Physical Activity, Leisure-Time, Cognition and Academic Grades: Connections and Causal Effects in Chinese Students

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ABSTRACT Academic achievement and positive leisure activities are traditionally considered significant determinants of economic growth and human capital accumulation. This paper estimates the impact of physical activity on academic outcome and time allocation to 25 different types of leisure activity by Chinese adolescents. We use structural equation models (SEM) to explore the channels of this transmission. Our results suggest that physical exercise not only exerts a positive direct effect on academic outcome but also increases (decreases) students' time devoted to activities that are positively (negatively) correlated with academic outcome. All the effects are statistically significant but modest at the individual level. Our findings are robust to different exercise frequencies and academic outcome indicators based on students' self-assessment, academic scores, and cognitive tests.

Keywords Structural equation models · Leisure-time activities · Academic performance · Physical activity · Instrumental variables

Jel classification: I20, Z20, C36, C38

1. Introduction

Education plays an essential role in human capital formation. A more educated society facilitates higher economic growth (Barro, 1991; Delgado, Henderson, & Parmeter, 2014) and makes people more concerned about themselves and others, enhancing social values (Sanborn & Thyne, 2014). Among the different ways to improve educational achievement, promoting physical exercise attracts increasing interest (Lipscomb, 2007; Pfeifer & Cornelißen, 2010). It has the advantage of being relatively cheap and easy to implement, and it could be applied at the school rather than the national level. However, the overall effect of physical exercise on educational outcome is still ambiguous. On the one hand, the medical literature generally finds a positive impact of physical activity on cognitive ability by, among other advantages, improving long-term brain plasticity and even increasing individuals' capacity to resist disease (Fernandes, Arida, & Gomez-Pinilla, 2017). On the other hand, exercise may also decrease students' attention to school work or indirectly affect academic outcomes by increasing the allocation of time to leisure activities (Golsteyn, Jansen, Van Kann, & Verhagen, 2020; Pfeifer & Cornelißen, 2010).

Despite these complex links, a common feature in the literature discussed above is the use of reduced-form specifications that mainly focus on identifying the effect of physical exercise on academic outcome using instrumental variables or matching or regression discontinuity designs. Compared to this approach, although there are practical difficulties in identifying a SEM, it has the advantage of providing a complete description of the complicated relationship between treatment, mediators and response variables. Moreover, the presence of cross-sectional disturbance terms associated to variables in the model allows us to control for measurement errors and common omitted variables, two common forms of endogeneity in applied economics analysis.

This paper analyses the impact of physical activity on academic outcome and time allocation to different types of leisure activities by Chinese adolescents. The study uses data from the China Education Panel Survey (CEPS), a comprehensive longitudinal database that contains information on individual adolescents in 28 counties. We conduct the analysis using structural equation models (SEM henceforth). The use of this methodology serves two essential purposes. First, it allows us to make the estimation problem more tractable by grouping a large and heterogeneous set of variables into a reduced number of latent variables with a more insightful interpretation that is jointly estimated with the model parameters. This is the case of information about 25 leisure activities that are grouped into four main latent variables and academic performance in three principal subjects (Math, Chinese and English) that are explained by a single measure of academic performance. This facilitates a simple and intuitive estimation of the impact of physical activity on academic performance. A second advantage of using SEM in our particular context is that it allows us to explore the path through which exercise affects educational outcome by distinguishing between a direct impact and an indirect impact through affecting the time devoted to different activities.

The analysis of the impact of physical activity on academic outcome has already attracted the attention of academics in previous literature. See Golsteyn et al. (2020) and Pfeifer and Cornelißen (2010) to cite just two examples. Our paper contributes to previous research in at least three ways. Firstly, our aim is not only to provide a final estimation of the impact of physical exercise on academic outcome but also to explore this impact's mechanisms. The use of an SEM approach is instrumental for this purpose. It allows us to disentangle the direct effect of physical activity on academic outcome and its indirect effect through its impact on leisure-time activities that act as moderators in this transmission. This is relevant for teachers, school managers, and policymakers to design policies that incentivise physical activity. Moreover, estimating the effect of physical activity on many positive and negative habits is interesting because they can affect human capital formation even if they do not affect academic outcome. Aadland et al. (2017) also study the impact of exercise on educational outcome in 1,100 10-year-old Norvegian children using an SEM model. However, the present paper studies this issue from a different angle focusing on the direct and indirect effect (through twenty-five leisure activities) of physical exercise on cognition and academic outcome. Another remarkable difference with Aadland et al. (2017) is that the present research considers a representative sample of a whole nation and instruments to deal with the potential endogeneity of physical exercise.

