DISCUSSION PAPER SERIES

DP11330

QUALITY LEISURE TIME AND YOUTH DEVELOPMENT

Benjamin Fuchs and Aderonke Osikominu

LABOUR ECONOMICS

ISSN 0265-8003

QUALITY LEISURE TIME AND YOUTH DEVELOPMENT

Benjamin Fuchs and Aderonke Osikominu

Discussion Paper 11330
Published 15 June 2016
Submitted 15 June 2016

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

QUALITY LEISURE TIME AND YOUTH DEVELOPMENT

Abstract

This paper first develops a simple model to clarify the links between leisure time use and skill formation. It then explores empirically how youths allocate their time. We focus on sports as a popular activity and estimate its effect on behavioral and economic outcomes. We exploit data from the German Socio-Economic Panel that offers the unique advantage of both a large, representative sample and high quality behavioral measures. We employ a flexible strategy combining propensity score matching and regression to account for self selection. Our results suggest that structured leisure activities like sports contribute to the development of nonacademic skills.

JEL Classification: I21, J13, J24

Keywords: Human Capital, nonacademic skills, leisure activities, sports, youth development, treatment effect

Benjamin Fuchs - benjamin.fuchs@uni-hohenheim.de
University of Hohenheim

Aderonke Osikominu - a.osikominu@uni-hohenheim.de
University of Hohenheim, IAB and CEPR

Acknowledgements
We are grateful to Maximilian Blömer for excellent research assistance. The paper also benefited from many helpful comments by seminar and conference participants in Basel, Berlin, Bonn, Dresden, Freiburg, Göttingen, Hamburg, Mannheim, Nuremberg, Stuben, Toulouse, Turin and Zurich. Financial support from the German Excellence Initiative, the Austrian Science Fund (Aderonke Osikominu, FWF grant no.\ S~10304-G16), and the German Research Foundation (DFG grant no.\ OS-431/2-1) is gratefully acknowledged. This paper uses data from the German Socio-Economic Panel Study that has been made available by the German Institute for Economic Research (DIW), Berlin.

1 Introduction

Parents and policymakers alike worry about what activities may provide valuable learning experiences to youths beyond the domain of schooling. The learning environment at school is tightly structured and offers little opportunities for young people to develop initiative and motivation of their own (Larson, 2000). It centers on knowledge and cognitive skills. Schools may fail to engage students with weaker academic inclinations.[1] Research on extracurricular and out-of-school activities documents sizeable positive associations between the engagement in structured leisure activities on the one hand and various behavioral, educational, and labor market outcomes on the other hand (e.g. Farb and Matjasko, 2012; Postlewaite and Silverman, 2005).[2] While these studies provide valuable descriptions of empirical regularities they do not shed light on the potential mechanisms linking activities and outcomes which complicates the evaluation of the causal effect of an activity of interest. Such evidence would be necessary to inform the public aiming to support youth development.

In this paper, we propose to study the effects of leisure activities on skill formation based on an economic framework in which youths allocate their time between different types of activities that may contribute to the production of human capital. A key implication of our framework is that, with a production technology that depends on multiple simultaneously determined inputs, the common empirical approach that focuses on modeling the consequences of exogenously assigning a single input of interest does not allow one to quantify the direct causal effect of this input on human capital. The optimal choice of other inputs may respond to a change in the input of interest, if the production technology exhibits cross effects in the sense that the level of one input affects the productivity of other inputs. Specifically, consider a social experiment that randomly assigns young people to a treatment group that has access to a sports club and a nontreatment group that is denied access to the

[1] In the context of remedial education programs for school dropouts, research by Heckman and coauthors for the US suggests that character skills (e.g. self-esteem, conscientiousness) rather than academic skills are the constraining factor explaining the low academic and labor market performance of these people (Heckman, Humphries, and Mader, 2011; Heckman and Rubinstein, 2001).

[2] Persico, Postlewaite, and Silverman (2004) provide tentative evidence suggesting that adolescent experiences may contribute to the development of economically relevant nonacademic skills. The authors investigate the causes for the height wage premium, i.e. the fact that taller workers earn more than otherwise equal shorter persons. They show that the height premium is essentially explained by differences in height as a teenager that in turn are positively related with participation in extracurricular activities, in particular high school athletics. Case and Paxson (2008) challenge this view showing that parental socioeconomic status and cognitive skills as a child predict height and growth during adolescence.

club. A regression of a human capital measure on an indicator for treatment assignment allows one to recover a gross effect that mixes the direct effect of sports and indirect effects triggered by a reallocation of time devoted to other activities, such as studying and playing music. Thus, one cannot use a simple randomization to quantify the direct causal effect of an activity on skills. Disentangling direct from indirect effects is crucial to identify and quantify the technology of skill formation. This knowledge is important to improve the external validity of an evaluation and to formulate precise policy recommendations.

Based on these theoretical insights we introduce an econometric potential outcome framework in which the treatment is vector valued. The simultaneously determined inputs of the production technology constitute the elements of the vector valued treatment. If the production technology exhibits cross effects, the elements of the treatment vector depend on each other. We show how one can identify the conditional causal effect of an input of interest under a selection on observables strategy. Specifically, the idea is to compare the observed outputs obtained with the same allocation of other inputs but a differing use of the input of interest, keeping constant also background characteristics that affect productivity. Economically this means that, by appropriately varying the marginal costs of all inputs, one can find two individuals that have the same background characteristics, the same allocation of other inputs, but a differing allocation of the input of interest. Thus, heterogeneity in the marginal costs of the inputs across individuals provides exogenous variation in the level of the input of interest keeping everything else constant. In a second step, we obtain the average direct effect of the input by integrating the conditional causal effects over the distribution of background characteristics and other inputs. While the assumption of selection on observables cannot be tested, we can test its implications. For instance, we can test whether human capital measures that are determined before the skill input of interest are conditionally independent of this input.[3] In our empirical application, we devise a number of such specification tests to probe our identifying strategy.

Our approach integrates also behavioral perspectives on the development of skills over the life cycle and the measurement of different types of skills. Behavioral research distinguishes a multiplicity of different skills that have different developmental trajectories. Some skills are potentially susceptible to experiences during youth, whereas others are predetermined with respect to adolescent influences. Motivated by this observation we focus on measures of skills that continue to be malleable

[3] In a similar vein, Heckman and Hotz (1989) propose to test whether matched treatment and comparison units differ in their pretreatment outcomes.

throughout adolescence as outcomes, while we use measures of skills that are predetermined with respect to choices during later childhood and youth to test the plausibility of our empirical strategy.

Two leading examples of skills that are determined already at an early age are height and intelligence. In developed countries, height and growth during adolescence are essentially determined by genes (80%) and the quality of the uterine through early childhood environment (Case and Paxson, 2008; Silventoinen 2003; Visscher et al., 2006). Thus, height during adolescence evolves independently of adolescent experiences but is correlated with family background and skills. Similarly, somebody's rank in the intelligence distribution is stable after about age six, with genes accounting for the majority (up to 80%) of the variation across adolescents and adults in a given cohort (Cunha, Heckman, Lochner and Masterov, 2006; Neisser et al., 1996; Nisbett et al., 2012).

Other skills continue to be malleable until later ages. Character skills, often assessed through the Big Five personality inventory, continue to develop long into adulthood until they reach a maximum level of stability at age 50-70 (Almlund, Duckworth, Heckman, and Kautz, 2011). Recent neuropsychological research shows that the human brain undergoes significant changes during adolescence, comparable to those taking place during early childhood (Best and Miller, 2010; Best, Miller, and Jones, 2009; Blakemore and Choudhury, 2006; Giedd et al., 1999; Singer, 2006). The restructuring of the brain comes along with developments in the ability to control thoughts and behavior (i.e. executive function) as well as abilities involving social cognition (e.g. self-awareness, perspective taking) and the understanding of social emotions (e.g. fairness).[4]

Character, social and executive function skills are key drivers of economic success. Character skills such as conscientiousness (i.e. the tendency to be organized and hard working) are positively associated with economic outcomes (Almlund et al., 2011). Executive function skills enable future-oriented thinking, e.g. formulating career aspirations and expectations, which motivates and controls future attainment (Beal and Crockett, 2010). Recent theoretical and experimental research in economics demonstrates the importance of social skills in shaping economic interactions and their outcomes (Bowles and Polanía-Reyes, 2012; Brown, Falk, and Fehr, 2004; Fehr, 2009).

[4]See also the experimental studies by Fehr, Bernhard, and Rockenbach (2008), Almås, Cappelen, Sørensen, and Tungodden (2010), and Fehr, Rützler and Sutter (2011) that examine how social preferences develop during childhood and adolescence.

In the empirical part of the paper we investigate the leisure time use of youths as well as the effects of athletic involvement on nonacademic skills and educational attainment. Our focus on sports is motivated by its popularity across socioeconomic groups and general accessibility. For youths from less advantaged family backgrounds, sports constitutes often the only quality pastime they engage in.[5] The empirical analysis exploits data from the German Socio-Economic Panel (SOEP) that offers the unique advantage of both a large, representative sample and high quality measures of behavioral outcomes. For instance, we have validated measures of intelligence, personality, reciprocity and risk aversion. We focus on youths who are administered a biography questionnaire in the year in which they turn 17, providing details about their current and past educational and leisure activities as well as their attitudes on a number of domains such as their work values. We further add information from the parental surveys. The panel nature of the SOEP allows us to track the youths and their families over time which we exploit to construct a detailed history of family background as well as subsequent behavioral and economic outcomes of the youths.

We take advantage of the richness of the SOEP data to carefully implement our empirical strategy when we estimate the effect of sports on skill formation assuming selection on observables. In particular, we consider a rich set of conditioning variables that includes detailed measures of family background and parental behaviors as well as the youth's past academic achievement, and current engagement in educational and other leisure activities. We assess the plausibility of selection on observables with human capital measures that are predetermined with respect to athletic status. We exploit that height and intelligence are largely determined by genetic factors and early childhood environments, which means that they are determined before children and youth decide on their educational and leisure activities. Specifically, we show that height and intelligence are balanced in the matched treatment and comparison samples. To estimate the treatment effects we combine propensity score matching with a flexible regression adjustment in the matched sample. This approach allows us to combine the advantages of both methods. The semiparametric matching estimator requires a careful choice of a suitable comparison group for youths playing sports. Thus, we avoid comparisons based on extrapolations that are not supported by the data. The regression adjustment yields consistent and efficient treatment ef-

[5] A couple of studies investigate the relationship between sports at around age 16-18 and educational and labor market outcomes at later ages, e.g. Barron, Ewing, and Waddell (2000) and Stevenson (2010) for the US as well as Pfeifer and Cornelißen (2010) for Germany. They all document sizeable positive relationships between teenage athletic involvement and later educational and labor market outcomes.

fect estimates if the conditional expectation of the outcome is correctly specified. It can easily be modified to examine effect heterogeneity and to assess the robustness of results. In particular, we verify that our results are robust to including family fixed effects.

Our main findings are as follows. Three quarters of the youths on the academic school track that prepares for university entry play sports at least once a week. The corresponding number for youths attending the vocational school track is 50%. Athletic engagement and non-engagement largely persists through adolescence and into young adulthood. While young men favor team sports and especially soccer, young women have more diverse preferences and play more individual sports. Regardless of type of sport and gender, the vast majority of the athletes play sports in a club or with others. Thus, sports is generally a social activity. Our results further suggest that young people who regularly play sports spend a higher share of their free time on structured and non-sedentary activities than those who do not. Nevertheless, undirected and passive leisure pursuits clearly dominate among all youths. Parental athletic involvement is highly predictive of the youth's athletic involvement. Athletes tend to be positively selected in terms of family background, intelligence and height. These differences disappear after matching treatment and comparison observations. In particular, the matched treatment and comparison units are balanced with respect to the predetermined human capital measures height and intelligence. This suggests that our matching strategy effectively balances heterogeneity in skills related to genetic factors and early childhood environments.

We find beneficial effects of athletic involvement on a broad range of behavioral outcomes including conscientiousness, reciprocity, and career aspirations and expectations. The effects are sizeable for youths on the vocational track, attaining 10-30% of a standard deviation, whereas they are small and insignificant for youths on the academic track. The magnitude of the effects sometimes differs across gender, too. However, the impacts generally point in the same direction. Athletes, in particular youths on the vocational track, show better educational outcomes, than comparable youths who do not play sports. We further examine treatment effects conditional on the engagement in other structured leisure activities. It turns out that the sizeable beneficial effects of sports among youths on the vocational track are largely driven by the sizeable effects among youths who do not engage in any other structured activities. This pattern is similar for youths on the academic track. We therefore interpret our treatment effect estimates as estimates of the broader effect of having access to an enriched social environment rather than the pure effect of physical exercise. In a sensitivity analysis, we verify that the effects are robust to includ-

ing family fixed effects. Overall, the effects of athletic involvement on behavioral outcomes are consistent with the hypothesis that experiences and informal learning activities during adolescence influence the development of nonacademic skills.

The remainder of the paper is organized as follows. The next Section summarizes main findings from behavioral research on skill formation. Section 2 lays out the analytic framework. Section 3 describes the data source and the analysis sample. We present the empirical results in Section 4. Section 5 concludes. The Online Appendix contains further information on the variables used and detailed estimation results.

2 Analytic Framework

2.1 Conceptual Background

To support our argument we sketch a theoretical model of time use and its relationships with skill formation and labor market outcomes. The framework combines an allocation-of-time model (Becker, 1965) with the approach of Akerlof and Kranton (2000, 2002) that introduces social incentives to the standard economic model of utility maximization. Youths may allocate their daily time between studying at school or working on homework assignments (formal learning) and two types of leisure activities. We distinguish between structured activities that take place in an organized setting and/or involve goal-directed effort like playing sports or music and unstructured activities such as watching TV or meeting with peers. Let $0 \leq e \leq 1$ and $0 \leq s \leq 1$ denote the share of time a teenager spends on formal education and structured leisure activities, respectively.

A teenager's human capital, $H(e, s, x)$, is a function of the time engaged in formal learning and structured activities as well as an index of family background x capturing parental investments and inherited human capital. A higher value of x corresponds to a more advantaged background. We assume that family background positively affects human capital for a given time allocation, i.e. $H_x > 0$, where subscripts on functions denote partial derivatives. Human capital is increasing and strictly concave as a function of formal education e, i.e. $H_e > 0$ and $H_{ee} < 0$. Further, cross effects between formal learning and family background are nonnegative, i.e. $H_{ex} \geq 0$. This captures the idea that youths with a better skill endowment and/or parental support are more productive at studying. We assume further that human capital is nondecreasing and concave with respect to s, i.e. $H_s \geq 0$ and $H_{ss} \leq 0$. Thus, we rule out that engagement in structured activities destroys hu-

man capital. Engagement in structured activities also does not harm formal learning, i.e. $H_{es} \geq 0$, and a more advantaged family background does not reduce the effect of structured activities on human capital formation, i.e. $H_{sx} \geq 0$. Let ω denote the net present value of future earnings per unit of human capital. Thus, the economic reward of studying and engaging in structured activities arises through higher future earnings $\omega H(e, s, x)$.

