseline]	[baseline]
	(0.014)	(0.014)		(0.019)	(0.017)		
Training$_{ie}$ × 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: post$_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.000	0.091	0.160	0.006	0.023
H_0: 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 1). *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-7: 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			
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × pre$_{t-1}$	0.207***	0.125***	[baseline]	0.000	–0.001	[baseline]	[baseline]
	(0.011)	(0.010)		(0.015)	(0.013)		
Training$_{ie}$ × 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: post$_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.000	0.163	0.285	0.118	0.141
H_0: 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 A-6 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-8: 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 A-6 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-9: 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 A-6 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-10: Work-Related Training and Cultural Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: cultural participation score							
	Not matched			Matched			
$\text{Training}_{ie} \times \text{post}_{t+3}$	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)
$\text{Training}_{ie} \times \text{post}_{t+2}$	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)
$\text{Training}_{ie} \times \text{post}_{t+1}$	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)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	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)
$\text{Training}_{ie} \times \text{pre}_{t-1}$	43.080***	22.872***	[baseline]	–0.153	0.094	[baseline]	[baseline]
	(2.334)	(2.180)		(3.405)	(3.149)		
$\text{Training}_{ie} \times \text{pre}_{t-2}$	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: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.000	0.000	0.008	0.057	0.055	0.023	0.033
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.000	0.000	0.016	0.063	0.074	0.031	0.038

Notes: See Table A-6 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-11: 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 A-6 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: 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	10.583	11.024	–2.698
	(0.021)***	(5.233)**	(4.351)**	(4.866)
	[0.028]***	[6.878]**	[5.962]**	[6.573]
Training$_{ie}$ × post$_{t+2}$	0.041	12.243	10.738	–1.468
	(0.017)**	(4.436)***	(4.017)***	(4.396)
	[0.025]**	[5.658]***	[5.152]***	[5.689]
Training$_{ie}$ × post$_{t+1}$	0.044	4.461	6.544	0.178
	(0.014)***	(4.148)	(3.467)*	(3.638)
	[0.021]***	[5.254]	[4.726]*	[4.831]
Training$_{ie}$ × treat$_{t=0}$	0.039	8.554	3.551	3.421
	(0.011)***	(3.403)**	(3.046)	(3.461)
	[0.017]***	[4.273]**	[3.967]	[4.576]
Training$_{ie}$ × pre$_{t-2}$	0.001	0.054	0.666	0.304
	(0.010)	(3.425)	(3.136)	(2.833)
	[0.015]	[3.811]	[3.419]	[3.494]
Observations	20,696	20,998	20,998	20,998
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	8.572	8.867	–1.451
	(0.015)***	(3.698)**	(3.045)***	(3.580)
	[0.019]***	[4.378]**	[3.794]***	[4.272]
Observations	16,777	17,160	17,160	17,160
Treatment-by-evaluation period fixed effects	x	x	x	x
Control variables	x	x	x	x
Individual-by-evaluation period fixed effects	x	x	x	x

Notes: The table replicates the baseline models from Tables 3 and A-6. 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-13: 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
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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)
Training$_{ie}$ × 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: 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: 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
Training$_{ie}$ × 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-14: 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 A-15: 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 A-16: Balanced Panel

	(1)	(2)	(3)	(4)
Panel A: treatment effects by treatment period				
	Earnings	Civic/political	Cultural	Social
$\text{Training}_{ie} \times \text{post}_{t+3}$	0.082***	10.952*	10.657**	–2.926
	(0.023)	(5.828)	(4.875)	(5.444)
$\text{Training}_{ie} \times \text{post}_{t+2}$	0.051***	11.052**	10.653**	–0.877
	(0.019)	(5.631)	(4.750)	(5.067)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.054***	7.530	6.088	–0.227
	(0.020)	(5.462)	(4.445)	(4.732)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	0.045***	6.657	4.563	0.152
	(0.016)	(4.370)	(3.993)	(4.615)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	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: $\text{post}_{t+1,t+2} = 0$ (pvalue)	0.009	0.144	0.080	0.980
H_0: $\text{post}_{t+1,t+2,t+3} = 0$ (pvalue)	0.004	0.223	0.111	0.942
Panel B: treatment effects averaged over post-treatment periods				
	Earnings	Civic/political	Cultural	Social
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	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 A-17: 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 A-6 and 6 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.