A second contribution is the joint consideration of self-assessed and objective measures of academic performance in different subjects and cognitive test results. This extensive range of response variables allows us to explore the robustness of the results and identify the subjects where students' performance is more likely to be affected by physical exercise. A final contribution is our focus on Chinese students. To our knowledge, this is the first analysis of this type for a developing country. We consider this is relevant as these countries require to close the gap with more developed economies in terms of school attainment (Hanushek, 2013) to increase economic growth. Moreover, their populations face more significant obstacles to practising exercise and other types of leisure activity (Reichert, Barros, Domingues, & Hallal, 2007). China is one of the most interesting cases to study. It is the most populous country and the second-largest economy globally but has relatively low per capita income.

Our results suggest that physical exercise positively affects academic outcome and leisure-time activities positively correlated with educational outcomes such as studying and cultural activities. Moreover, physical activity reduces students' time devoted to activities negatively associated with academic outcome, such as different types of harmful habits that includes, for example, quarrelling, bullying and truancy. Our results are robust to various academic outcome measures and econometric considerations on the simultaneity between leisure-time activities and academic outcome in the SEM.

This paper proceeds as follows. The next section discusses the related literature. Section 3 describes the theoretical framework employed in the paper. Section 4 describes our database and the variables considered in the paper. Empirical analysis and extended analysis are contained in Sections 5 and 6, respectively. The last section concludes.

2. Related literature

Empirical research about the impact of sport participation and physical activity on academic outcome is very heterogeneous in many aspects, such as subjects and countries included in the analysis, methodologies and variables employed. Therefore, while some papers have found a positive impact of physical activity on academic performance (Muñoz-Bullón, Sanchez-Bueno, & Vos-Saz, 2017; Pfeifer & Cornelißen, 2010), others find weak positive evidence (Barron, Ewing, & Waddell, 2000) or even a negative relationship (Golsteyn et al., 2020). However, a common feature of this literature is that it is mainly based on reduced-form specifications; see, for example, Bradley and Conway (2016) and Muñoz-Bullón et al. (2017) for a detailed review.

Given that practising physical exercise is a voluntary decision and, therefore, randomisation is typically not possible in this context, research papers appeal to approaches such as difference-in-difference, matching or instrumental variables. For example, Golsteyn et al. (2020) exploit an exogenous shock, a political intervention in the Netherlands that incentivises physical activity during school hours, allowing a causal effect identification. Using a difference-in-difference analysis, they find that students affected by this policy did not improve their school performance compared to other groups. Although their research has important implications for policymakers and educators, the authors also suggest that their results cannot be generalised to physical activity in everyday life. Moreover, similar to other research methods, a difference-in-difference analysis is also subject to subjectivity. It is based on the assumption that in the absence of treatment, the response variable is monotonic in the unobservables. Moreover, the distribution of such unobservables is invariant across time (Athey & Imbens, 2006).

Felfe, Lechner, and Steinmayr (2016) and Cabane, Hille, and Lechner (2016) consider propensity score techniques to identify the causal effect of physical exercise on education. Although they consider reduced-form specifications, these two papers are closely related to our research as they explore the potential channels of transmission. In particular, Felfe et al. (2016) find that participation in sports clubs positively affects children's school performance in Germany by crowding out passive leisure-time activities such as TV consumption. Cabane et al. (2016) compare the impact that physical exercise and an alternative leisure-time activity, playing music, exert on educational performance finding that playing music has a relatively bigger impact on the scholarly output of adolescents. Where a longitudinal database is available, some papers have used individual fixed effects as a way to control for unobserved heterogeneity, i.e. personal characteristics that do not change over time. Rees and Sabia (2010) and Lipscomb (2007) are two examples of this approach, finding in both cases a positive but small effect of sport participation on education outcomes. As discussed by Rees and Sabia (2010), although fixed effects allow controlling for time-invariant unobservables, casual estimates could still be biased under this approach if individual motivations to demand education change through time. Moreover, this approach does not control other forms of endogeneity such as simultaneity or measurement errors.