The teenager trades the future economic reward from formal learning and structured activities off against the immediate nonmonetary utility gains from being idle, $\theta(1-e-s)$, $\theta > 0$, and engaging in structured activities, $I(s, x)$, as well as the immediate costs associated with studying, γe, $\gamma > 0$, and structured leisure activities, κs, $\kappa > 0$. The term $I(s, x)$ represents the net identity utility associated with spending share s of leisure in structured activities for somebody with family background x. We assume that $I_s > 0$ and $I_{ss} < 0$. The identity utility reflects that people's decisions to engage in structured leisure activities may depend on social rather than economic incentives. In particular, the dependence on family background reflects that parents are role models for their children and shape the environment in which the children grow up. We assume that the marginal identity utility of structured leisure activities is nondecreasing in family background, which is motivated by the observation that youths from more advantaged family backgrounds engage to a larger extent in structured leisure activities, i.e. $I_{sx} \geq 0$. In sum, the utility function of the teenager is given by:

$$U(e, s) = \omega H(e, s, x) + \theta(1 - e - s) + I(s, x) - \gamma e - \kappa s\,, \tag{1}$$

and the teenager chooses e and s so as to maximize (1).

The two first order conditions form a system of equations that implicitly determines the optimal shares of time spent studying e^* and engaged in structured activities s^* as a function of the parameters ω, x, θ, γ, κ. Comparative static analysis yields the following results for which we provide proofs in the Online Appendix.

Lemma 1.

(i) $e^*_x \geq 0$ and with strict inequality if $H_{ex} > 0$.

(ii) $s^*_x \geq 0$ and with strict inequality if $I_{sx} > 0$.

Lemma 1 says that, if anything, youths from more advantaged backgrounds engage more in formal learning and structured leisure activities. In the case in which family background positively affects learning ability or marginal identity utility from

structured activities a more advantaged family background decreases the amount of time allocated to unstructured leisure activities. Having established how e^* and s^* depend on x, we can work out how human capital, $H^* \equiv H(e^*, s^*, x)$, studying and engagement in structured leisure activities respond to variation in family background.

Proposition 1. A change in x affects H^* , e^*, and s^* in the same direction if $H_{ex} > 0$ and $I_{sx} > 0$.

Proof: Observe that $H_x^* = H_e\, e_x^* + H_s\, s_x^* + H_x$. The result follows from Lemma 1 and the property $H_x > 0$.

From an empirical point of view, Proposition 1 means that, conditional on engagement in formal learning, one tends to find a positive relationship between the engagement in structured leisure activities and measures of human capital, regardless of whether structured activities affect skill formation ($H_s > 0$) or not ($H_s = 0$), if heterogeneity in family background is not taken into account.

Lemma 2.

(i) The optimal amount of time allocated to formal learning, e^*, and structured leisure activities, s^*, depends negatively on their respective unit costs, γ and κ, i.e. $e_\gamma^* < 0$ and $s_\kappa^* < 0$.

(ii) If there are positive cross effects between structured leisure activities and studying on skill formation, i.e. $H_{es} > 0$, e^* also depends negatively on κ and s^* negatively on γ, i.e. then $e_\kappa^* < 0$ and $s_\gamma^* < 0$. Otherwise $e_\kappa^* = s_\gamma^* = 0$.

Proposition 2. If anything, a change in γ or κ changes H^*, e^*, and s^* in the same direction.

Proof: Observe that $H_\gamma^* = H_e\, e_\gamma^* + H_s\, s_\gamma^* < 0$ and $H_\kappa^* = H_e\, e_\kappa^* + H_s\, s_\kappa^* < 0$ by application of Lemma 2.

In particular, if structured leisure activities affect skill formation ($H_s > 0$) and there exist cross effects between formal learning and structured activities ($H_{es} > 0$), a change in the unit cost of one of them affects the optimal choices of both. With positive complementarities between formal learning and structured activities, an increase in the marginal cost of formal education will decrease not only the optimal amount of formal learning but also of structured activities. From an empirical point of view, the potential existence of cross effects makes the use of an instrumental variables framework unattractive for estimation of the ceteris paribus effect of an

activity of interest on human capital formation. In the presence of cross effects, the activities are correlated with each other and endogeneity in one of them transmits to the others. This would require to instrument all activities that contribute to human capital formation with their respective cost shifters, which is typically not feasible in practice. Researchers may be tempted to resort to a model that focuses on a single activity of interest for which they have an instrument and omit the other activities from the structural equation. Such a strategy is questionable because, if there are cross effects between the activity of interest and the omitted activities, the instrument would be correlated with the error term of the structural equation. The reduced form regression of a human capital variable on the instrument would be informative to test for the existence of nonzero causal effects. Under the null hypothesis of a zero effect the instrument is uncorrelated with the error term that contains the omitted activities.[6]

Further, cross-effects between different inputs of human capital also limit the evidence generated by (natural) experiments. Suppose a researcher randomizes access to a single activity of interest. If their exist cross-effects, participants will respond to the randomization of one activity with an adjustment of the time allocation of other activities. This means that the treatment effect identified under randomization of a single activity consists of a mixture of the direct effect of the activity on human capital and indirect effects arising through an adjustment of the other activities. In the extreme, a positive gross treatment effect in an experiment may be entirely caused by positive indirect effects rather than a positive direct effect of the activity of interest.

After these theoretical considerations, let us examine how we can recover the ceteris paribus effect of athletic involvement on human capital formation empirically. Consider first the case that $H_s = 0$. Thus, athletic involvement does not itself affect skill formation but confounding factors may cause a spurious relationship between athletic involvement and human capital measures. For instance, athletic involvement and skills are positively correlated if family background affects the marginal identity utility of sports ($I_{sx} > 0$). Similarly if athletic involvement does contribute to the accumulation of skills ($H_s > 0$), its true effect may be misstated when heterogeneity in family background is not taken into account. In our empirical analysis, we therefore take great care to control for family background. Further, if athletic in-

[6] If the activity of interest does not affect skill formation, i.e. the first derivative of human capital with respect to the activity of interest is zero, there can be no cross effects with other activities that affect skills, i.e. the cross derivative of human capital with respect to the activity of interest and the other activity is zero.

volvement contributes to skill formation ($H_s > 0$), we need to keep the engagement in formal learning and other structured activities fixed. Athletic involvement is correlated with the other activities whose productivity with respect to skill formation interacts with athletic involvement. Heterogeneity in the marginal costs associated with the different activities will provide the necessary exogenous variation in sports participation conditional on family background and engagement in other activities.

2.2 Econometric Approach

In order to estimate the ceteris paribus effect of playing sports on the formation of human capital we rely on a version of the potential outcome approach (Neyman, 1923; Roy, 1951; Rubin, 1974) in which the treatment is vector valued. A vector valued treatment arises naturally in the context of a production technology with multiple inputs that are determined simultaneously. Specifically, let $\mathbf{A}$ denote the vector of inputs. The different elements of $\mathbf{A}$ are random variables that potentially depend on each other. If the elements of $\mathbf{A}$ depend on each other, the production technology exhibits cross-effects in the sense that the level of one input affects the productivity of other inputs. In our case, $\mathbf{A}$ corresponds to a string of variables indicating the extent to which somebody engages in different types of educational and leisure activities. To be concrete suppose that $\mathbf{A} \equiv (\mathbf{E}, S, \mathbf{L})$, where $\mathbf{E}$ is a vector of dummy variables measuring the engagement in formal education, S a dummy equal to one if somebody plays sports (the treatment of interest) and $\mathbf{L}$ a vector of dummy variables measuring the engagement in other leisure activities. Denote by the scalar random variable $Y(\mathbf{a})$ the potential output prevailing under input setting $\mathbf{A} = \mathbf{a} = (\mathbf{e}, s, \mathbf{l})$. We use the scalar random variable Y to denote the actual output. It holds that for somebody producing with input setting $\mathbf{a}$ we observe $Y(\mathbf{a})$, while potential outputs associated with alternative input settings $\mathbf{a}' \neq \mathbf{a}$, $Y(\mathbf{a}')$, are counterfactual.

Our goal is to contrast potential outputs associated with input settings that involve sports, i.e. $S = 1$, to potential outputs associated with input settings that do not involve sports, i.e. $S = 0$, keeping the other inputs constant. In particular, we are interested in the average direct effect of sports on those who play sports

$$(2) \quad \Delta_T \equiv \sum_j \sum_k \Pr(\mathbf{E} = \mathbf{e}_j, \mathbf{L} = \mathbf{l}_k \,|\, S = 1) \mathrm{E}[Y(\mathbf{e}_j, 1, \mathbf{l}_k) - Y(\mathbf{e}_j, 0, \mathbf{l}_k) \,|\, S = 1] \,,$$

where j and k index the possible settings of $\mathbf{E}$ and $\mathbf{L}$, the average direct effect on

the untreated

$$(3) \quad \Delta_U \equiv \sum_j \sum_k \Pr(\mathbf{E} = \mathbf{e}_j, \mathbf{L} = \mathbf{l}_k \,|\, S = 0) \mathrm{E}[Y(\mathbf{e}_j, 1, \mathbf{l}_k) - Y(\mathbf{e}_j, 0, \mathbf{l}_k) \,|\, S = 0] \,,$$

and the average direct effect in the total population

$$(4) \qquad \Delta \equiv \Pr(S = 1)\Delta_T + \Pr(S = 0)\Delta_U \,.$$

The expectations $\mathrm{E}[Y(\mathbf{E}, 0, \mathbf{L}) \,|\, S = 1]$ and $\mathrm{E}[Y(\mathbf{E}, 1, \mathbf{L}) \,|\, S = 0]$ are counterfactual. In order to solve the evaluation problem we rely on the conditional independence assumption (CIA):

$$(5) \qquad \begin{aligned} &\mathrm{E}[Y(\mathbf{e}, s, \mathbf{l}) \,|\, \mathbf{X} = \mathbf{x}, \mathbf{E} = \mathbf{e}, S = 1, \mathbf{L} = \mathbf{l}] \\ &= \mathrm{E}[Y(\mathbf{e}, s, \mathbf{l}) \,|\, \mathbf{X} = \mathbf{x}, \mathbf{E} = \mathbf{e}, S = 0, \mathbf{L} = \mathbf{l}] \,, \; s = 0, 1 \,, \end{aligned}$$

with $\mathbf{X}$ a vector of observed background characteristics. According to the CIA the potential outcomes $(Y(\mathbf{e}, 1, \mathbf{l}), Y(\mathbf{e}, 0, \mathbf{l}))$ are mean independent of the athletic status S conditional on the observed covariates $\mathbf{X}$ and engagement in other activities $(\mathbf{E}, \mathbf{L})$. Economically the CIA means that, by appropriately varying the marginal costs of all inputs, $\mathbf{A}$, we can find two individuals that have the same background characteristics $\mathbf{X}$, the same allocation of inputs $\mathbf{E}$ and $\mathbf{L}$, but a differing allocation of S. Thus, heterogeneity in the marginal costs of the inputs across individuals provides exogenous variation in the level of input S conditional on background characteristics $\mathbf{X}$ and keeping constant the allocation of $\mathbf{E}$ and $\mathbf{L}$. We motivate the empirical content of the CIA in our application in Section 2.3 below. Under the CIA, the conditional causal effect $\mathrm{E}[Y(\mathbf{e}, 1, \mathbf{l}) - Y(\mathbf{e}, 0, \mathbf{l}) \,|\, \mathbf{X} = \mathbf{x}, \mathbf{E} = \mathbf{e}, \mathbf{L} = \mathbf{l}]$ is identified from the conditional contrast of the actual outcomes:

$$(6) \qquad \begin{aligned} &\mathrm{E}[Y(\mathbf{e}, 1, \mathbf{l}) - Y(\mathbf{e}, 0, \mathbf{l}) \,|\, \mathbf{X} = \mathbf{x}, \mathbf{E} = \mathbf{e}, \mathbf{L} = \mathbf{l}] = \\ &\mathrm{E}[Y \,|\, \mathbf{X} = \mathbf{x}, \mathbf{E} = \mathbf{e}, S = 1, \mathbf{L} = \mathbf{l}] - \mathrm{E}[Y \,|\, \mathbf{X} = \mathbf{x}, \mathbf{E} = \mathbf{e}, S = 0, \mathbf{L} = \mathbf{l}] \,. \end{aligned}$$

Further, we require that the conditional probability of participating in sports is strictly greater than zero and smaller than one, which gives rise to the following common support assumption:

$$(7) \quad 0 < P(\mathbf{x}; \mathbf{e}, \mathbf{l}) < 1 \,, \text{ where } P(\mathbf{X}; \mathbf{e}, \mathbf{l}) \equiv \Pr(S = 1 \,|\, \mathbf{X} = \mathbf{x}; \mathbf{E} = \mathbf{e}, \mathbf{L} = \mathbf{l}) \,.$$

Finally, we assume that potential outcomes are independent across individuals, ruling out general equilibrium effects.

Under the common support assumption, the ATT given $\mathbf{E} = \mathbf{e}$ and $\mathbf{L} = \mathbf{l}$ is identified by integrating the conditional causal effect, equ. (6), over the distribution of $\mathbf{X}$ given

$\mathbf{E} = \mathbf{e}$, $S = 1$ and $\mathbf{L} = \mathbf{l}$:

(8)

$$\Delta_T(\mathbf{e}, \mathbf{l}) \equiv$$

$$\int \cdots \int \mathrm{E}[Y(\mathbf{e}, 1, \mathbf{l}) - Y(\mathbf{e}, 0, \mathbf{l}) \,|\, \mathbf{X}, \mathbf{E} = \mathbf{e}, S = 1, \mathbf{L} = \mathbf{l}] dF(\mathbf{X} \,|\, \mathbf{E} = \mathbf{e}, S = 1, \mathbf{L} = \mathbf{l})$$

because $F(\mathbf{X} \,|\, \mathbf{E} = \mathbf{e}, S = 1, \mathbf{L} = \mathbf{l}) = \dfrac{P(\mathbf{X}; \mathbf{e}, \mathbf{l}) F(\mathbf{X} \,|\, \mathbf{E} = \mathbf{e}, \mathbf{L} = \mathbf{l})}{\Pr(S = 1, \mathbf{E} = \mathbf{e}, \mathbf{L} = \mathbf{l})}$. Finally, we can obtain the grand ATT of activity S by integrating $\Delta_T(\mathbf{e}, \mathbf{l})$ over the distribution of $\mathbf{E}$ and $\mathbf{L}$:

$$\Delta_T = \sum_j \sum_k \Delta_T(\mathbf{e}_j, \mathbf{l}_k) \Pr(\mathbf{E} = \mathbf{e}_j, \mathbf{L} = \mathbf{l}_k \,|\, S = 1)\,, \tag{9}$$

where j and k index the possible settings of $\mathbf{E}$ and $\mathbf{L}$, respectively. The grand ATU of S is obtained analogously.

Collect all conditioning variables in a vector denoted by $\mathbf{Z} \equiv (\mathbf{X}, \mathbf{E}, \mathbf{L})$. The estimation proceeds in two steps. In a first step, we apply kernel matching techniques and reweight observations so as to align the distribution of $\mathbf{Z}$ in the treatment and comparison samples. With a large number of elements in $\mathbf{Z}$, it is typically easier to match on a low dimensional balancing score rather than on $\mathbf{Z}$ itself, see Rosenbaum and Rubin (1983).[7] Here, we match on the index of the estimated propensity score. We implement a stratified version of kernel matching in order to align treated and comparison observations exactly by gender and school track. Also we specify separate propensity score models for each of the four subsamples defined by gender and school track.