Table A-18: Heterogeneity by Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Gender		University education		Blue collar worker		Wage distribution				
								Median splits		Tertile splits		
		Female	Male	Yes	No	Yes	No	Below	Above	Bottom	Middle	Top
Panel A: civic/political participation												
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.605**	16.378***	4.962	17.436**	0.757	–6.321	10.172**	6.821	9.086**	3.328	10.650	6.878
	(3.697)	(5.498)	(5.477)	(6.885)	(4.625)	(11.498)	(4.148)	(6.676)	(4.472)	(11.973)	(6.554)	(5.404)
R-squared	0.657	0.594	0.686	0.681	0.640	0.599	0.661	0.604	0.682	0.590	0.607	0.695
Panel B: cultural participation												
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.868***	11.236**	6.006	9.113	9.420**	16.892**	8.232**	7.450	9.930***	7.021	9.502*	10.889**
	(3.046)	(4.549)	(4.218)	(6.072)	(3.689)	(7.870)	(3.370)	(5.039)	(3.727)	(7.130)	(5.265)	(4.393)
R-squared	0.583	0.591	0.583	0.582	0.561	0.548	0.580	0.589	0.583	0.608	0.581	0.587
Panel C: social participation												
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	–1.434	0.035	–2.654	–1.392	–0.772	1.999	–1.319	–0.775	–4.104	–17.561*	–2.060	0.387
	(3.579)	(5.711)	(4.787)	(6.747)	(4.408)	(11.154)	(3.890)	(6.245)	(4.411)	(10.125)	(7.058)	(5.012)
R-squared	0.538	0.526	0.551	0.564	0.528	0.573	0.533	0.514	0.553	0.512	0.508	0.570
Treatment-by-evaluation period FE	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
Individual-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x	x
Observations	17,159	7,369	9,790	5,860	11,299	2,786	14,373	5,916	11,243	3,155	5,648	8,356
Mean absolute $\tilde{\Delta}$	1.49	3.88	3.02	3.62	2.38	7.33	1.92	4.01	2.32	6.84	3.87	3.05
Median absolute $\tilde{\Delta}$	1.15	3.22	2.59	2.62	1.78	6.44	1.33	3.07	1.92	6.60	2.79	2.66
P75 absolute $\tilde{\Delta}$	1.97	5.71	4.34	5.76	3.28	10.33	3.16	5.08	3.59	10.91	5.29	4.74