An alternative approach involves using instruments (Barron et al., 2000; Muñoz-Bullón et al., 2017; Pfeifer & Cornelißen, 2010; Rees & Sabia, 2010). Instruments are expected to help to predict the decision to practice sport, but there should not be a direct relationship between the instrument and the response variable, educational outcome. While the former condition can be formally tested in a regression analysis, the latter is untestable and can only be justified based on logical arguments as the real error components are unobservable. Thus, Barron et al. (2000) use as instruments the size of the school and characteristics of the geographical area where the school is located. Rees and Sabia (2010) use height as an instrument, and Muñoz-Bullón et al. (2017) choose the number of sports clubs serving the population in the student's region of residence. These papers provide mixed evidence about the impact of sports participation on education. In particular, while Pfeifer and Cornelißen (2010) and Muñoz-Bullón et al. (2017) find that sports have a significant and positive effect on the attainment of educational goals, Rees and Sabia (2010) and Barron et al. (2000) only find evidence of a small but positive effect.

We contribute to this literature by estimating a general picture of the impact of physical exercise on academic outcome both directly and indirectly through 25 habits and leisure-time activities. They are grouped into harmful activities, visual media exposure, study time and cultural activities. Thus, compared to reduced form specifications, SEM does not focus on estimating the final effect of treatment but is more informative about transmission channels. This approach is not free of criticism. In particular, it is based on subjective hypotheses on how different variables in the model are interrelated. However, it can naturally deal with two common forms or endogeneity, such as omitted variables and observation errors, by allowing correlation across disturbance terms in each of the variables in the model. Moreover, model structure can be chosen in a way that allows for a causal economic interpretation.

3. Theoretical framework

Physical activity may affect academic outcome in several direct and indirect ways. Barron et al. (2000) employed the two-period model of time allocation proposed by Becker (1965). Under this framework, a student's utility depends on the time devoted to education, leisure time and physical activities. The reward to time spent acquiring education is a higher stock of human capital, and therefore, a higher income in the future period. Although this assumption is subsequently relaxed in Barron et al. (2000), the model initially assumes that participation in physical activity makes no direct contribution to an individual's stock of human capital. According to this, if we abstract from the impact of physical activity on human capital, we can hypothesise that physical exercise may harm academic outcome if it reduces the time that students devote to their education (H1). An alternative possibility is that participants in physical activity do not necessarily reduce the time devoted to study if they replace time devoted to physical activity with other leisure-time activities. If this is the case, the impact of physical activity on academic outcome is ambiguous. On the one hand, it could displace negative leisure-time activities that do not contribute, or have a lesser contribution than physical exercise, to educational attainment. Still, on the other hand, it could crowd out positive activities in terms of education, especially time devoted to study. In the former case, we would assume that physical activity would positively impact academic output (H2) while the impact would be negative (H3) in the latter case.

Even if we do not consider the hypotheses discussed in the previous paragraph and instead ignore any effect of participation in physical activity on time devoted to leisure-time activities and study time, physical exercise could still influence academic outcome. As suggested by the medical literature, this would be the case if it positively affects health, concentration, and/or ability (H4).

A key point to note is that hypotheses H1 to H4 are not mutually exclusive. For example, physical activity could increase students' concentration, which is consistent with H4, but, at the same time, it could reduce the time devoted to study, H3. If this were the case, the two effects could be offset, making the total impact close to zero. This suggests that, in order to have a complete picture of the mechanism through which physical activity influences academic outcome, it is necessary to estimate its impact on the time devoted to different types of leisure-time activity.

4. Data

The study uses data from the China Education Panel Survey (CEPS) conducted by the National Survey Research Center at Renmin University of China. The CEPS is a nationally representative and school-based survey that samples approximately 20,000 students' observations from 438 classrooms in 112 junior high schools in 28 counties in Mainland China. It provides information at different levels, including individual, family and school. The CEPS includes demographic characteristics and education outcomes, as well as basic household and school information. Our sample contains seventh-year students in the 2013/14 academic year and subsequent observations of the same students in the 2014/15 academic year. As we will explain later, we restrict our analysis to the second wave, given that our treatment variable is only observed in that period. However, the longitudinal nature of our database is relevant as it allows us to consider lagged instrumental variables of our treatment to control for potential simultaneity between physical exercise and response variables. Therefore, our final estimation sample consists of 7197 observations in the second wave after removing missing values. In a non-reported experiment, we also considered tackling data irregularities with an EM algorithm, which increased the number of observations to 7935 (Graham, 2009). However, it did not produce any material change in the analysis reported in the subsequent sections.