Then we estimate the average treatment effect on the treated (ATT) by means of the following weighted regression

$$\min_{\{\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta}\}} \sum_n \hat{g}_n \left[Y_n - \hat{\alpha} - \hat{\beta} S_n - \hat{\gamma} \mathbf{Z}_n - \hat{\delta} S_n (\mathbf{Z}_n - \bar{\mathbf{Z}}) \right]^2, \tag{10}$$

where $n = 1, 2, \ldots$ indexes the observations, $\hat{g}$ is a weight, and $\bar{\mathbf{Z}}$ is the mean of $\mathbf{Z}$ across the treated observations, i.e. $\bar{\mathbf{Z}} = \sum_n \hat{g}_n S_n \mathbf{Z}_n / \sum_n \hat{g}_n \mathbf{Z}_n$. The coefficient β corresponds to Δ_T, the ATT.[8]

For any treated observation i, $\hat{g}_i$ equals the sampling weight v_i of that observation. For any comparison observation j, $\hat{g}_j$ is given by $\sum_{i \in \{n: S_n = 1\}} v_i \hat{w}_{ij}$, where $\hat{w}_{ij}$ is the

[7] To see that the balancing theorem of Rosenbaum and Rubin (1983) holds also in our setting write $\mathrm{E}[S \,|\, Y(\mathbf{e}, 1, \mathbf{l}), Y(\mathbf{e}, 0, \mathbf{l}), P(\mathbf{X}; \mathbf{e}, \mathbf{l})] = \mathrm{E}\{\mathrm{E}[S \,|\, Y(\mathbf{e}, 1, \mathbf{l}), Y(\mathbf{e}, 0, \mathbf{l}), P(\mathbf{X}; \mathbf{e}, \mathbf{l}), \mathbf{X}, \mathbf{E} = \mathbf{e}, \mathbf{L} = \mathbf{l}] \,|\, Y(\mathbf{e}, 1, \mathbf{l}), Y(\mathbf{e}, 0, \mathbf{l}), P(\mathbf{X}; \mathbf{e}, \mathbf{l})\}$ and apply the CIA to the inner expectation.

[8] We obtain the average treatment effect on the nontreated, Δ_U, analogously using an indicator variable for nontreatment status instead of S. The negative of β then corresponds to Δ_U.

matching weight that is larger the closer comparison observation j is to treated observation i in terms of the estimated propensity score. In our case of the local linear estimator $\hat{w}_{ij}$ equals

$$(0,1)\left[\sum_j \left((\hat{P}_j-\hat{P}_i),1\right)' K\left(\frac{\hat{P}_j-\hat{P}_i}{h}\right)\left((\hat{P}_j-\hat{P}_i),1\right)\right]^{-1}\left((\hat{P}_j-\hat{P}_i),1\right)' K\left(\frac{\hat{P}_j-\hat{P}_i}{h}\right),$$

where $K(.)$ is the Gaussian kernel, $\hat{P}$ the fitted propensity score, and h the bandwidth.[9]

Estimating the ATT as in (10) with an additional regression adjustment allows us to combine the advantages of both methods, matching and regression. The semiparametric matching estimator requires a careful choice of suitable control observations for each treated observation. Thus, we avoid comparisons based on extrapolations that are not supported by the data. The regression model yields a consistent and efficient treatment effect estimate if the conditional independence assumption, eq. (5), holds and if eq. (10) correctly models the conditional expectation $\mathrm{E}[Y \mid \mathbf{X}, \mathbf{E}, S, \mathbf{L}]$. Combining matching with an additional regression adjustment has the advantage that the treatment effect estimate is consistent if either the propensity score (and thus w_{ij}) or the outcome regression model is correctly specified (Robins and Ritov, 1997; Imbens, 2004). Put differently, if the treatment status is random in the reweighted sample, the estimated treatment effect should be robust to modifications of the outcome regression model. If the treatment effect estimates obtained with different regression adjustments coincide we interpret this as supporting evidence for our matching model. Finally, we use the regression on the reweighted sample to examine treatment effect heterogeneity.

We obtain standard errors and confidence bands for our estimated treatment effects through bootstrapping based on 250 resamples. We resample families to account for serial correlation across siblings. In each resample, we recompute the propensity score using a draw from the asymptotic distribution of the coefficients in the propensity score model. This allows us to take account of the estimation error in the propensity score.

[9] We obtain the bandwidth through a crossvalidation procedure suggested in Bergemann, Fitzenberger, and Speckesser (2009). We also implemented the Nadaraya-Watson estimator to examine the sensitivity of our results to the choice of matching estimator. The treatment effect estimates are nearly the same.

2.3 Specification of the Propensity Scores and Balancing Tests

Our theoretical framework highlights the importance to control for the youths' family background and time use. We consider detailed information on the youths' involvement in other leisure activities such as television and computer usage, frequency of reading a book, doing cultural and musical activities, volunteering and working part-time to improve pocket money. We control for the youths' migration background, birth order and quarter of birth. As proxies for lagged human capital and cognitive skills we condition on the teacher's recommendation for secondary school type at the end of elementary school as well as an indicator for whether the youth has ever repeated a grade.

At the level of the family, we control for educational attainment of the parents as well as their average past earnings and standard deviation to capture income variations. We also use information about parental locus of control, measured by the Rotter scale, and personality traits, measured by the Big-Five model.[10] We further take into account parental leisure activities like sports, cultural activities, volunteering as well as their television and computer usage. In addition, we control for the number of years a youth lived with either parent up to the age of 15. We also include indicators on the quality of the relationship between adolescent and parents, e.g. importance of parents, frequency of conflicts. As proxies for the neighborhood and local environment we include indicators for the German federal states, the type of region in which one grew up (e.g. metropolitan area or countryside) and variables measuring local labor market conditions. Further, we consider the composition of the school class, i.e. the share of students with a foreign origin.

We fit the propensity scores separately for each of the subsamples, stratified by gender and school track, and run an extensive specification search. We start with a comprehensive specification and drop variables that are grossly insignificant. This procedure leads to satisfactory specifications in most cases. In the few cases in which the balancing condition fails, we further revise the specification and include additional interactions until we achieve balance. The final specifications are chosen along the following criteria: (i) our theoretical knowledge regarding potentially important drivers of participation and outcomes, (ii) empirical significance, and (iii) balancing of the covariates in the treatment and control samples.

As a first balancing test, we use the regression test suggested in Smith and Todd

[10] Detailed information on the covariates is provided in Section B of the Online-Appendix.

(2005). We regress each covariate used in a given propensity score specification on a quartic in the estimated propensity score, the treatment dummy and the cubic of the propensity score interacted with the treatment dummy. If the terms involving the treatment dummy are jointly insignificant, the treatment and comparison samples are balanced with respect to the regressor under consideration. As a second balancing test, we apply our matching procedure to a set of important variables (regardless of whether they were finally included in a particular propensity score model) and check whether the means differ across matched treatment and comparison samples.

In the spirit of Heckman and Hotz (1989) we further assess the validity of our matching strategy by testing whether the means of placebo-outcomes are balanced in the treatment and comparison samples after matching. The placebo-outcomes are human capital measures that are predetermined with respect to athletic involvement during late childhood and youth. In particular, we consider measures of height and intelligence. In developed countries, height and growth during adolescence are essentially determined by genes (80%) and the quality of the uterine through early childhood environment, see Silventoinen (2003), Visscher et al. (2006) and the discussion in Case and Paxson (2008). Thus, height during adolescence evolves independently of adolescent experiences such as sports but is correlated with parental socioeconomic background and skills. Similarly, somebody's rank in the intelligence distribution is stable after about age 6, with genes accounting for the majority (up to 80%) of the variation across adolescents and adults in a given cohort (Cunha et al., 2006; Neisser et al., 1996; Nisbett et al., 2012). Consequently, we apply our matching procedure to measures of height and intelligence. If our matching procedure works well, these predetermined human capital measures should be balanced in the matched treatment and comparison samples.

3 Data and Analysis Sample

Our empirical analysis uses data from the German Socio-Economic Panel Study (SOEP), a representative annual household panel covering more than 11,000 households in Germany.[11] In addition to the standard household and person questionnaires, the SOEP devises since 2000 a specific youth biography questionnaire to all young people turning 17 in the corresponding year. It includes detailed information on family background and childhood, past and current involvement in different

[11] We use the data distribution 1984-2011, `http://dx.doi.org/10.5684/soep.v28`. See Wagner et al. (2007) and Wagner et al. (2008) for further information.

leisure and educational activities, academic performance, career plans as well as attitudes about different topics. Our main analysis sample consists of all youths who completed this questionnaire in the years 2001 to 2011. We add information from past and current parental questionnaires to construct further variables describing the family background, such as parental earnings and involvement in leisure activities. Using the surveys conducted in subsequent years we collect additional information on behavioral and economic outcomes of the youths until their early twenties.

Our main measures of athletic involvement are based on the following two questions in the youth biography questionnaire: *Do you play a particular sport?* and *How often do you play sports?* We define as athletes all those who play sports at least on a weekly basis. We exclude individuals with missing or ambiguous answers on the two questions as well as disabled adolescents. In some of our analyses, we further distinguish between different sport intensities (daily, weekly), sport types (team, individual) and social contexts (nonprofit club, commercial facility, unorganized). In most of our analyses, we stratify the sample according to gender and type of secondary school track. In particular, we distinguish between a vocationally and an academically oriented school track. Tracking generally takes place at age 9-10 and depends on academic ability and socioeconomic background, with more advantaged students in terms of ability and family background attending the academic track.[12] We also exclude youths with missing information on school track or attending integrated school types. Overall our sample consists of 3,343 young people (see table 1).

— Insert table 1 here. —

4 Empirical Results

4.1 Patterns of Athletic Involvement and Leisure Time Use

In our sample of (almost) 17-year olds, about two thirds of the young men and about half of the young women engage in sports at least on a weekly basis, see figure 1.

[12]The vocationally oriented school track subsumes the two lower tiers of general secondary schooling in Germany, Hauptschule and Realschule. They last until grade nine and ten, respectively, and prepare for vocational training. The academically oriented school track, Gymnasium, lasts until grade twelve or 13 and prepares for tertiary education. Students on the vocational track with good marks may move on to the academic track after completing the tenth grade. We classify the movers also in the vocational track to ensure that the adolescents in each subsample have a comparable school history.

24% of the young men and 11% of the young women exercise even daily. 36% (21%) of the young men (women) participate in athletic competitions and 37% (20%) of the young men (women) play a team sport. Among male athletes, the by far most popular sport is soccer (42.50%) followed by training in a fitness club (8.27%) and biking (5.08%). The picture is more diverse for female athletes. The top three sports are dancing (13.35%), horseback riding (10.24%) and volleyball (9.89%), see table 2.

— Insert figure 1 here. —

— Insert table 2 here. —

For the vast majority of young athletes sports is a social activity. Table 3 provides a breakdown by sport type and social context. Two thirds of the athletes play sports in a nonprofit club. In Germany there exists a wide network of such clubs, covering also rural areas. They rely on small membership fees[13] and, importantly, volunteer work by the members and their relatives. Thus, they provide important opportunities for social engagement beyond exercising a particular sport. The local clubs are part of umbrella associations that set general rules and structures. For instance, the German Football Association (Deutscher Fussball-Bund) regulates the organization of youth teams and leagues, provides training for coaches and referees, and formulates athletic as well as psychosocial goals of youth work.

— Insert table 3 here. —

Figure 2 illustrates how the athletic involvement of the 17-year olds evolves with age. Panel (a) shows how many of the young athletes as of age 17 were already exercising their main current sport at a given earlier age denoted on the horizontal axis. 78% of the male athletes and 69% of the female athletes played their current sport already at age 13. Likewise, panel (b) shows how many of the athletes continue to be active during young adulthood. According to panel (b), 67% of the male athletes and 55% of the female athletes continue to exercise at least weekly at age 21. Thus, there is a higher degree of persistence in the athletic involvement over time for males than for females. Figure 3 shows that 70% (80%) of the male (female) non-athletes as of

[13]The median fee for youths is €3.60 per month, Breuer et al. (2005), table 1. About a quarter of the clubs charge small admission fees (the median is €10) and the majority offers reduced family rates.

age 17 continue to be inactive throughout their early 20s. In sum, these patterns suggest that athletic engagement and non-engagement largely persist throughout adolescence and into young adulthood.

— Insert figure 2 here. —

— Insert figure 3 here. —

Figure 4 provides an overview over how the 17-year olds in our sample allocate their free time. They devote about two thirds of their leisure time to sedentary activities (i.e. reading, listening to music, media use, doing nothing) and more than 80% to unstructured activities (i.e. sedentary activities plus activities with peers). Students on the academic track tend to spend more time in structured activities or reading than those on the vocational track (panels a, b versus c, d). While the general patterns are similar for youths who play sports at least on a weekly basis (panels a, c) and those who do not (panels b, d), athletes spend a higher share of their discretionary time on non-sedentary and structured activities. In particular, young athletes on the vocational track spend 14% and 34% of their free time on structured activities and non-sedentary activities, respectively, whereas non-athletes spend only 8% and 29% on such activities. The corresponding numbers for youths on the academic track are 16% and 34% for athletes versus 12% and 31% for non-athletes. These differences between athletes and non-athletes are statistically significant. Further, the clear dominance of passive, undirected leisure pursuits among all groups suggests that overscheduling is no issue. A similar dominance of passive, undirected leisure activities has also been documented in studies investigating the time use of teenagers in the US (Wight et al., 2009) and other Western countries (Larson and Verma, 1999).

— Insert figure 4 here. —

Table 4 shows the engagement in other, non-athletic structured leisure activities by athletic status. We consider all non-athletic structured activities (i.e. playing music or singing, acting, technical activities, and volunteering) that are performed at least on a weekly basis. The table reveals interesting differences between youths on the vocational track and youths on the academic track. Among youths on the vocational track, athletes are no less likely to engage in other structured leisure activities than non-athletes. On the contrary, while more than half of the female athletes engage in

an additional structured activity, only a third of the female non-athletes engages in a non-athletic structured activity. Among youths on the academic track, the pattern is reversed. Non-athletes show an about 10 percentage point higher probability to engage in non-athletic structured leisure activities than athletes. Overall, these patterns are in line with the evidence in figure 4. For youths on the academic track sports seems to be just one of several structured leisure activities. Those youths who do not play sports engage to a larger extent in non-athletic structured activities. Among youths on the vocational track, in contrast, a sizeable share of youths engages in no structured leisure activity (i.e. 20% of the males and 40% of the females, combining the information in tables 1 and 4) or in just one activity, which is sports in the majority of cases. In this sense, sports can be seen as an entry-level structured activity.

— Insert table 4 here. —

4.2 Selectivity of Athletic Involvement

Tables 5 and 6 show descriptive statistics for a subset of the covariates used in the propensity score estimations and predetermined human capital measures referring to height and intelligence.[14] Most remarkable is the strong positive relationship between parental athletic involvement and the youths' own involvement. The correlation is stronger for youths on the vocational school track and girls as well as between parents and children of the same sex. For instance, athlete girls exhibit a 1.3 to 1.8 times higher share of mothers who play sports than non-athlete girls.

Further, in each school track, athletes tend to be positively selected with respect to socioeconomic background. In both school tracks, this effect is stronger for girls than for boys, who exhibit a higher athletic involvement than girls. For instance, athletes are 4 to 12 percentage points (8-27% of a standard deviation in the full sample) more likely to have a parent with a tertiary education degree. Athletes are also more likely to have grown up with both parents. The parents of female athletes earn (before taxes) between €3,600 and 6,500 more a year than those of non-athletes, while there are no clear differences in the male samples. Consistent with research documenting a positive relationship between teen height, socioeconomic background, and extracurricular engagement (Postlewaite et al. 2004, Case and Paxson, 2008), we find differences in height of 1 to 2 cm (0.4-0.9 in, 11-20% of a standard deviation)

[14]Descriptive statistics of the remaining covariates can be found in Section B of the Online-Appendix.

between athletes and non-athletes. However, the differences in socioeconomic status between athletes and non-athletes within a given school track tend to be much smaller than the differences in socio-economic status between youths on different school tracks. In particular, the parental earnings gap between school tracks is about €20,000 (more than 60% of a standard deviation).