Notes: The table shows baseline regressions on sample splits, with the column header indicating the sample. 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 $\text{post}_{t+1,t+2,t+3}$ 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. 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 A-19 provides treatment period-specific results and Table 3 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 Heterogeneity by Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Gender		University education		Blue collar worker		Wage distribution				
								Median splits		Tertile splits		
		Female	Male	Yes	No	Yes	No	Below	Above	Bottom	Middle	Top
Panel A: civic/political participation												
$\text{Training}_{ie} \times \text{post}_{t+3}$	10.624**	21.110***	3.964	17.063*	5.926	–17.262	14.225**	11.011	11.004*	12.715	16.240*	5.223
	(5.234)	(7.990)	(7.215)	(9.940)	(6.425)	(14.578)	(5.744)	(9.858)	(6.441)	(16.890)	(8.620)	(7.903)
$\text{Training}_{ie} \times \text{post}_{t+2}$	12.273***	21.800***	6.831	26.170***	3.925	8.740	12.419**	9.515	12.031**	6.699	12.974*	10.009
	(4.435)	(6.698)	(6.298)	(8.167)	(5.443)	(12.900)	(4.946)	(8.134)	(5.494)	(13.924)	(7.687)	(6.610)
$\text{Training}_{ie} \times \text{post}_{t+1}$	4.492	8.055	3.825	9.297	–2.805	–7.703	5.452	2.942	5.426	–2.876	4.939	4.450
	(4.147)	(6.431)	(5.872)	(7.510)	(5.296)	(11.670)	(4.677)	(8.000)	(4.905)	(13.037)	(8.320)	(5.887)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	8.567**	8.565*	9.120*	12.316*	5.833	4.590	9.331**	2.548	10.953***	2.543	11.611*	8.647*
	(3.402)	(5.134)	(5.059)	(6.378)	(4.373)	(9.587)	(3.796)	(6.074)	(4.132)	(9.791)	(6.130)	(4.956)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.053	–0.061	–0.517	0.054	0.173	1.714	0.098	0.153	0.285	0.405	1.266	–0.214
	(3.426)	(5.267)	(4.623)	(5.938)	(4.120)	(13.724)	(3.860)	(6.327)	(4.153)	(9.725)	(6.376)	(4.923)
Panel B: cultural participation												
$\text{Training}_{ie} \times \text{post}_{t+3}$	11.047**	13.379**	8.879	13.685	9.538*	21.929**	10.275**	9.917	11.910**	3.759	9.341	12.129*
	(4.352)	(6.262)	(6.230)	(8.466)	(5.136)	(10.985)	(4.858)	(7.390)	(5.586)	(10.217)	(7.363)	(6.515)
$\text{Training}_{ie} \times \text{post}_{t+2}$	10.774***	13.787**	8.855	3.735	14.177***	9.241	10.969**	11.429*	10.617**	15.598	9.821	11.649**
	(4.018)	(5.776)	(5.701)	(7.430)	(4.805)	(10.717)	(4.495)	(6.214)	(4.884)	(9.612)	(7.426)	(5.649)
$\text{Training}_{ie} \times \text{post}_{t+1}$	6.496*	8.527	2.669	11.374	5.592	22.302**	5.101	4.797	7.909*	6.410	8.607	9.282*
	(3.468)	(5.219)	(4.924)	(7.265)	(4.061)	(10.132)	(3.881)	(5.677)	(4.423)	(9.053)	(5.833)	(5.166)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	3.569	4.454	2.510	0.837	3.747	13.692	2.962	2.212	5.323	–2.374	6.600	4.307
	(3.045)	(4.641)	(4.281)	(5.743)	(3.590)	(12.451)	(3.359)	(5.172)	(3.796)	(7.932)	(5.153)	(4.565)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.661	0.719	0.610	0.056	0.500	1.216	0.662	0.659	0.579	0.487	0.243	0.401
	(3.137)	(4.707)	(4.284)	(6.182)	(3.687)	(9.274)	(3.485)	(5.201)	(3.935)	(7.498)	(5.071)	(4.659)
Panel C: social participation												
$\text{Training}_{ie} \times \text{post}_{t+3}$	–2.646	–8.134	2.406	–5.968	1.790	11.569	–3.610	2.465	–7.915	–28.961**	2.308	–3.502
	(4.868)	(8.098)	(6.499)	(8.896)	(5.685)	(12.986)	(5.322)	(8.637)	(6.270)	(14.743)	(9.019)	(6.895)