Response variables represent students' academic outcome and cognition. Students' academic output is measured based on three sets of variables indicating: (1) their self-assessment, (2) score in academic tests, and (3) score in cognitive tests. For simplicity, we denote these three sets of indicators as Subjective academic assessment (*SAA*), Objective academic performance (*OAP*) and *Cognition*, respectively. In turn, *SAA* is measured by three variables that indicate the difficulty of learning Mathematics, Chinese and English at present evaluated by students denoted by *Math*, *Chinese*, and *English*. They are ordinal indicators taking discrete values from 1 to 4, ranging from greater to lesser difficulty for the student. Having a subjective student evaluation of academic outcome has the advantage of offering more comprehensive information about this variable than the one obtained from exam results, which may depend on the type of questions and marking conventions. However, it has the disadvantage that, as a subjective evaluation, it could be affected by idiosyncratic shocks. Thus, to have a complete measurement of academic performance, we further consider three *OAP* items, including the mid-term marks of students' Mathematics, Chinese and English modules in the second wave, ranging from 0 to 150, denoted by *Mathscore, Chinesescore* and *Englishscore* respectively. *Cognition* measures students' basic logical thinking and problem-solving ability, rather than memorising or being taught by the school curriculum. This variable takes values from 0 to 35 and includes information on students' capabilities such as language, space, and calculation and logic.

Our treatment (*Exercise*) is a continuous variable measuring the usual weekly exercise time. This variable is defined by exercise days per week times exercise minutes per day. For convenience, this magnitude is rescaled dividing by 30, so the variable is measured in half-hour units. Our sample includes 25 different leisure-time activity variables classified into four main groups: harmful habits, visual media, study and cultural activities. Detailed descriptions of all these variables are presented in Appendix Table A1.

We also consider different predisposing and enabling variables that, in principle, are the main determinants of academic output. Our predisposing variables include the following individual characteristics: *Age* and *Male*. More specifically, *Age* is included because of the different brain maturation and lifestyle for different age groups (Lebel, Walker, Leemans, Phillips, & Beaulieu, 2008). *Male* is a binary variable that takes value 1 for male and is 0 otherwise. It controls for potential gender differences that could affect treatment allocation, evaluation of academic performance and cognition. For example, boys could be more active than girls (Trost et al., 2002) and are in general better equipped with electronic media devices (Mossle, Kleimann, Rehbein, & Pfeiffer, 2010). In addition, there might be gender inequalities in educational performance and attainment (Buchmann, DiPrete, & McDaniel, 2008) as a female advantage in school marks is commonly found in previous research (Voyer & Voyer, 2014).

Enabling variables refer to the availability of educational resources and participation in specific activities. We include *School ranking*, *Household registration type* (*Hukou*), *Income level* and *Poor health* in this variable list. *School ranking* takes values 1 to 5, ranging from low to high ranking. *Hukou* is a dummy variable that takes value 1 or 0 depending on whether a student has an agriculture hukou. This variable is considered since individuals with the agriculture hukou typically come from rural China and could have more restricted access to social resources than people with other hukou types. *Income level* takes values 1 to 5, ranging from very poor up to wealthy individuals. Children of wealthy families, in general, get a better education and can participate in a wide variety of activities. *Poor health* takes values 1 or 0 depending on whether a student's self-rated health status is lacking. Health measurements are included because fitness has a significant relationship with academic achievement (Chomitz et al., 2009). Additionally, it is also related to the ability to engage in specific activities.

Table 1

Summary statistics (number of observations= 7197)

	(1)	(2)	(3)	(4)