Consistent with the patterns found for socioeconomic background and height, the descriptive statistics suggest moderate differences between athletes and non-athletes with respect to past academic performance and intelligence. While the share of youths who have ever repeated a grade is about equal in the athlete and non-athlete groups, a larger share of the athletes was recommended at the end of grade four to continue on the academic secondary school track (4-13 percentage points, 8-25% of a standard deviation). Athletes also tend to score higher in the three ability tests.[15] For verbal and numerical ability of male students on the academic track and numerical ability of female students on the academic track, the differences are significant at the ten percent level. However, male athletes on the vocational track score significantly lower in verbal ability than non-athletes. Again, the differences in intelligence between athletes and non-athletes within a given school track are much smaller than the differences between youths across school tracks. Finally, regional conditions do not seem to matter much for athletic engagement. There are no systematic patterns for whether someone grew up in a city and only a weakly negative relationship between the regional unemployment rate and athletic involvement.

— Insert table 5 here. —

— Insert table 6 here. —

Similar selectivity patterns emerge, as those apparent in the descriptive statistics, when we fit the propensity scores. The propensity scores rely on a rich set of covariates and we specify separate models for each of the four subsamples.[16] The overlap of the propensity score distributions between athlete and non-athlete groups is all in all satisfactory. We delete only a small fraction of observations that lie outside the common support region (panel a in table 7). We achieve excellent balancing of the covariates included in the propensity scores as well as excluded variables.

[15] The three measures of intelligence have been standardized in the full sample. They are based on a validated short version of a standard intelligence test used in German speaking countries, see Amthauer et al. (2001) and Solga et al. (2005).

[16] See Section B in the Online-Appendix for a complete list of the variables used and Section C for the estimation results involving the propensity scores.

According to panel (b) in table 7, for nearly all the covariates included in a given propensity score specification the Smith/Todd (2005)-test fails to reject at the five percent level. This suggests that athletic status does not predict the covariate under consideration after conditioning on the propensity score. Panels (c) and (d) in table 7 show further that, before matching, between 13% (men, academic track) and 26% (women, academic track) of the covariates had significantly different means in the target and comparison groups. Once the matching weights are applied there are no significant differences anymore.

To further probe our matching strategy we examine the balancing of human capital measures that are determined at an age before children start playing sports. In particular, we consider measures of height and intelligence. Table 8 shows that there are indeed significant differences between athletes and non-athletes before matching, especially for youths on the vocational track. However, in the matched samples the p-values from a test of equality of means are large in the vast majority of cases. Only in one case, intelligence for men in the vocational track the p-value after matching is smaller than 0.05. In fact, male athletes on the vocational track score actually worse than non-athletes. This evidence lends support to our matching strategy as there likely remain no unmeasured confounders. From a substantive point of view the findings suggest that our matching strategy effectively balances heterogeneity in skills related to genetic and early childhood environments.

— Insert table 7 here. —

— Insert table 8 here. —

4.3 Athletic Involvement and Behavioral Outcomes

Tables 9 to 20 show the sample means and treatment effect estimates for the behavioral outcome variables that reflect character, social, and executive function skills. The behavioral variables are derived from a series of factor analyses that are documented in Section D in the Online-Appendix. All outcome variables are standardized to allow a comparison of effect sizes across outcomes. The results for youths on the vocational school track and the academic school track are reported in separate tables. Each table reports estimates for men and women separately as well as for the pooled sample. In any case, we match exactly on gender, the estimates differ only in the regression adjustment that is done separately in the male and female samples

and jointly in the pooled sample.[17]

We first turn to impact estimates for outcome variables reflecting character skills. In particular, we focus on the Big Five personality inventory and locus of control. The Big Five model distinguishes five dimensions of personality: openness to experience, conscientiousness (i.e. the tendency to be organized, responsible and hardworking), extraversion, agreeableness (i.e. the tendency to act in a cooperative, unselfish manner) and neuroticism (i.e. the tendency to be emotionally instable and prone to psychological distress), see Almlund et al. (2011) for an overview.[18] Locus of control refers to the extent to which people believe that they can control their life (internal and external locus of control).[19] A growing body of empirical research has started to document the importance of character skills in predicting economic outcomes such as educational attainment and earnings. Almlund et al. (2011) survey evidence showing that, of the Big Five, conscientiousness stands out for its strong positive association with educational and labor market performance. Agreeableness and an internal locus of control have also been found to be positively related with economic outcomes.

Tables 9 and 10 show the effects of athletic involvement on the Big Five personality dimensions. Girls score higher in each of the personality traits than boys, regardless of the school track. For the vocational track we find in most cases a positive effect of participating in sports on the students' personality traits, except for neuroticism. The effects are in four out of five cases larger for male students and also more often statistically significant. In particular, the average treatment effects (ATE) for conscientiousness and agreeableness are at 28% and 17% of a standard deviation and statistically significant, respectively. The pooled impact estimates for extraversion and openness are at 18-19% of a standard deviation and statistically significant. For youths on the academic track, we find positive (7-15% of a standard deviation) and insignificant effects on extraversion and openness.

— Insert table 9 here. —

— Insert table 10 here. —

Table 11 and 12 display the effects on locus of control. We find in general similar

[17]The outcome regression model for the pooled sample includes in addition a gender dummy.

[18]The items for the Big Five personality inventory in the SOEP have been developed and validated by Gerlitz and Schupp (2005). They are included in the questionnaire since 2006.

[19]The items on locus of control in the SOEP are based on the framework by Rotter (1966), see Weinhardt and Schupp (2011).

patterns across gender and school track. Athletic involvement decreases the extent to which youths believe that events in their life are a consequence of luck or destiny (external locus of control) and increases the extent to which they believe that events are a consequence of their own effort (internal locus of control). For youths on the vocational track, the ATEs are in the order of 15-17% of a standard deviation for young men and 15-19% for young women (table 11). The effects for youths on the academic track tend to be smaller again and not statistically significant.

— Insert table 11 here. —

— Insert table 12 here. —

Next we turn to impact estimates for outcome variables reflecting social skills and risk preferences. Panels (a) and (b) of table 13 and 14 show the estimates for reciprocity.[20] While positive reciprocity measures the inclination to reward fair and cooperative behavior of another person, negative reciprocity refers to the willingness to punish somebody who behaves unfair or uncooperative. The treatment effect estimates for the vocational track samples suggest that athletic involvement reduces a teenager's willingness to punish unfair or uncooperative behavior, panel (a) of table 13. The treatment effects for females are almost twice as large than those for males. For instance, the average treatment effect (ATE) is -24% of a standard deviation for girls as opposed to -11% for boys. Unlike the results on negative reciprocity, the effects on positive reciprocity are generally smaller and insignificant, panel (b) of table 13. The patterns for the vocational track samples differ from those for young people on the academic track, where the treatment effect estimates are mostly small and insignificant, panels (a) and (b) of table 14. Only positive reciprocity of female students on the academic track increases by 25% of a standard deviation through playing sports. However, the treatment effects are not significant.

— Insert table 13 here. —

Panel (c) of tables 13 and 14 show the results on willingness to take risks. We find stronger and significant effects for youths on the vocational track, see panel (c) of table 13.[21] The average treatment effects (ATE) are 22% for boys and 17% for girls,

[20] The measures of reciprocity in the SOEP are based on the framework of Perugini et al. (2003). Dohmen et al. (2009) document that the SOEP survey responses on reciprocity are consistent with the behavioral patterns generated in experiments.

[21] Dohmen et al. (2011) validate the SOEP risk measure experimentally. They document that the SOEP question reliably predicts risk taking behavior in the experiment.

and statistically significant. The impact estimates for the academic track samples are again insignificant and close to zero, panel (c) of table 14.

— Insert table 14 here. —

What are the economic implications of our findings on social skills and risk preferences? Brown et al. (2004), Dohmen et al. (2009) and Kube et al. (2012) show that positive reciprocity is important for sustaining employment relationships in which the employer pays the employee an efficiency wage in order to stipulate a higher effort. Thus, there is a positive relationship between positive reciprocity and wages. Similarly, an employer may find it rational to dismiss an employee rather than to lower the wage in order to avoid a retaliatory response (Bewley, 1998). This argument suggests a positive relationship between negative reciprocity and nonemployment, which is confirmed empirically by Dohmen et al. (2009) and Kube et al. (2013). Further empirical research (see e.g. Bonin et al., 2007, and the references therein) documents a positive association between risk tolerance on the one hand and educational attainment, choice of occupation and earnings on the other. Thus, our findings regarding social and risk preferences may contribute to explaining the positive effects of athletic involvement on educational and labor market outcomes.

Next, we discuss the results on job values.[22] In the psychological and sociological literature job values play a prominent role in describing young people's identity and career aspirations (see e.g. Rosenberg, 1957, Johnson and Mortimer, 2011). They are a key driver of occupational choices and career attainment at later ages. Tables 15 and 16 display the results on five different work values for the vocational track samples and the academic track samples. Comparing the means across gender, we see that males score lower than females in all but one (i.e. pay and promotion) cases. This pattern suggests that young men have on average less idealistic views about themselves and their future career than young women. For pay and promotion, in contrast, we observe a clear socioeconomic divide. Youths attending the vocational track value pay and promotion much higher than those on the academic track.

— Insert table 15 here. —

The treatment effect estimates for youths on the vocational track are positive and often significant. Their magnitude ranges between 10 and 30% of a standard devi-

[22]The theory and measurement of job values go back to Rosenberg (1957). The questions on job values in the SOEP include additional items on work-life balance, see Weinhardt and Schupp (2011).

ation, with the effects for males often exceeding those for females. Contrary to the general pattern, there is no effect of athletic involvement on how important young men rate work-life balance, while the ATE for females attains 18% and is statistically significant. Importantly, the effects on how important youths rate high pay and good promotion opportunities (panel b of table 15) are with around 20% of a standard deviation large and highly significant. Sociological research documents a positive correlation between values reflecting extrinsic orientations, including pay, promotion and security, as well as hours worked and earnings (Johnson and Mortimer, 2011). Unlike for the vocational track samples, the impact estimates for the academic track samples are often small and insignificant, table 16.

— Insert table 16 here. —

At this point it is interesting to compare the effects of athletic involvement on the youths' aspirations with those on their expectations about their own future and the determinants of social success more generally. Tables 17 and 18 show the results for their attitudes about the determinants of social success.[23] We distinguish between three major factors of social success. The first one refers to extrinsic factors, such as gender and family background, the second to positive intrinsic factors, such as achievement and industriousness, and the third to negative intrinsic factors, such as being tough and exploiting others. Athletic involvement clearly appears to have a positive effect on how youths on the vocational track think about moving up in society. Playing sports makes them belief more strongly that success depends on positive intrinsic factors rather than extrinsic or negative intrinsic factors. The effects tend to be larger in absolute value for girls than for boys. In particular, the ATE for young women is -33% of a standard deviation for extrinsic factors, -27% for negative intrinsic factors and 14% for positive intrinsic factors. This suggests that athletic involvement contributes to reinforcing gender differences in beliefs about success. The patterns for the academic track samples in table 18 are less clear cut. For young women on the academic track, the point estimates tend to be smaller compared with those for the vocational track and statistically insignificant. In contrast for young men on the academic track, we find sizeable and statistically significant adverse effects of athletic involvement on extrinsic and negative intrinsic factors.

— Insert table 17 here. —

[23]The battery of items included in the SOEP is originally due to Sandberger (1983), see Weinhardt and Schupp (2011) for further information.

— Insert table 18 here. —

Tables 19 and 20 display means and impact estimates for outcomes reflecting future expectations. Our expectation measures capture career related as well as family related aspects. The means of all three variables are lower in the vocational track samples than in the academic track samples, which suggests that young people from less advantaged backgrounds have less optimistic expectations. Athletic involvement has a positive effect on career and family expectations. When significant the treatment effects attain 19 to 30% of a standard deviation in the vocational track samples (table 19). The patterns for the academic track samples closely match those for the vocational track samples (table 20). For instance, the ATEs on career expectations attain 22-25% of a standard deviation and are statistically significant for boys. The positive treatment effects on career expectations are consistent with the positive effects of athletic involvement on career aspirations. Taken together they support the hypothesis that athletic involvement positively affects educational attainment and labor market outcomes because it raises the teenagers' self-confidence and optimism as well as their aspirations.

— Insert table 19 here. —

— Insert table 20 here. —

4.4 Athletic Involvement and Economic Outcomes

As a consistency check on the effects on economically relevant behavioral outcomes, we also investigate the effects of athletic involvement on educational and labor market outcomes. In order to make the impact estimates comparable to those on behavioral outcomes, the outcome variables are again standardized. Tables 21 and 22 show the treatment effects on educational attainment. Consistent with the effects on behavioral outcomes, the impact estimates in tables 21 and 22 indicate beneficial effects of athletic involvement on educational attainment. This is remarkable, since we carefully condition on past and current educational activities of the youths at the time we measure their athletic status. For young men on the vocational track, athletic involvement reduces the probability to leave school without a degree and increases the probability to successfully complete the vocational track. We observe a similar pattern for young women on the vocational track: The probability to continue to and complete the academic track increases, while the probability to leave

school with a vocational track certificate is reduced. In addition, we find a positive (but insignificant) effect on the probability to attend university. For the academic track samples there are no statistically significant effects, but the patterns suggest again positive effects on educational attainment.

— Insert table 21 here. —

— Insert table 22 here. —

Tables 23 and 24 show the results for enrolment in vocational training. Panels (a) and (b) display the effect of participating in sports on the probability of attending vocational training for at least one and two consecutive years, respectively. Panel (c) shows the effect on the probability to successfully complete vocational training. The results for vocational training match those for educational attainment. For the vocational track samples we find a positive and significant effect for boys and a negative (and partially significant) effect for girls. For boys the average treatment effects are sizeable and exceed 20% of a standard deviation. For youths on the academic track, the effects are generally smaller and insignificant. In sum, the results in tables 21 to 24 suggest interesting gender differences in the effects of athletic involvement on educational and labor market outcomes. While sports increases the probability that young men successfully complete vocationally oriented education, it has a positive effect on enrolling in academically oriented education for young women.

— Insert table 23 here. —

— Insert table 24 here. —

4.5 Effect Heterogeneity and Sensitivity Analysis

To examine the heterogeneity of treatment effects we modify the outcome regression model and include different sets of interactions with the treatment dummy. The matching step is performed as in the benchmark scenario. First, we investigate heterogeneity of treatment effects according to whether youths engage in other structured activities besides sports. The results of this exercise are documented in Section E.1 in the Online-Appendix. In the majority of cases, it turns out that treatment effects of sports are stronger among youths who do not engage in any

other structured activity (e.g. playing music, volunteering). This pattern holds both for youth on the vocational and on the academic track. For job values we observe the reverse pattern: the treatment effect of playing sports is larger among youths who engage also in other structured activities.

Second, we calculate treatment effects separately by the type of sport and the setting in which youths play sports. As for the vast majority of young people playing sports is a social activity we investigate whether treatment effects depend on the particular social context (recall table 3). We consider the subcategories team sport, individual sport, sports in a club and sports with others in an informal setting. In further analyses, we break treatment effects down by whether or not somebody takes part in athletic competitions and by the frequency of athletic involvement. We do not find systematic patterns of treatment effect heterogeneity.[24] Taken together the patterns found in these two analyses are consistent with the idea that playing sports means being part of a social network. In particular, joining a sports club usually is not limited to playing sport once or twice a week but it means being part of a social community whose members share responsibilities and meet also for activities not directly related to the sport. We therefore interpret our treatment effect estimates as estimates of the broader effect of having access to an enriched social environment rather than the pure effect of physical exercise.