$\text{Training}_{ie} \times \text{post}_{t+2}$	–1.481	1.674	–5.387	0.480	–2.122	–1.125	–1.285	–4.591	–2.952	–11.773	–5.380	1.398
	(4.394)	(6.840)	(5.717)	(8.199)	(5.367)	(12.350)	(4.760)	(7.795)	(5.322)	(10.649)	(8.613)	(6.171)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.190	3.744	–1.602	0.786	–0.310	1.803	0.368	1.471	–2.075	–11.085	–0.088	2.084
	(3.637)	(5.540)	(4.946)	(6.902)	(4.603)	(12.054)	(3.938)	(6.573)	(4.575)	(9.880)	(7.342)	(5.115)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	3.440	5.548	2.576	3.798	4.283	11.751	3.251	1.220	2.707	–8.413	3.601	3.749
	(3.461)	(5.357)	(4.874)	(6.463)	(4.314)	(12.745)	(3.826)	(6.465)	(4.344)	(8.945)	(7.110)	(4.996)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.298	0.132	0.321	0.449	–0.189	–0.952	0.314	–0.375	0.266	0.796	0.027	0.148
	(2.834)	(4.080)	(4.031)	(4.431)	(3.654)	(7.113)	(3.071)	(5.739)	(3.357)	(8.408)	(5.225)	(3.673)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x			
Control variables	x	x	x	x	x	x	x	x	x			
Individual-by-evaluation period FE	x	x	x	x	x	x	x	x	x			
Observations	20,997	9,014	11,983	7,192	13,805	3,390	17,607	7,213	13,784	3,846	6,883	10,268
Mean absolute $\tilde{\Delta}$	1.49	3.88	3.02	3.62	2.38	7.33	1.92	4.01	2.32	6.84	3.87	3.05
Median absolute $\tilde{\Delta}$	1.15	3.22	2.59	2.62	1.78	6.44	1.33	3.07	1.92	6.60	2.79	2.66
P75 absolute $\tilde{\Delta}$	1.97	5.71	4.34	5.76	3.28	10.33	3.16	5.08	3.59	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 A-18 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-20: Training-Induced Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Baseline	Training intensity		Firm-specific training		Previous training		Employer-induced		Firm size	
		Below median	Above median	Yes	No	Yes	No	Yes	No	Large	Small/ medium
Panel A: civic/political participation											
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.605**	8.321**	9.030**	8.998**	8.263**	9.349**	6.371	7.584**	11.296*	6.893	13.233**
	(3.697)	(4.187)	(4.316)	(4.506)	(4.101)	(4.185)	(4.488)	(3.793)	(6.677)	(4.438)	(6.436)
R-squared	0.657	0.671	0.642	0.672	0.650	0.670	0.625	0.664	0.618	0.666	0.658
Panel B: cultural participation											
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	8.868***	7.607**	10.043***	9.747***	8.510**	9.627***	7.076*	8.683***	9.805*	8.628**	8.836*
	(3.046)	(3.386)	(3.563)	(3.430)	(3.499)	(3.394)	(3.831)	(3.111)	(5.249)	(3.809)	(4.977)
R-squared	0.583	0.567	0.597	0.573	0.586	0.581	0.584	0.580	0.606	0.585	0.586
Panel C: social participation											
$\text{Training}_{ie} \times \text{post}_{t+1,t+2,t+3}$	–1.434	–0.231	–2.551	–4.518	0.406	–2.260	–0.265	–1.102	–3.190	–2.586	–0.691
	(3.579)	(4.199)	(4.057)	(4.330)	(3.966)	(3.931)	(4.607)	(3.678)	(6.657)	(4.519)	(6.184)
R-squared	0.538	0.549	0.527	0.540	0.537	0.541	0.532	0.549	0.471	0.559	0.527
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x
Control variables	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
Observations	17,159	11,678	11,834	10,246	13,209	13,436	10,076	15,698	7,792	10,366	6,394
Mean absolute $\tilde{\Delta}$	1.49	1.99	2.50	3.23	2.47	3.52	5.01	1.80	7.08	2.74	4.09
Median absolute $\tilde{\Delta}$	1.15	1.57	2.02	2.31	1.87	2.29	3.07	1.38	4.88	2.08	2.62
P75 absolute $\tilde{\Delta}$	1.97	2.78	3.82	4.39	3.28	4.13	4.59	2.67	10.98	4.10	6.80