Variable	Mean	Standard. Deviation.	Minimum	Maximum
SAA				
Math	2.502	0.873	1	4
Chinese	2.857	0.753	1	4
English	2.395	0.983	1	4
OAP				
Mathscore	78.29	30.66	0	150
Chinesescore	83.24	18.97	0	142.5
Englishscore	75.71	28.98	0	149.5
Cognition	23.60	6.466	0	35
Time allocation				
Harmful habits				
Curse	2.212	0.977	1	5
Quarrel	1.821	0.866	1	5
Fight	1.325	0.681	1	5
Bully	1.133	0.479	1	5
Violent	1.857	0.972	1	5
Notconcentrate	2.219	1.020	1	5
Skip	1.074	0.380	1	5
Copy	1.471	0.765	1	5
Smokeordrink	1.094	0.447	1	5
Netbar	1.182	0.600	1	5
Undersleep	0.380	0.485	0	1
Visual media				
Time_tv1	2.419	1.372	1	6
Time_net1	2.201	1.400	1	6
Time_tv7	2.745	1.178	1	6
Time_net7	2.592	1.328	1	6
Study				
Time_teacher1	3.541	1.130	1	6
Time_pa1	1.773	1.033	1	6
Time_cram1	1.607	1.245	1	6
Time_teacher7	3.029	1.022	1	6
Time_pa7	1.614	0.830	1	6
Time_cram7	1.709	1.154	1	6
Cultural activities				
Museum	2.153	1.278	1	6
Film	2.470	1.488	1	6
Museum_family	2.090	1.058	1	6
Film_family	2.131	1.182	1	6
Treatment variable				
Exercise	4.590	3.744	0	18.67
Predisposing variables				
Age	13.89	0.850	12	19
Male	0.503	0.500	0	1
Enabling variables				
Rank school	4.020	0.825	1	5
Agriculture hukou	0.518	0.500	0	1
Income	2.956	0.599	1	5

Poor health	0.061	0.239	0	1

Source: Own computation using the CEPS database.

Table 1 shows descriptive statistics of our variables. The sample used in the baseline analysis includes students whose age ranges from 12 to 19 with an average age of 14 and a standard deviation of 0.85. The diversity in age for students in the same grade is due to grade retention. However, the number of these students is small (only 35 out of 7197 students are more than 16 years old). The other confounders show that, for example, the sample is roughly equally split between males and females and that, on average, individuals are in the middle-income level of 3.

For our treatment variable, the mean exercise frequency is 4.56 half-hours a week with a standard deviation of 3.744. Fig. 1 shows the distribution of our dependent variables. In general, with the only exception of *Math* and *Chinesescore*, they are asymmetric and left-skewed. However, most ranges of values are represented in the sample.

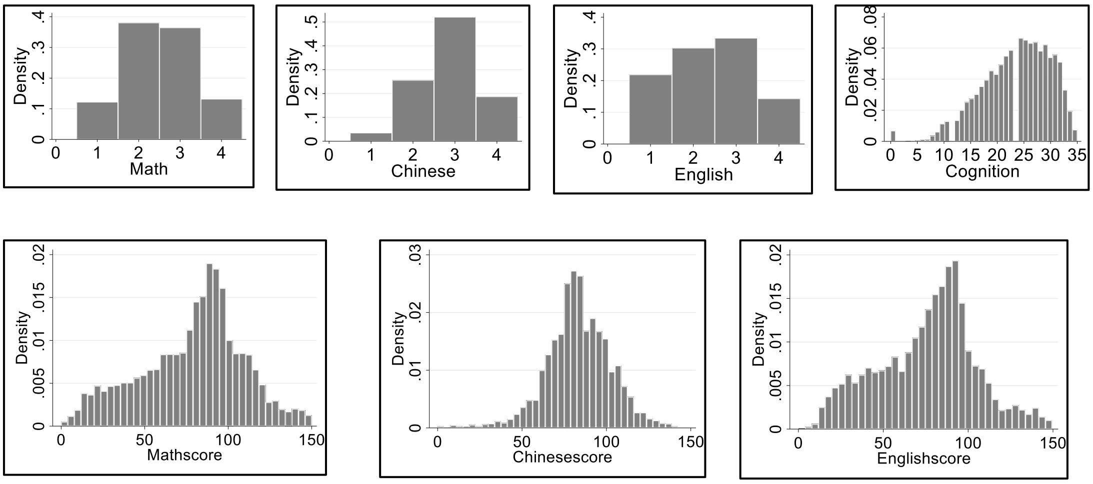

Fig. 1 Distribution of the dependent variables

5. Empirical analysis

Three SEM models are specified and estimated for each of the three groups of response variables defined in the previous section: *SAA*, *OAP* and *Cognition*. In each model, physical exercise can impact academic outcomes directly and indirectly through different activities. In the first two cases, *SAA* and *OAP* report information on *Math*, *Chinese* and *English*. We group these three variables into a single latent variable, given that our focus is on total academic output. We report individual estimation for each subject in the next section.