As a sensitivity analysis, we extract a subsample of families in which some of the children play sports while some do not and modify the outcome regression model to include in addition family fixed effects. With the family fixed effects we can examine the sensitivity of our results to potential unobserved confounders that are constant within families. In particular, if the athletic status is random in the reweighted sample using the matching weights, the estimated treatment effects should not be sensitive to how we specify the outcome regression model. In the outcome regression, we pool across gender and school track to obtain a sufficiently large sample of siblings with mixed athletic involvement. The matching step is performed as before at the individual level, with exact matching on gender and school track.

Section E.2 in the Online-Appendix shows the results for selected outcome variables for which we have enough observations. In each table the columns labeled 'Full Sample' show, for comparison, the results for the full sample when pooling across gender and school track. The columns labeled 'Sibling Sample' show the estimates obtained from the sibling subsample without and with family fixed effects, columns 'ATE' and 'ATE (FE)'. Going from the full sample to the sibling subsample we see

[24]The results of these estimations are available on request.

that the point estimates are in general very close whereas the standard errors are by a factor 1.5 to two larger in the sibling sample. The similarity of the point estimates in the two samples suggests that the sibling sample is well representative of the full sample. Next comparing the two treatment effect estimates in the sibling sample, we see that the point estimates are again in 14 out of 18 cases very similar while the standard errors increase somewhat when using family fixed effects. The high similarity of the treatment effect estimates with and without family fixed effects in the sibling sample suggests that our matching and regression adjustment suffices to remove potential confounders that are constant at the family level. Further refining the adjustment with family fixed effects does not affect the results. This evidence supports the hypothesis that particular experiences during adolescence, i.e. playing sports or not, influence the development of skills and attitudes over and above endowments transmitted through the parents.

5 Conclusion

Sports has been singled out as a popular pastime that is positively related with educational and labor market outcomes at later ages. While existing research supports the hypothesis that athletic participation may have a positive effect on educational attainment and labor market outcomes we know little about the underlying mechanisms. We address this question exploring what youths do in their leisure and whether athletic participation affects behavioral and economic outcomes reflecting character, social and executive function skills. To set the analytic framework of our empirical analysis we develop a simple model linking leisure time use and skill formation of youths. We exploit data from the German Socio-Economic Panel that offers the unique advantage of both a large, representative sample and high quality behavioral measures. We employ a flexible strategy involving propensity score matching and regression to account for selfselection into athletic involvement. We assess the validity of the empirical strategy with various tests.

Our main findings are as follows. The majority of young people play sports and their athletic engagement largely persists during adolescence and into young adulthood. While young men favor team sports and especially soccer, young women have more diverse preferences and play more individual sports. Regardless of type of sport and gender, the vast majority of the athletes play sports in a club or with others. Thus, sports is generally a social activity. Our results further suggest that young people who regularly play sports spend a higher share of their free time on struc-

tured and non-sedentary activities than those who do not. Nevertheless, undirected and passive leisure pursuits clearly dominate among all youths. Parental athletic involvement is highly predictive of the youth's athletic involvement. Athletes tend to be positively selected in terms of family background, intelligence and height. These differences disappear after matching treatment and comparison observations. In particular, the matched treatment and comparison units are balanced with respect to the predetermined human capital measures height and intelligence. This suggests that our matching strategy effectively balances heterogeneity in skills related to genetic factors and early childhood environments.

We find beneficial effects of athletic involvement on a broad range of behavioral outcomes including character skills and career aspirations and expectations. The effects are sizeable for youths on the vocational track, attaining 10-30 % of a standard deviation, whereas they are small and insignificant for youths on the academic track. The magnitude of the effects sometimes differs across gender, too. However, the impacts generally point in the same direction for young men and women. Athletes, in particular youths on the vocational track, show better educational outcomes than comparable youths who do not play sports. We further examine treatment effects conditional on the engagement in other structured leisure activities. It turns out that the sizeable beneficial effects of sports among youths on the vocational track are largely driven by the sizeable effects among youths who do not engage in any other structured activities. This pattern is similar for youths on the academic track. We therefore interpret our treatment effect estimates as estimates of the broader effect of having access to an enriched social environment rather than the pure effect of physical exercise. Overall our results lend support to the hypothesis that structured leisure activities such as sports positively affect the development of nonacademic skills.

References

Akerlof, George A., and Rachel E. Kranton (2000). "Economics and Identity", *Quarterly Journal of Economics*, 115 (3), 715-753.

Akerlof, George A., and Rachel E. Kranton (2002). "Identity and Schooling: Some Lessons for the Economics of Education", *Journal of Economic Literature*, 40 (4), 1167-1201.

Almås, Ingvild, Alexander W. Cappelen, Erik Ø. Sørensen and Bertil Tungodden (2010). "Fairness and the Development of Inequality Acceptance", *Science*,

328 (5982), 1176-1178.

Almlund, Mathilde, Angela L. Duckworth, James Heckman, and Tim Kautz (2011). "Personality Psychology and Economics", in Eric A. Hanushek, Stephen Machin and Ludger Wössmann (eds.), *Handbook of the Economics of Education*, Vol. 4, Amsterdam: Elsevier Science, ch. 1, 1-181.

Amthauer, Rudolf, Burkhard Brocke, Detlev Liepmann, and André Beauducel (2001). "Intelligenz-Struktur-Test 2000 R", Göttingen: Hogrefe, second edition.

Barron, John M., Bradley T. Ewing, and Glen R. Waddell (2000). "The Effects of High School Athletic Participation on Education and Labor Market Outcomes", *Review of Economics and Statistics*, 82 (3), 409-421.

Beal, Sarah J., and Lisa J. Crockett (2010). "Adolescents' Occupational and Educational Aspirations and Expectations: Links to High School Activities and Adult Educational Attainment", *Developmental Psychology*, 46 (1), 258-265.

Becker, Gary S. (1965). "A Theory of the Allocation of Time", *Economic Journal*, 75 (299), 493-517.

Bergemann, Annette, Bernd Fitzenberger, and Stefan Speckesser (2009). "Evaluating the Dynamic Employment Effects of Training Programs in East Germany Using Conditional Difference-in-Differences", *Journal of Applied Econometrics*, 24 (5), 797-823.

Best, John R. and Patricia H. Miller (2010). "A Developmental Perspective on Executive Function", *Child Development*, 81 (6), 1641-1660.

Best, John R., Patricia H. Miller, and Lara L. Jones (2009). "Executive Functions after Age 5: Changes and Correlates", *Developmental Review*, 29 (3), 180-200.

Bewley, Truman F. (1998). "Why not Cut Pay?" *European Economic Review*, 42 (3-5), 459-490.

Blakemore, Sarah-Jayne and Suparna Choudhury (2006). "Development of the Adolescent Brain: Implications for Executive Function and Social Cognition", *Journal of Child Psychology and Psychiatry*, 47 (3), 296-312.

Bonin, Holger, Thomas Dohmen, Armin Falk, David Huffman, and Uwe Sunde (2007). "Cross-Sectional Earnings Risk and Occupational Sorting: The Role of Risk Attitudes", *Labour Economics*, 14 (6), 926-937.

Bowles, Samuel and Sandra Polanía-Reyes (2012). "Economic Incentives and Social Preferences: Substitutes or Complements?" *Journal of Economic Literature*, 50 (2), 368-425.

Breuer, Christoph, Antje Haase, Heinz-Dieter Horch, Gregor Hovemann, Volker Rittner, Manfred Schubert (2005). "Sportvereine in Deutschland", Sportenwicklungsbericht 2005/2006, Arbeitsgruppe Sportentwicklungsbericht, Deutsche Sporthochschule Köln.

Brown, Martin, Armin Falk, and Ernst Fehr (2004). "Relational Contracts and the Nature of Market Interactions", *Econometrica*, 72 (4), 747-780.

Case, Anne, and Christina Paxson (2008). "Stature and Status: Height, Ability, and Labor Markete Outcomes", *Journal of Political Economy*, 116 (3), 499-532.

Cunha, Flavio, James J. Heckman, Lance Lochner and Dimitriy V. Masterov (2006). "Interpreting the Evidence on Life Cycle Skill Formation", in Eric A. Hanushek and Finis Welch (eds.), *Handbook of the Economics of Education*, Vol. 1, Elsevier Science, Amsterdam, 697-812.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde (2009). "Homo Reciprocans: Survey Evidence on Behavioral Outcomes", *Economic Journal*, 119 (536), 592-612.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011). "Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally-Validated Survey". *Journal of the European Economic Association*, 9 (3), 522-550.

Farb, Amy F. and Jennifer L. Matjasko (2012). "Recent Advances in Research on School-Based Extracurricular Activities and Adolescent Development", *Developmental Review*, 32 (1), 1-48.

Fehr, Ernst (2009). "On the Economics and Biology of Trust", *Journal of the European Economic Association*, 7 (2-3), 235-266.

Fehr, Ernst, Helen Bernhard, and Bettina Rockenbach (2008). "Egalitarianism in Young Children", *Nature*, 454 (7208), 1079-1084.

Fehr, Ernst, Daniela Rützler, Matthias Sutter (2011). "The Development of Egalitarianism, Altruism, Spite and Parochialism in Childhood and Adolescence, IZA Discussion Paper No. 5530, IZA Bonn.

Gerlitz, Jean-Yves and Jürgen Schupp (2005). "Zur Erhebung der Big-Five basierten Persönlichkeitsmerkmale im SOEP", DIW Research Notes 4, DIW Berlin.

Giedd, J.N., J. Blumenthal, N.O. Jeffries, F.X. Castellanos, H. Liu, A. Zijdenbos, T. Paus, A.C. Evans, J.L. Rapoport (1999). "Brain Development during Childhood and Adolescence: A Longitudinal MRI Study", *Nature Neuroscience*, 2 (10), 861-863.

Heckman, James J. and V. Joseph Hotz (1989). "Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training", *Journal of the American Statistical Association*, 84 (408), 862-874.

Heckman, James J., John E. Humphries, and Nicholas S. Mader (2011). "The GED", in Eric A. Hanushek, Stephen Machin and Ludger Wössmann (eds.): *Handbook of the Economics of Education*, Vol. 3, Amsterdam: Elsevier, ch. 9, 423-483.

Heckman, James J. and Yona Rubinstein (2001). "The Importance of Noncognitive Skills: Lessons from the GED Testing Program", *American Economic Review*, 91 (2), 145-149.

Imbens, Guido (2004). "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review", *Review of Economics and Statistics*, 86 (1), 4-29.

Johnson, Monica Kirkpatrick, and Jeylan T. Mortimer (2011). "Origins and Outcomes of Judgments about Work", *Social Forces*, 89 (4), 1239-1260.

Kube, Sebastian, Michel A. Maréchal, and Clemens Puppe (2012). "The Currency of Reciprocity: Gift Exchange in the Workplace", *American Economic Review*, 102 (4), 1644-1662.

Kube, Sebastian, Michel A. Maréchal, and Clemens Puppe (2013). "Do Wage Cuts Damage Work Morale? Evidence from a Natural Field Experiment", *Journal of the European Economic Association*, 11(4), 853-870.

Larson, Reed W. (2000). "Toward a Psychology of Positive Youth Development", *American Psychologist*, 55 (1), 170-183.

Larson, Reed W., and Suman Verma (1999). "How Children and Adolescents Spend Time Across the World: Work, Play, and Developmental Opportunities", *Psychological Bulletin*, 125 (6), 701-736.

Naef, Michael, and Jürgen Schupp (2009). "Measuring Trust: Experiments and Surveys in Contrast and Combination", SOEP Paper # 167, DIW Berlin.

Neisser, Ulric, Gwyneth Boodoo, Thomas J. Bouchard, A. Wade Boykin, Nathan Brody, Stephen J. Ceci, Diane F. Halpern, John C. Loehlin, Robert Perloff, Robert J. Sternberg, Susana Urbina (1996). "Intelligence: Knowns and Unknowns", *American Psychologist*, 51 (2), 77-101.

Neyman, Jerzy (1923), edited and translated by Dorota M. Dabrowska and Terrence P. Speed (1990). "On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9", *Statistical Science*, 5 (4), 465-472.

Nisbett, Richard E., Joshua Aronson, Clancy Blair, William Dickens, James Flynn, Diane F. Halpern, Eric Turkheimer (2012). "Intelligence: New Findings and Theoretical Developments", *American Psychologist*, 67 (2), 130-159

Persico, Nicola, Andrew Postlewaite, and Dan Silverman (2004). "The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height." *Journal of Political Economy*, 112 (5), 1019-1053.

Perugini, Marco, Marcello Gallucci, Fabio Presaghi, and Anna Paola Ercolani (2003). "The Personal Norm of Reciprocity", *European Journal of Personality*, 17, 251-283.

Pfeifer, Cristian, and Thomas Cornelißen (2010). "The Impact of Participation in Sports on Educational Attainment – New Evidence from Germany", *Economics of Education Review*, 29 (1), 94-103.

Postlewaite, Andrew, and Dan Silverman (2005). "Social Isolation and Inequality", *Journal of Economic Inequality*, 3 (3), 243-262.

Robins, James M., and Ya'acov Ritov (1997). "Towards a Curse of Dimensionality Appropriate (CODA) Asymptotic Theory for Semi-Parametric Models", *Statistics in Medicine*, 16 (3), 285-319.

Rosenbaum, Paul R., and Donald B. Rubin (1983). "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika*, 70 (1), 41-55.

Rosenberg, Morris (1957). *Occupations and Values*, Free Press, Glencoe, IL.

Roy, Andrew D. (1951). "Some Thoughts on the Distribution of Earnings", *Oxford Economic Papers*, 3 (2), 135-146.

Rubin, Donald B. (1974). "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies", *Journal of Educational Psychology*, 66 (5), 688-701.

Sandberger, Johann-Ulrich (1983). "Zwischen Legitimation und Kritik. Vorstellungen von Akademikern, Studenten und Bevölkerung zur sozialen Ungleichheit", *Zeitschrift für Soziologie*, 12 (3), 181-202.

Silventoinen, Karri (2003). "Determinants of Variation in Adult Body Height", *Journal of Biosocial Science*, 35 (02), 263-285.

Singer, Tania (2006). "The Neuronal Basis and Ontogeny of Empathy and Mind Reading: Review of Literature and Implications for Future Research", *Neuroscience and Behavioral Reviews*, 30, 855-863.

Smith, Jeffrey A., and Petra Todd (2005). "Rejoinder", *Journal of Econometrics*, 125 (2), 365-375.

Solga, Heike, Elisabeth Stern, Bernhard von Rosenbladt, Jürgen Schupp, and Gert G. Wagner (2005). "The Measurement and Importance of General Reasoning Potentials in Schools and Labor Markets", DIW Research Notes 10, DIW, Berlin.

Stevenson, Betsey (2010). "Beyond the Classroom: Using Title IX to Measure the Return to High School Sports", *Review of Economics and Statistics*, 92 (2), 284-301.

Visscher, Peter M., Sarah E. Medland, Manuel A.R. Ferreira, Katherine I. Morley, Gu Zhu, Belinda K. Cornes, Grant W. Montgomery, Nicholas G. Martin (2006). "Assumption-Free Estimation of Heritability from Genome-Wide Identity-by-Descent Sharing between Full Siblings", *PLoS Genetics*, 2 (3), e41, 0316-0325.