Notes: The table shows baseline regressions on sample splits, with the column header indicating the sample. 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 $\text{post}_{t+1,t+2,t+3}$ 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. 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 A-19 provides treatment period-specific results and Table 3 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-21: Treatment Period-Specific Training-Induced Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Baseline	Training intensity		Firm-specific training		Previous training		Employer-induced		Firm size	
		Below median	Above median	Yes	No	Yes	No	Yes	No	Large	Small/ medium
Panel A: civic/political participation											
$\text{Training}_{ie} \times \text{post}_{t+3}$	10.624**	10.377*	11.248*	8.871	11.352**	10.076*	10.785*	10.000*	9.773	10.277	16.117*
	(5.234)	(6.234)	(5.871)	(6.424)	(5.730)	(5.946)	(6.367)	(5.374)	(9.356)	(6.512)	(9.097)
$\text{Training}_{ie} \times \text{post}_{t+2}$	12.273***	12.025**	12.601**	11.307**	12.868***	13.216***	9.857*	11.652**	12.908	11.204**	16.765**
	(4.435)	(5.108)	(5.291)	(5.473)	(4.942)	(5.071)	(5.552)	(4.538)	(8.427)	(5.546)	(7.787)
$\text{Training}_{ie} \times \text{post}_{t+1}$	4.492	4.185	4.721	7.248	2.942	6.047	1.191	3.009	11.204	0.386	8.903
	(4.147)	(4.698)	(4.866)	(5.143)	(4.541)	(4.702)	(5.212)	(4.271)	(7.186)	(5.096)	(6.685)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	8.567**	7.312*	9.979**	10.028**	7.838**	10.412***	6.069	7.376**	15.897**	5.663	10.658*
	(3.402)	(3.955)	(3.919)	(4.222)	(3.736)	(3.973)	(4.128)	(3.477)	(6.569)	(4.449)	(5.753)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.053	–0.167	0.121	–0.042	0.164	0.113	0.264	0.144	0.447	–0.003	–0.512
	(3.426)	(4.013)	(3.943)	(4.216)	(3.745)	(3.870)	(4.193)	(3.499)	(6.369)	(4.681)	(5.653)
Panel B: cultural participation											
$\text{Training}_{ie} \times \text{post}_{t+3}$	11.047**	10.015**	11.987**	15.216***	8.875*	13.101***	7.099	11.167**	10.010	6.585	16.036**
	(4.352)	(5.027)	(4.976)	(5.331)	(4.745)	(4.782)	(5.636)	(4.505)	(7.675)	(5.751)	(7.440)
$\text{Training}_{ie} \times \text{post}_{t+2}$	10.774***	10.569**	11.042**	10.208**	11.334**	12.713***	7.100	10.458**	13.483**	11.126**	6.656
	(4.018)	(4.433)	(4.745)	(4.618)	(4.575)	(4.374)	(5.161)	(4.111)	(6.840)	(5.295)	(6.558)
$\text{Training}_{ie} \times \text{post}_{t+1}$	6.496*	4.532	8.313**	7.357*	6.095	5.812	7.263	6.055*	8.378	5.932	8.022
	(3.468)	(3.938)	(3.995)	(4.018)	(3.954)	(3.815)	(4.511)	(3.566)	(5.926)	(4.530)	(5.387)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	3.569	5.398	1.705	1.294	5.200	4.234	2.830	3.458	4.454	3.363	0.338
	(3.045)	(3.489)	(3.473)	(3.694)	(3.380)	(3.320)	(3.907)	(3.164)	(5.041)	(4.166)	(4.781)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.661	1.002	0.334	0.889	0.515	1.004	0.260	0.512	1.495	–0.295	0.673
	(3.137)	(3.656)	(3.505)	(3.874)	(3.423)	(3.504)	(3.858)	(3.253)	(5.155)	(4.409)	(4.926)
Panel C: social participation											
$\text{Training}_{ie} \times \text{post}_{t+3}$	–2.646	–0.869	–4.327	–6.670	–0.248	–2.698	–2.732	–2.813	–1.301	–8.302	5.026
	(4.868)	(5.620)	(5.488)	(5.762)	(5.315)	(5.366)	(6.077)	(5.004)	(8.760)	(6.410)	(8.283)
$\text{Training}_{ie} \times \text{post}_{t+2}$	–1.481	–0.400	–2.454	–7.911	1.989	–3.132	0.605	–0.541	–7.835	–3.095	–2.650
	(4.394)	(5.108)	(5.005)	(5.252)	(4.859)	(4.866)	(5.488)	(4.501)	(8.319)	(5.517)	(7.197)
$\text{Training}_{ie} \times \text{post}_{t+1}$	0.190	1.994	–1.573	–0.327	0.636	0.039	0.088	0.481	–1.137	0.024	–0.578
	(3.637)	(4.314)	(4.174)	(4.494)	(4.036)	(3.926)	(5.037)	(3.750)	(6.950)	(4.670)	(6.070)
$\text{Training}_{ie} \times \text{treat}_{t=0}$	3.440	4.591	2.130	3.249	4.098	3.835	2.663	3.292	5.052	3.998	3.220
	(3.461)	(4.124)	(3.980)	(4.341)	(3.811)	(3.792)	(4.671)	(3.597)	(6.677)	(4.538)	(5.641)
$\text{Training}_{ie} \times \text{pre}_{t-2}$	0.298	0.582	0.006	0.397	0.114	0.392	0.015	0.274	–0.029	–0.164	0.290
	(2.834)	(3.143)	(3.302)	(3.436)	(3.067)	(2.962)	(3.926)	(2.916)	(4.746)	(3.670)	(4.433)
Treatment-by-evaluation period FE	x	x	x	x	x	x	x	x	x	x	x
Control variables	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
Observations	20,997	14,300	14,470	12,540	16,160	13,091	7,906	19,208	9,535	12,683	7,827
Mean absolute $\tilde{\Delta}$	1.49	1.99	2.50	3.23	2.47	3.52	5.01	1.80	7.08	2.74	4.09
Median absolute $\tilde{\Delta}$	1.15	1.57	2.02	2.31	1.87	2.29	3.07	1.38	4.88	2.08	2.62
P75 absolute $\tilde{\Delta}$	1.97	2.78	3.82	4.39	3.28	4.13	4.59	2.67	10.98	4.10	6.80