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

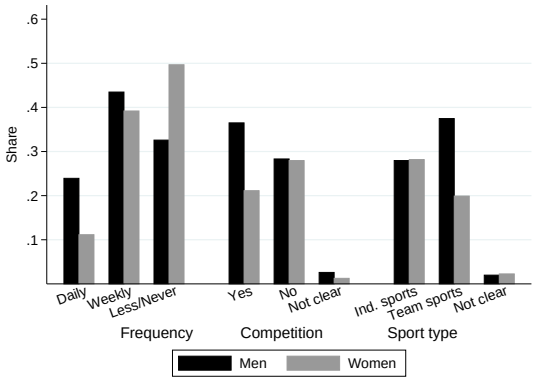
Wagner, Gert G., Jan Göbel, Peter Krause, Rainer Pischner, and Ingo Sieber (2008). "Das Sozio-oekonomische Panel (SOEP): Multidisziplinäres Haushaltspanel und Kohortenstudie für Deutschland – Eine Einführung (für neue Datennutzer) mit einem Ausblick (für erfahrene Anwender)", *AStA Wirtschafts- und Sozialstatistisches Archiv*, 2 (4), 301-328.

Weinhardt, Michael, and Jürgen Schupp (2011). "Multi-Itemskalen im SOEP Jugendfragebogen", Data Documentation # 60, DIW Berlin.

Wight, Vanessa R., Joseph Price, Suzanne M. Bianchi and Bijou R. Hunt (2009). "The Time Use of Teenagers", *Social Science Research*, 38 (4), 792-809.

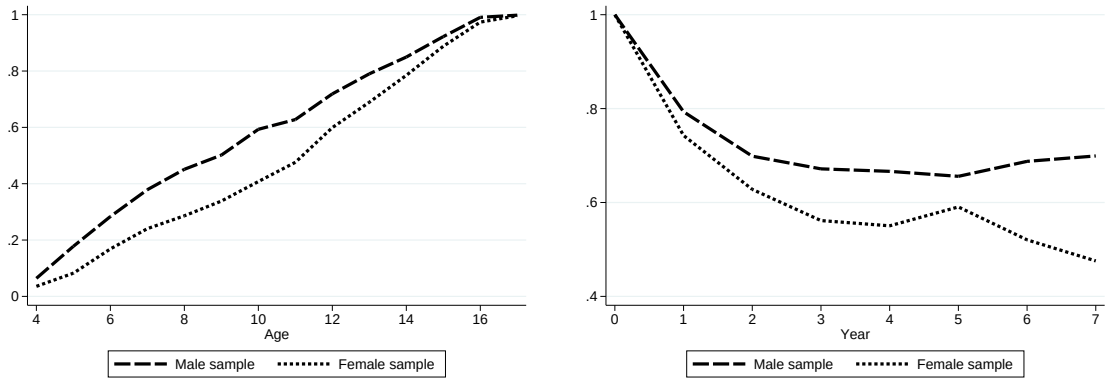
Figures

Figure 1: Athletic Involvement of 17-Year Olds



Source: SOEP V28 and authors' calculations. Note: Proportions based on weighted samples.

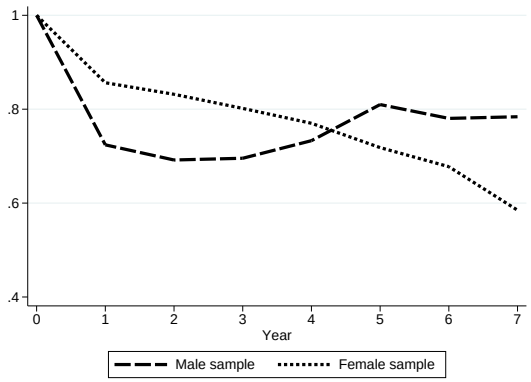
Figure 2: Athletic Involvement of Athletes During Childhood and Young Adulthood



(a) Cumulative fraction active (current sport) (b) Cumulative fraction still active (any sport)

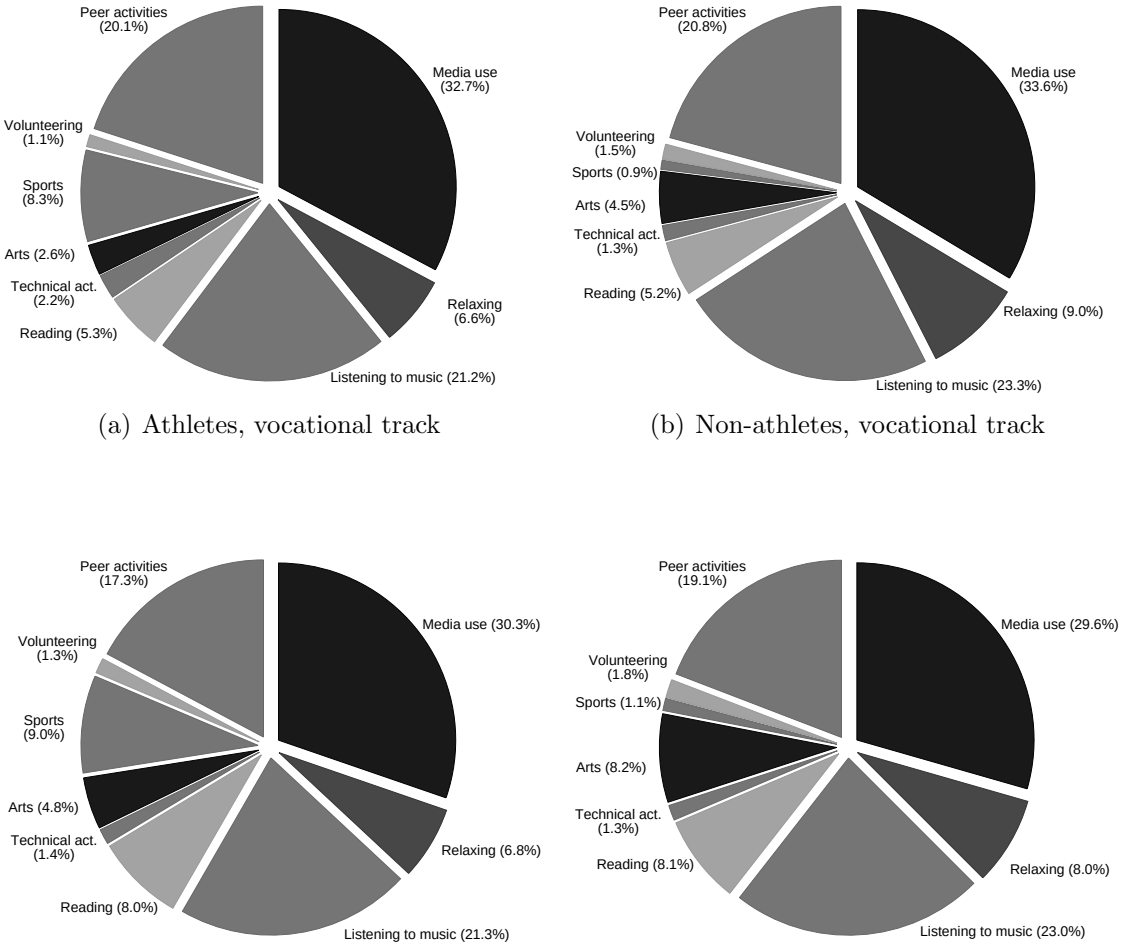
Source: SOEP V28 and authors' calculations. Note: Panel (a) shows the cumulative share of athletes as of age 17 who play their current main sport already at younger ages. Panel (b) shows the share of athletes as of age 17 who play sports at least once a week at later ages. In 2002, 2004, 2006, and 2010, the person questionnaire does not include the question about athletic involvement and its frequency. We impute the information based on the athletic involvement in the adjacent years. Proportions calculated using SOEP sample weights.

Figure 3: Athletic Involvement of Non-Athletes During Young Adulthood



Source: SOEP V28 and authors' calculations. Note: The figure shows the share of non-athletes as of age 17 who do not play sports at all or less than weekly at later ages. In 2002, 2004, 2006, and 2010, the person questionnaire does not include the question about athletic involvement and its frequency. We impute the information based on the athletic involvement in the adjacent years. Proportions calculated using SOEP sample weights.

Figure 4: Leisure Time Use of 17-Year Olds



(a) Athletes, vocational track

(b) Non-athletes, vocational track

(c) Athletes, academic track

(d) Non-athletes, academic track

Source: SOEP V28 and authors' calculations. Note: The percentages are derived from a set of questions about how the young people allocate their leisure time. We impute the share of time spent on each activity according to its frequency, i.e. a daily activity is weighted by 30.44, a weekly activity by 4.35, and a monthly activity by 1. Then we average across all youths. The category *media use* comprises *watching television/video*, *playing computer games* and *using the internet*. The activity *volunteering* includes also *attending church/being involved in a religious community*. The activities *spending time with steady/best friend, clique, and in youth clubs* are combined to the category *peer activities*. The category *arts* comprises the activities *performing arts*, *playing music*, and *singing*. The category *technical activities* summarizes *crafting*, *programming* and related activities. Calculations use SOEP sample weights.

Tables

Table 1: Sample Sizes

	Vocational school track				Academic school track			
	Men Athlete		Women Athlete		Men Athlete		Women Athlete	
	Yes	No	Yes	No	Yes	No	Yes	No
Observations								
	1,104		977		593		669	
	654	450	405	572	455	138	455	214
Unweighted proportion (%)								
	59.24	40.76	41.45	58.55	76.73	23.27	68.01	31.99
Weighted proportion (%)								
	61.68	38.32	39.45	60.55	80.04	19.96	69.97	30.03

Source: SOEP V28 and authors' calculations. Note: Weighted proportions calculated with SOEP sample weights.

Table 2: Most Popular Sports by Gender

	Men		Women	
Rank	Sport type	%	Sport type	%
1.	Soccer	42.50	Dancing	13.35
2.	Fitness, Bodybuilding	8.27	Horseback Riding	10.24
3.	Bike Riding	5.08	Volleyball	9.89
4.	Basketball	4.33	Walking, Jogging	7.24
5.	Handball	3.97	Soccer	7.04

Source: SOEP V28 and authors' calculations. Note: Percentages calculated using SOEP sample weights.

Table 3: Type of Sport and Social Context

	Team sport		Individual sport		Total	
	Freq.	%	Freq.	%	Freq.	%
At nonprofit sports club	577.01	81.27	405.26	50.16	1,023.61	65.20
At commercial sports facility	19.03	2.68	101.43	12.55	124.11	7.91
At another organization	4.69	0.66	5.17	0.64	9.82	0.63
With others, not organized	99.92	14.07	138.25	17.11	242.71	15.46
Alone	9.34	1.32	157.89	19.54	169.75	10.81
Total	710	100.00	808	100.00	1,570	100.00

Source: SOEP V28 and authors' calculations. Note: Calculations use SOEP sample weights. The column labeled 'Total' includes in addition observations with unclear or missing type of sport.

Table 4: Engagement in Other Structured Leisure Activities Besides Sports

	Men			Women		
	Athlete			Athlete		
	Yes	No	p-Value	Yes	No	p-Value
Vocational track						
Any other activity	0.535	0.514	0.503	0.516	0.365	**0.000**
	(0.499)	(0.500)		(0.500)	(0.482)	
Number of other act.	0.767	0.837	0.222	0.736	0.613	**0.047**
	(0.895)	(0.973)		(0.895)	(0.978)	
Academic track						
Any other activity	0.652	0.772	**0.012**	0.623	0.525	**0.018**
	(0.477)	(0.421)		(0.485)	(0.501)	
Number of other act.	1.038	1.402	**0.001**	0.993	0.874	0.176
	(0.999)	(1.130)		(1.023)	(1.069)	

Source: SOEP V28 and authors' calculations. Note: Calculations use SOEP sample weights. Rows labeled 'Any other activity' show the share of youths who do at least one structured activity except sports on a weekly basis. Rows labeled 'Number of other act.' show the number of structured activities excluding sports that are performed on a weekly basis. Columns labeled 'p-Value' show the p-value from a t-test of equality of means.

Table 5: Descriptive Statistics for Key Covariates – Vocational Track

	Men				Women			
		Athlete				Athlete		
	Obs.	Yes	No	p-Value	Obs.	Yes	No	p-Value
Height (cm)	963	178.7	177.5	**0.014**	859	167.5	165.6	**0.000**
		(7.646)	(6.826)			(6.431)	(6.342)	
Verbal ability	519	-0.327	-0.153	**0.034**	425	-0.317	-0.430	0.191
		(0.868)	(1.001)			(0.827)	(0.922)	
Numerical ability	519	-0.039	-0.183	**0.092**	425	-0.289	-0.271	0.861
		(0.946)	(0.990)			(0.968)	(1.062)	
Figural ability	519	-0.191	-0.321	0.134	425	-0.068	-0.117	0.598
		(0.977)	(0.983)			(0.932)	(0.939)	
Ever repeated grade	1,104	0.324	0.338	0.648	977	0.211	0.240	0.284
		(0.468)	(0.473)			(0.408)	(0.427)	
Acad. track recomm.	1,073	0.135	0.099	**0.085**	951	0.212	0.109	**0.000**
		(0.342)	(0.299)			(0.409)	(0.312)	
Migrant background	1,104	0.284	0.213	**0.009**	977	0.276	0.320	0.135
		(0.451)	(0.410)			(0.447)	(0.467)	
Parent with tert. educat.	1,104	0.138	0.102	**0.081**	976	0.134	0.097	**0.073**
		(0.345)	(0.303)			(0.341)	(0.296)	
Parental earnings	1,033	3.595	3.586	0.951	915	3.585	3.469	0.490
(10,000 €)		(2.316)	(2.570)			(2.301)	(2.633)	
Grew up with both	1,104	0.687	0.639	**0.100**	977	0.715	0.668	0.121
parents		(0.464)	(0.481)			(0.452)	(0.471)	
Father athlete	756	0.449	0.384	**0.078**	652	0.440	0.382	0.143
		(0.498)	(0.487)			(0.497)	(0.486)	
Mother athlete	908	0.482	0.463	0.564	800	0.567	0.320	**0.000**
		(0.500)	(0.499)			(0.496)	(0.467)	
Grew up in city	1,100	0.638	0.645	0.821	970	0.571	0.700	**0.000**
		(0.481)	(0.479)			(0.496)	(0.459)	
Local unemployment (%)	1,011	10.99	11.60	**0.038**	906	11.03	11.22	0.557
		(4.504)	(4.638)			(4.469)	(4.912)	

Source: SOEP V28 and authors' calculations. Note: Columns labeled 'Obs.' show the number of observations. Columns labeled 'Yes' and 'No' show the means and standard deviations (in parentheses). Columns labeled 'p-Value' show the p-value from a t-test of equality of means. Calculations use the SOEP sample weights. The cognitive ability measures are only available for cohorts from 2006 onwards. A detailed description of all covariates and additional descriptive statistics are provided in Section B of the Online-Appendix.

Table 6: Descriptive Statistics for Key Covariates – Academic Track

	Men				Women			
		Athlete				Athlete		
	Obs.	Yes	No	p-Value	Obs.	Yes	No	p-Value
Height (cm)	531	180.0	180.2	0.838	593	168.1	167.1	**0.073**
		(7.319)	(7.588)			(6.061)	(6.460)	
Verbal ability	290	0.767	0.498	**0.022**	315	0.637	0.580	0.577
		(0.873)	(0.757)			(0.796)	(0.941)	
Numerical ability	290	0.616	0.414	**0.039**	315	0.294	0.092	**0.087**
		(0.697)	(0.736)			(0.902)	(1.097)	
Figural ability	290	0.404	0.206	0.127	315	0.506	0.566	0.557
		(0.903)	(1.060)			(0.849)	(0.775)	
Ever repeated grade	593	0.117	0.130	0.702	669	0.061	0.042	0.327
		(0.322)	(0.337)			(0.240)	(0.201)	
Acad. track recomm.	585	0.834	0.794	0.308	662	0.861	0.739	**0.000**
		(0.373)	(0.406)			(0.346)	(0.440)	
Migrant background	593	0.178	0.151	0.494	669	0.193	0.230	0.279
		(0.383)	(0.359)			(0.395)	(0.422)	
Parent with tert. educat.	593	0.577	0.535	0.412	669	0.493	0.378	**0.006**
		(0.495)	(0.501)			(0.501)	(0.486)	
Parental earnings	564	5.559	5.974	0.260	640	5.293	4.962	0.255
(10,000 €)		(3.562)	(3.374)			(3.447)	(3.261)	
Grew up with both	593	0.750	0.848	**0.023**	669	0.766	0.749	0.641
parents		(0.433)	(0.360)			(0.424)	(0.435)	
Father athlete	418	0.570	0.563	0.906	458	0.592	0.493	**0.049**
		(0.496)	(0.499)			(0.492)	(0.502)	
Mother athlete	464	0.747	0.583	**0.002**	547	0.642	0.490	**0.001**
		(0.435)	(0.495)			(0.480)	(0.501)	
Grew up in city	590	0.722	0.715	0.878	661	0.712	0.645	**0.089**
		(0.449)	(0.453)			(0.453)	(0.480)	
Local unemployment (%)	529	11.16	11.54	0.447	610	11.21	12.78	**0.000**
		(4.500)	(4.966)			(4.751)	(5.598)	

Source: SOEP V28 and authors' calculations. Note: Columns labeled 'Obs.' show the number of observations. Columns labeled 'Yes' and 'No' show the means and standard deviations (in parentheses). Columns labeled 'p-Value' show the p-value from a t-test of equality of means. Calculations use the SOEP sample weights. The cognitive ability measures are only available for cohorts from 2006 onwards. A detailed description of all covariates and additional descriptive statistics are provided in Section B of the Online-Appendix.

Table 7: Summary of Common Support and Balancing Tests on Variables Included in the Propensity Score

	Vocational track		Academic track	
	Men	Women	Men	Women
(a) Percent within common support region				
Athlete obs.	99.2	97.1	96.8	95.9
Non-athlete obs.	99.3	96.2	100.0	100.0
(b) Smith/Todd (2005)-test				
p-Value$\leq$ 0.05	2	1	2	1
p-Value$\leq$ 0.10	3	1	3	3
(c) t-Tests of equality of means				
Unmatched	9	7	7	12
ATT-weights	0	0	0	0
ATU-weights	0	0	0	0
(d) Total number of covariates				
	49	40	52	47

Source: SOEP V28 and authors' calculations. Panel (a) shows the percentage of observations that are within the common support region. It is defined as the interval between the minimum propensity score of athletes and the maximum propensity score of non-athletes. Panel (b) shows the number of covariates for which the null of no influence of the athletic status on a given covariate conditional on a polynomial of the propensity score is rejected. The rows in panel (c) show the number of covariates with p-values $\leq$ 0.05 in a t-test of equality of means in the athlete and non-athlete samples before and after matching. Panel (d) shows the total number of covariates considered in the propensity score model. See Section 2 for further details on the balancing tests and Section C of the Online-Appendix for the additional results.

Table 8: Summary of Balancing Tests on Excluded Variables

	Men			Women		
	Before	ATT-weights	ATU-weights	Before	ATT-weights	ATU-weights
(a) Vocational track						
Height	0.042	0.358	0.376	0.001	0.328	0.143
Intelligence	0.000	0.178	0.010	0.570	0.914	0.978
(b) Academic track						
Height	0.862	0.712	0.658	0.403	0.932	0.790
Intelligence	0.061	0.515	0.255	0.413	0.093	0.496

Source: SOEP V28 and authors' calculations. Note: The table shows the p-values from Hotelling tests of equality of means between the treated and comparison samples. The test for height includes two variables (height and missing dummy), that for intelligence four variables (verbal, figural, and numerical ability and missing dummy). Calculations are based on the complete samples. Missing values in a covariate are imputed with the sample mean and a missing dummy is set to one. See Section 2 for further details on the balancing tests and Section C of the Online-Appendix for additional results. All calculations use SOEP sample weights.