Notes: The table shows treatment period-specific baseline regressions on sample splits, with the column header indicating the sample. Table A-20 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 1 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 B-1 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 1). Information are imputed by the years indicated.

C Trust and Non-Pecuniary Outcomes

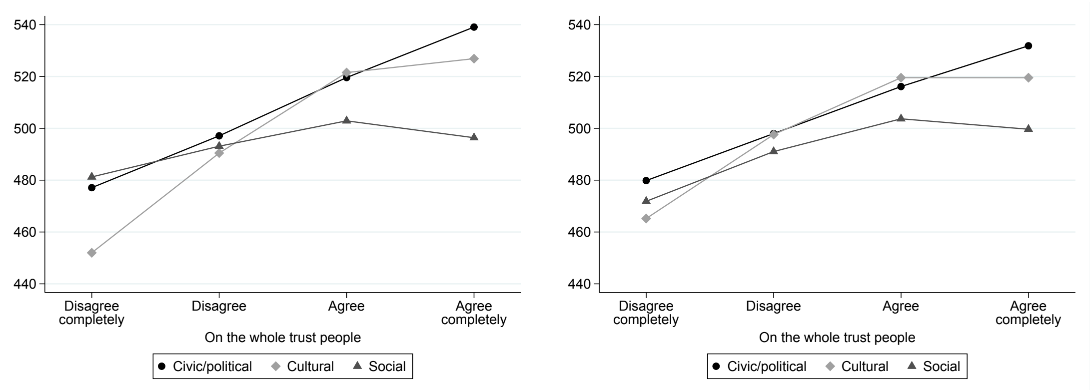
In many applications, trust is an important dimension of social capital. The SOEP provides information on trust in the years 2003, 2008, and 2013. The question asks to what extent people can agree or disagree with the statement that people can be trusted. The variable is measured on a 4-point scale from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

Figure C-1 shows average participation scores by level of trust. The measures are averaged over all available years (2003, 2008, and 2013). In Figure C-1(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 C-1(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 C-1 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 C-2 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 C-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 C-1(a) plots the raw values. Figure C-1(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 C-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 C-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.

D Number of Close Friends and Non-Pecuniary Outcomes

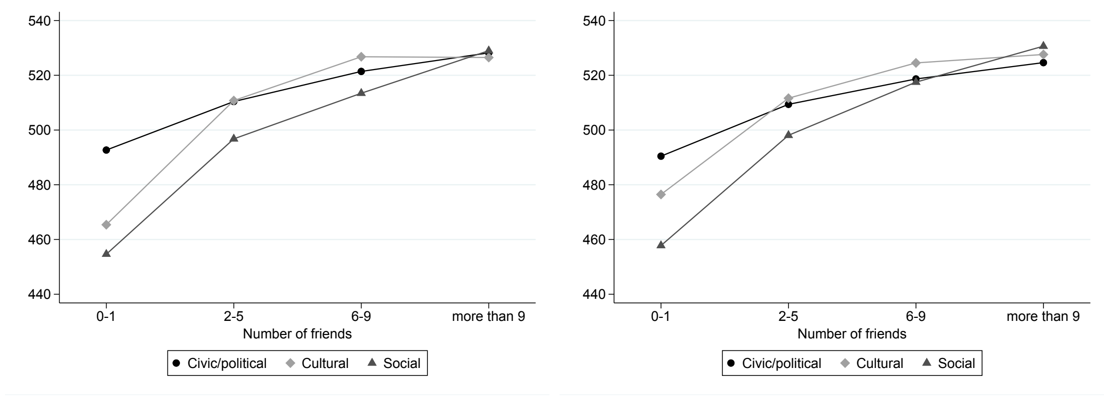
In this section, we study the number of close friends as a proxy for the quality indicator of social ties. The SOEP provides information on the number of close friends in the years 2003, 2008, 2011, and 2013. The question asks the respondent to report the number of close friends. The average (median) 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 D-1 shows average participation scores by the number of friends. The measures are averaged over all available years (2003, 2008, 2011, and 2013). In Figure D-1(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 D-1(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 D-1 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 D-2 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 D-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 D-1(a) plots the raw values. Figure D-1(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 D-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 D-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$_{ie}$ × 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$_{ie}$ × 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$_{ie}$ × 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$_{ie}$ × 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.