Table 9: Big Five Personality – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Conscientiousness			
Men	960	−0.035	0.229**	0.299***	0.255***	0.281***
		(0.994)	(0.092)	(0.081)	(0.081)	(0.078)
Women	812	0.178	0.120	0.107	0.116	0.112
		(0.949)	(0.096)	(0.084)	(0.088)	(0.081)
Pooled	1,772	0.061	0.129**	0.281***	0.217***	0.250***
		(0.980)	(0.065)	(0.058)	(0.059)	(0.055)
			(b) Extraversion			
Men	960	−0.094	0.110	0.097	0.115	0.104
		(1.020)	(0.116)	(0.083)	(0.081)	(0.079)
Women	812	0.084	0.161	0.165*	0.141	0.151
		(0.990)	(0.102)	(0.099)	(0.110)	(0.100)
Pooled	1,772	−0.014	0.091	0.162**	0.221***	0.191***
		(1.010)	(0.075)	(0.065)	(0.070)	(0.063)
			(c) Openness			
Men	960	−0.148	0.076	0.140	0.119	0.131
		(1.025)	(0.108)	(0.089)	(0.091)	(0.087)
Women	812	0.084	0.142	0.162*	0.129	0.143
		(0.992)	(0.101)	(0.095)	(0.100)	(0.093)
Pooled	1,772	−0.044	0.055	0.173**	0.185***	0.179***
		(1.017)	(0.072)	(0.068)	(0.070)	(0.065)
			(d) Agreeableness			
Men	960	−0.162	0.087	0.214**	0.108	0.171*
		(1.006)	(0.092)	(0.093)	(0.089)	(0.088)
Women	812	0.208	−0.022	−0.024	−0.154	−0.099
		(1.010)	(0.117)	(0.100)	(0.100)	(0.095)
Pooled	1,772	0.004	−0.039	0.159**	−0.010	0.077
		(1.024)	(0.072)	(0.068)	(0.065)	(0.063)
			(e) Neuroticism			
Men	960	−0.228	−0.091	−0.019	0.018	−0.004
		(0.928)	(0.095)	(0.082)	(0.083)	(0.079)
Women	812	0.255	−0.024	0.007	−0.014	−0.005
		(1.030)	(0.103)	(0.098)	(0.104)	(0.096)
Pooled	1,772	−0.010	−0.156**	−0.042	−0.061	−0.051
		(1.004)	(0.071)	(0.065)	(0.070)	(0.063)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 10: Big Five Personality – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Conscientiousness			
Men	533	−0.304	−0.001	−0.154	−0.135	−0.149
		(0.968)	(0.152)	(0.127)	(0.134)	(0.120)
Women	586	0.061	0.063	0.066	0.094	0.075
		(1.051)	(0.134)	(0.144)	(0.139)	(0.137)
Pooled	1,119	−0.121	−0.010	0.029	0.030	0.029
		(1.027)	(0.101)	(0.099)	(0.091)	(0.092)
			(b) Extraversion			
Men	533	−0.026	0.293*	0.112	0.152	0.122
		(0.973)	(0.154)	(0.164)	(0.150)	(0.153)
Women	586	0.074	0.155	0.140	0.092	0.125
		(0.990)	(0.126)	(0.132)	(0.135)	(0.127)
Pooled	1,119	0.024	0.200**	0.176*	0.144	0.167*
		(0.982)	(0.097)	(0.094)	(0.095)	(0.088)
			(c) Openness			
Men	533	−0.016	0.177	0.087	0.004	0.067
		(0.939)	(0.135)	(0.146)	(0.144)	(0.136)
Women	586	0.185	0.121	0.103	0.057	0.089
		(0.954)	(0.113)	(0.120)	(0.113)	(0.111)
Pooled	1,119	0.085	0.119	0.114	0.105	0.112
		(0.951)	(0.086)	(0.089)	(0.085)	(0.082)
			(d) Agreeableness			
Men	533	−0.126	0.077	−0.045	−0.158	−0.072
		(0.928)	(0.130)	(0.157)	(0.154)	(0.148)
Women	586	0.107	0.080	0.096	0.061	0.085
		(0.964)	(0.116)	(0.114)	(0.119)	(0.110)
Pooled	1,119	−0.009	0.049	0.069	−0.009	0.047
		(0.953)	(0.085)	(0.096)	(0.092)	(0.089)
			(e) Neuroticism			
Men	533	−0.197	−0.233	−0.133	−0.064	−0.117
		(0.983)	(0.144)	(0.166)	(0.150)	(0.153)
Women	586	0.206	0.122	0.092	0.120	0.101
		(0.969)	(0.120)	(0.134)	(0.136)	(0.129)
Pooled	1,119	0.006	−0.082	−0.026	0.024	−0.012
		(0.996)	(0.093)	(0.099)	(0.094)	(0.092)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 11: Locus of Control – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) External locus of control			
Men	952	0.124	−0.281**	−0.092	−0.227**	−0.146*
		(1.081)	(0.123)	(0.088)	(0.091)	(0.085)
Women	800	0.130	−0.231**	−0.235**	−0.149	−0.186*
		(0.983)	(0.100)	(0.101)	(0.106)	(0.096)
Pooled	1,752	0.126	−0.249***	−0.126*	−0.197***	−0.160**
		(1.038)	(0.080)	(0.067)	(0.072)	(0.064)
			(b) Internal locus of control			
Men	952	0.065	0.154	0.175*	0.154	0.167*
		(1.084)	(0.117)	(0.100)	(0.103)	(0.097)
Women	800	0.059	0.161*	0.222**	0.100	0.153*
		(0.977)	(0.093)	(0.091)	(0.100)	(0.090)
Pooled	1,752	0.062	0.151**	0.191***	0.088	0.142**
		(1.038)	(0.077)	(0.070)	(0.071)	(0.065)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 12: Locus of Control – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) External locus of control			
Men	529	−0.364	−0.315**	−0.108	−0.115	−0.109
		(0.894)	(0.135)	(0.165)	(0.156)	(0.156)
Women	585	−0.183	−0.170*	−0.108	−0.097	−0.105
		(0.832)	(0.101)	(0.097)	(0.098)	(0.092)
Pooled	1,114	−0.273	−0.255***	−0.083	−0.059	−0.076
		(0.868)	(0.082)	(0.080)	(0.073)	(0.072)
			(b) Internal locus of control			
Men	529	−0.134	0.157	0.165	0.225	0.179
		(0.911)	(0.119)	(0.147)	(0.147)	(0.138)
Women	585	−0.140	−0.153	−0.057	−0.026	−0.047
		(0.924)	(0.121)	(0.112)	(0.114)	(0.106)
Pooled	1,114	−0.137	−0.019	0.010	0.103	0.036
		(0.917)	(0.086)	(0.092)	(0.088)	(0.086)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 13: Social Skills and Risk Preferences – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Negative reciprocity			
Men	730	0.260	−0.145	−0.072	−0.163	−0.110
		(0.981)	(0.106)	(0.100)	(0.104)	(0.097)
Women	609	−0.133	−0.233	−0.257**	−0.228	−0.240*
		(1.065)	(0.164)	(0.121)	(0.141)	(0.125)
Pooled	1,339	0.078	−0.101	−0.136*	−0.150*	−0.143*
		(1.040)	(0.101)	(0.080)	(0.084)	(0.076)
			(b) Positive reciprocity			
Men	730	−0.081	0.003	0.063	0.037	0.052
		(1.038)	(0.112)	(0.099)	(0.106)	(0.096)
Women	609	0.144	−0.003	−0.064	−0.023	−0.040
		(0.942)	(0.133)	(0.109)	(0.113)	(0.104)
Pooled	1,339	0.023	−0.044	0.056	0.009	0.033
		(1.000)	(0.090)	(0.072)	(0.081)	(0.070)
			(c) Willingness to take risks			
Men	1,000	0.142	0.157*	0.233***	0.209**	0.224***
		(1.011)	(0.094)	(0.080)	(0.091)	(0.080)
Women	863	−0.162	0.191*	0.192**	0.155	0.171*
		(1.027)	(0.102)	(0.093)	(0.101)	(0.093)
Pooled	1,863	0.003	0.230***	0.211***	0.205***	0.208***
		(1.029)	(0.068)	(0.063)	(0.072)	(0.063)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 14: Social Skills and Risk Preferences – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Negative reciprocity			
Men	394	0.023	−0.248*	0.028	0.017	0.025
		(0.869)	(0.142)	(0.172)	(0.161)	(0.163)
Women	448	−0.280	0.043	0.090	0.120	0.099
		(0.905)	(0.135)	(0.162)	(0.169)	(0.157)
Pooled	842	−0.137	−0.018	0.085	0.023	0.067
		(0.901)	(0.096)	(0.102)	(0.104)	(0.096)
			(b) Positive reciprocity			
Men	394	−0.055	0.002	−0.171	0.051	−0.121
		(1.023)	(0.145)	(0.179)	(0.171)	(0.168)
Women	448	−0.046	0.300*	0.269	0.198	0.246
		(1.017)	(0.160)	(0.172)	(0.165)	(0.160)
Pooled	842	−0.050	0.179	0.106	0.173	0.125
		(1.019)	(0.111)	(0.117)	(0.108)	(0.108)
		(0.897)	(0.101)	(0.103)	(0.108)	(0.098)
			(c) Willingness to take risks			
Men	551	0.065	0.025	−0.035	0.070	−0.011
		(1.009)	(0.150)	(0.162)	(0.162)	(0.154)
Women	597	−0.060	0.038	0.034	−0.002	0.022
		(0.825)	(0.093)	(0.106)	(0.100)	(0.098)
Pooled	1,148	0.003	0.049	0.028	0.051	0.035
		(0.924)	(0.084)	(0.096)	(0.088)	(0.087)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 15: Job Values – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Interaction, recognition			
Men	1,075	−0.189	0.337***	0.367***	0.327***	0.351***
		(1.032)	(0.084)	(0.081)	(0.082)	(0.077)
Women	932	0.340	0.019	0.107	0.118	0.113
		(0.959)	(0.089)	(0.077)	(0.084)	(0.076)
Pooled	2,007	0.049	0.066	0.255***	0.199***	0.228***
		(1.034)	(0.061)	(0.062)	(0.062)	(0.057)
			(b) Pay, promotion			
Men	1,075	0.102	0.281***	0.230***	0.257***	0.241***
		(0.994)	(0.083)	(0.079)	(0.080)	(0.075)
Women	932	0.044	0.111	0.163*	0.156*	0.159**
		(1.015)	(0.086)	(0.084)	(0.082)	(0.078)
Pooled	2,007	0.075	0.207***	0.197***	0.207***	0.202***
		(1.004)	(0.059)	(0.063)	(0.063)	(0.059)
			(c) Personal development			
Men	1,075	−0.113	0.216**	0.224**	0.211**	0.219**
		(1.081)	(0.098)	(0.100)	(0.096)	(0.093)
Women	932	0.135	0.146*	0.113	0.159**	0.140*
		(0.965)	(0.082)	(0.072)	(0.078)	(0.072)
Pooled	2,007	−0.001	0.120*	0.190***	0.192***	0.191***
		(1.038)	(0.064)	(0.071)	(0.066)	(0.064)
			(d) Security, safety			
Men	1,075	−0.071	0.267***	0.212***	0.262***	0.232***
		(1.048)	(0.087)	(0.076)	(0.085)	(0.074)
Women	932	0.136	−0.002	0.069	0.130*	0.105
		(0.934)	(0.082)	(0.075)	(0.078)	(0.072)
Pooled	2,007	0.022	0.092	0.159***	0.193***	0.176***
		(1.003)	(0.059)	(0.060)	(0.058)	(0.054)
			(e) Work-life balance			
Men	1,075	−0.023	0.027	0.031	0.021	0.027
		(1.039)	(0.084)	(0.091)	(0.091)	(0.085)
Women	932	−0.008	0.127	0.146	0.197**	0.176**
		(0.997)	(0.087)	(0.090)	(0.092)	(0.086)
Pooled	2,007	−0.017	0.066	0.056	0.116*	0.085
		(1.020)	(0.059)	(0.065)	(0.063)	(0.058)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 16: Job Values – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) Interaction, recognition						
Men	577	−0.248	0.153	0.043	0.053	0.045
		(0.946)	(0.115)	(0.137)	(0.149)	(0.133)
Women	646	0.034	0.229**	0.109	0.176*	0.131
		(0.927)	(0.109)	(0.110)	(0.100)	(0.103)
Pooled	1,223	−0.105	0.152*	0.128	0.161**	0.137*
		(0.947)	(0.080)	(0.083)	(0.080)	(0.076)
(b) Pay, promotion						
Men	577	−0.113	0.152	0.075	0.172	0.098
		(0.983)	(0.127)	(0.143)	(0.145)	(0.136)
Women	646	−0.196	0.063	0.096	0.058	0.083
		(0.987)	(0.126)	(0.115)	(0.108)	(0.108)
Pooled	1,223	−0.155	0.111	0.138	0.107	0.130
		(0.986)	(0.091)	(0.090)	(0.085)	(0.083)
(c) Personal development						
Men	577	−0.125	−0.010	−0.032	0.009	−0.022
		(0.964)	(0.121)	(0.124)	(0.144)	(0.121)
Women	646	0.140	0.051	−0.001	−0.003	−0.002
		(0.888)	(0.106)	(0.111)	(0.115)	(0.107)
Pooled	1,223	0.010	−0.015	−0.020	0.004	−0.013
		(0.935)	(0.081)	(0.077)	(0.079)	(0.072)
(d) Security, safety						
Men	577	−0.155	0.173	0.034	0.116	0.053
		(1.027)	(0.143)	(0.128)	(0.140)	(0.122)
Women	646	0.039	0.062	0.059	0.087	0.068
		(0.976)	(0.109)	(0.119)	(0.109)	(0.109)
Pooled	1,223	−0.057	0.077	0.063	0.137*	0.084
		(1.006)	(0.087)	(0.085)	(0.083)	(0.078)
(e) Work-Life balance						
Men	577	0.034	0.063	0.072	0.119	0.083
		(0.949)	(0.119)	(0.153)	(0.162)	(0.148)
Women	646	0.038	0.064	0.065	0.127	0.085
		(0.950)	(0.103)	(0.113)	(0.109)	(0.105)
Pooled	1,223	0.036	0.062	0.107	0.106	0.107
		(0.950)	(0.078)	(0.094)	(0.089)	(0.086)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 17: Attitudes about Social Success – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) Extrinsic factors ("family background")						
Men	1,042	0.050	−0.132	−0.089	−0.167*	−0.121
		(1.003)	(0.087)	(0.092)	(0.097)	(0.091)
Women	912	−0.161	−0.337***	−0.349***	−0.317***	−0.330***
		(1.035)	(0.090)	(0.089)	(0.099)	(0.090)
Pooled	1,954	−0.047	−0.169***	−0.158**	−0.252***	−0.204***
		(1.023)	(0.064)	(0.064)	(0.063)	(0.060)
(b) Positive intrinsic factors ("achievement")						
Men	1,042	−0.030	0.075	0.172**	0.111	0.147**
		(1.014)	(0.084)	(0.075)	(0.076)	(0.072)
Women	912	−0.060	0.260***	0.097	0.167*	0.138
		(1.049)	(0.097)	(0.088)	(0.098)	(0.089)
Pooled	1,954	−0.044	0.159**	0.151**	0.134**	0.143**
		(1.030)	(0.069)	(0.059)	(0.063)	(0.056)
(c) Negative intrinsic factors ("toughness")						
Men	1,042	0.057	−0.161**	−0.066	−0.151*	−0.100
		(0.986)	(0.082)	(0.084)	(0.089)	(0.083)
Women	912	−0.254	−0.362***	−0.329***	−0.233**	−0.273***
		(0.941)	(0.078)	(0.085)	(0.094)	(0.086)
Pooled	1,954	−0.086	−0.172***	−0.160***	−0.209***	−0.184***
		(0.978)	(0.059)	(0.058)	(0.062)	(0.056)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 18: Attitudes about Social Success – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) Extrinsic factors ("family background")						
Men	570	0.143	0.135	0.283**	0.312**	0.290**
		(0.978)	(0.128)	(0.138)	(0.123)	(0.127)
Women	644	0.026	−0.154	−0.031	−0.040	−0.034
		(0.916)	(0.110)	(0.098)	(0.112)	(0.095)
Pooled	1,214	0.083	−0.016	0.122	0.130	0.124*
		(0.948)	(0.085)	(0.080)	(0.079)	(0.073)
(b) Positive intrinsic factors ("achievement")						
Men	570	−0.033	−0.050	0.054	−0.007	0.039
		(0.962)	(0.129)	(0.136)	(0.136)	(0.128)
Women	644	0.181	−0.070	−0.086	−0.104	−0.092
		(0.919)	(0.115)	(0.109)	(0.108)	(0.101)
Pooled	1,214	0.077	−0.089	−0.008	−0.024	−0.013
		(0.946)	(0.087)	(0.088)	(0.082)	(0.079)
(c) Negative intrinsic factors ("toughness")						
Men	570	0.314	0.259*	0.346**	0.367***	0.351***
		(1.049)	(0.145)	(0.143)	(0.126)	(0.131)
Women	644	0.034	−0.127	−0.022	−0.054	−0.032
		(0.961)	(0.123)	(0.106)	(0.112)	(0.100)
Pooled	1,214	0.170	0.072	0.169**	0.148*	0.163**
		(1.015)	(0.095)	(0.081)	(0.080)	(0.073)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 19: Beliefs about the Future – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Successful career			
Men	1,028	0.004	0.316***	0.296***	0.276***	0.288***
		(1.060)	(0.094)	(0.091)	(0.089)	(0.088)
Women	896	−0.043	0.164*	0.114	0.154*	0.137
		(1.034)	(0.088)	(0.088)	(0.093)	(0.086)
Pooled	1,924	−0.017	0.247***	0.241***	0.224***	0.233***
		(1.049)	(0.065)	(0.065)	(0.064)	(0.061)
			(b) Fulfilling career			
Men	1,028	−0.130	0.139	0.098	0.051	0.079
		(0.999)	(0.086)	(0.087)	(0.083)	(0.082)
Women	896	−0.174	0.302***	0.087	0.101	0.095
		(1.047)	(0.097)	(0.093)	(0.091)	(0.088)
Pooled	1,924	−0.150	0.213***	0.099	0.119*	0.109*
		(1.021)	(0.064)	(0.063)	(0.062)	(0.059)
			(c) Fulfilling family life			
Men	1,028	−0.190	0.221**	0.196**	0.183**	0.191**
		(1.008)	(0.088)	(0.089)	(0.086)	(0.085)
Women	896	0.072	0.186*	0.141	0.228**	0.192**
		(1.050)	(0.102)	(0.091)	(0.100)	(0.093)
Pooled	1,924	−0.072	0.142**	0.189***	0.228***	0.208***
		(1.035)	(0.067)	(0.068)	(0.066)	(0.062)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 20: Beliefs about the Future – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
			(a) Successful career			
Men	546	0.160	0.164	0.266**	0.073	0.220*
		(0.878)	(0.150)	(0.131)	(0.137)	(0.126)
Women	630	−0.018	0.237**	0.100	0.091	0.097
		(0.841)	(0.094)	(0.100)	(0.110)	(0.098)
Pooled	1,176	0.068	0.228***	0.195**	0.117	0.173**
		(0.864)	(0.082)	(0.085)	(0.076)	(0.076)
			(b) Fulfilling career			
Men	546	0.257	0.145	0.243**	0.281**	0.252**
		(0.885)	(0.111)	(0.122)	(0.130)	(0.118)
Women	630	0.331	0.325***	0.026	0.070	0.040
		(0.896)	(0.106)	(0.115)	(0.115)	(0.108)
Pooled	1,176	0.295	0.236***	0.118	0.181**	0.136*
		(0.891)	(0.077)	(0.079)	(0.080)	(0.073)
			(c) Fulfilling family life			
Men	546	0.122	0.181	0.179	0.062	0.151
		(0.938)	(0.124)	(0.128)	(0.141)	(0.123)
Women	630	0.176	0.175*	0.083	−0.007	0.054
		(0.892)	(0.104)	(0.120)	(0.120)	(0.114)
Pooled	1,176	0.150	0.167**	0.188**	0.039	0.145*
		(0.914)	(0.079)	(0.092)	(0.089)	(0.086)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 21: Educational Attainment – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) No school degree						
Men	594	0.071	−0.292**	−0.128	−0.293*	−0.196
		(1.288)	(0.139)	(0.136)	(0.153)	(0.138)
Women	506	−0.047	−0.093	0.000	−0.012	−0.007
		(0.745)	(0.078)	(0.026)	(0.071)	(0.048)
Pooled	1,100	0.018	−0.162**	−0.077	−0.133*	−0.105
		(1.081)	(0.077)	(0.081)	(0.073)	(0.072)
(b) School degree from vocational track						
Men	594	0.411	−0.025	0.094	0.067	0.083
		(0.768)	(0.079)	(0.093)	(0.085)	(0.087)
Women	506	0.436	−0.368***	−0.289***	−0.259***	−0.271***
		(0.745)	(0.089)	(0.097)	(0.097)	(0.089)
Pooled	1,100	0.422	−0.173***	−0.017	−0.121**	−0.069
		(0.758)	(0.056)	(0.068)	(0.061)	(0.059)
(c) School degree from academic track						
Men	594	−0.429	0.089	−0.066	−0.003	−0.040
		(0.737)	(0.075)	(0.085)	(0.076)	(0.078)
Women	506	−0.429	0.391***	0.291***	0.264***	0.275***
		(0.737)	(0.088)	(0.098)	(0.096)	(0.089)
Pooled	1,100	−0.429	0.209***	0.034	0.151***	0.092*
		(0.736)	(0.054)	(0.063)	(0.058)	(0.056)
(d) Ever attended university						
Men	813	−0.261	0.081	0.048	0.020	0.037
		(0.760)	(0.068)	(0.077)	(0.067)	(0.070)
Women	705	−0.322	0.105	0.112	0.090	0.099
		(0.678)	(0.063)	(0.074)	(0.077)	(0.071)
Pooled	1,518	−0.289	0.101**	0.040	0.062*	0.051
		(0.725)	(0.047)	(0.054)	(0.049)	(0.047)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 22: Educational Attainment – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) School degree from vocational track						
Men	235	−1.059	0.211*	−0.004	−0.192	−0.044
		(0.708)	(0.114)	(0.227)	(0.244)	(0.209)
Women	306	−1.144	−0.069	−0.109	−0.029	−0.079
		(0.604)	(0.105)	(0.109)	(0.128)	(0.110)
Pooled	541	−1.106	0.044	−0.002	−0.023	−0.008
		(0.653)	(0.085)	(0.080)	(0.077)	(0.074)
(b) School degree from academic track						
Men	235	1.090	−0.213*	0.004	0.194	0.045
		(0.713)	(0.115)	(0.229)	(0.246)	(0.210)
Women	306	1.175	0.069	0.110	0.029	0.080
		(0.608)	(0.105)	(0.110)	(0.129)	(0.111)
Pooled	541	1.137	−0.044	0.002	0.023	0.008
		(0.658)	(0.086)	(0.081)	(0.078)	(0.074)
(c) Ever attended university						
Men	395	0.673	−0.047	−0.105	0.090	−0.061
		(1.210)	(0.187)	(0.221)	(0.221)	(0.211)
Women	492	0.543	0.203	0.104	0.186	0.133
		(1.202)	(0.153)	(0.144)	(0.157)	(0.137)
Pooled	887	0.601	0.129	0.052	0.139	0.078
		(1.207)	(0.118)	(0.103)	(0.109)	(0.097)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 23: Enrolment in Vocational Training – Vocational Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) At least one year of vocational training						
Men	813	0.323	0.151*	0.226***	0.193**	0.212***
		(0.863)	(0.088)	(0.080)	(0.079)	(0.077)
Women	705	0.370	−0.195**	−0.042	−0.183**	−0.127*
		(0.831)	(0.087)	(0.083)	(0.081)	(0.076)
Pooled	1,518	0.344	−0.014	0.126**	−0.043	0.042
		(0.849)	(0.060)	(0.059)	(0.055)	(0.052)
(b) At least two consecutive years of vocational training						
Men	813	0.294	0.143	0.237***	0.234***	0.236***
		(0.977)	(0.093)	(0.091)	(0.089)	(0.087)
Women	705	0.282	−0.251**	−0.104	−0.306***	−0.225**
		(0.980)	(0.100)	(0.103)	(0.115)	(0.104)
Pooled	1,518	0.289	−0.028	0.092	−0.097	−0.001
		(0.978)	(0.067)	(0.069)	(0.077)	(0.068)
(c) Vocational training successfully completed						
Men	813	0.177	0.158*	0.266***	0.243***	0.257***
		(1.073)	(0.093)	(0.090)	(0.092)	(0.088)
Women	705	0.177	−0.010	−0.002	−0.085	−0.051
		(1.073)	(0.107)	(0.111)	(0.113)	(0.107)
Pooled	1,518	0.177	0.078	0.167**	0.036	0.102
		(1.073)	(0.070)	(0.070)	(0.078)	(0.069)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.

Table 24: Enrolment in Vocational Training – Academic Track

	Obs.	Mean	Raw Diff.	ATT	ATU	ATE
(a) At least one year of vocational training						
Men	395	−0.692	0.017	0.080	0.084	0.081
		(0.920)	(0.147)	(0.167)	(0.171)	(0.164)
Women	492	−0.663	−0.209*	−0.155	−0.192	−0.168
		(0.934)	(0.125)	(0.112)	(0.126)	(0.110)
Pooled	887	−0.676	−0.127	−0.048	−0.043	−0.047
		(0.927)	(0.097)	(0.081)	(0.089)	(0.076)
(b) At least two subsequent years of vocational training						
Men	395	−0.619	0.061	0.087	0.064	0.082
		(0.731)	(0.098)	(0.154)	(0.156)	(0.147)
Women	492	−0.519	−0.259**	−0.232**	−0.211*	−0.224**
		(0.813)	(0.114)	(0.103)	(0.122)	(0.104)
Pooled	887	−0.564	−0.153*	−0.089	−0.092	−0.090
		(0.778)	(0.083)	(0.073)	(0.081)	(0.069)
(c) Vocational training successfully completed						
Men	395	−0.402	0.048	−0.055	−0.056	−0.055
		(0.652)	(0.082)	(0.134)	(0.127)	(0.125)
Women	492	−0.310	−0.100	−0.065	0.007	−0.039
		(0.766)	(0.095)	(0.129)	(0.152)	(0.131)
Pooled	887	−0.351	−0.059	−0.062	0.016	−0.039
		(0.718)	(0.066)	(0.082)	(0.095)	(0.080)

Source: SOEP V28 and authors' calculations. Note: All outcome variables are standardized. Calculations use SOEP sample weights. Standard deviations (mean) and standard errors are in parentheses. Standard errors of the treatment effects are bootstrapped with 250 replications and clustered at the family level. *, ** and *** denote significance at the 10%-, 5%- and 1%-level, respectively.