Moreover, for the 3 SEM specifications, the 25 leisure activities presented in the previous section are grouped into four latent variables based on the CEPS's definition: *Harmful habits*, *Visual media*, *Study*, and *Cultural activities*. *Harmful habits* correspond to actions that can represent damage to the student's health or his/her relationship with the academic community, such as, for example, being involved in a quarrel, fight, bullying, being violent or skipping classes. *Cultural activities* include visits to museums, zoos, science museums, etc., and time spent watching films, shows, sports games, etc. At the same time, *Visual media* includes time spent watching TV and internet surfing or playing video games. The impact of these latter two latent variables on academic outcome is uncertain. On the one hand, they can incentivise students' intellectual curiosity and help to replenish attentional resources. Still, on the other hand, they could also crowd out time devoted to study. The fourth latent variable, *Study*, comprises different measures of time dedicated to doing homework or schoolwork by the students. The expected impact of this variable on academic outcome is positive. Note that the four common variables are jointly estimated as latent variables together with all other parameters (Bollen & Hoyle, 2012).

As discussed in section 3, the effect of *Exercise* in each of the four mediators discussed above is uncertain. For example, it could change life habits by either increasing or decreasing time devoted, for example, to *Study* or *Cultural activities*. Moreover, even if exercise does not affect the amount of time dedicated to different activities, it still can affect the quality of this time by increasing the student's capacity for concentration.

Fig. 2 describes how variables are connected in each of the three models under analysis. All of them have a similar structure. *Exercise* and other confounders in the model, already defined in the previous section, affect *SAA*, *OAP*, or *Cognition*. This effect could be direct or indirect through four latent groups of leisure-time activities already described. These latent variables are simultaneously estimated with the other parameters in the SEM models. Estimated loading factors for the different latent variables employed in the model are included in the Appendix, Table A1.

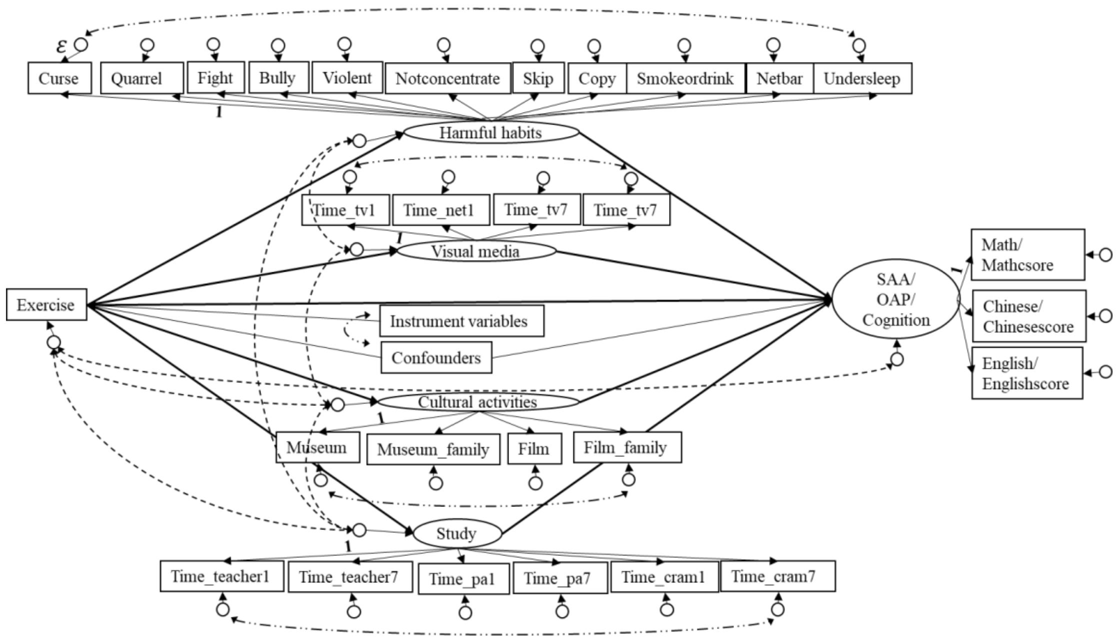

Fig. 2 Path model for relationships between exercise and academic outcome.

Note: Blank circle shapes correspond to disturbance terms.

An important point to mention at this stage is that all observed and latent variables are affected by disturbance terms that are allowed to be correlated across them. This is especially relevant to deal with at least two types of endogeneity problems such as observational errors and omitted variables that simultaneously affect treatment, confounding and response variables. However, other endogeneity issues may remain in our model. For this purpose, we include a set of variables that we hypothesise to impact academic performance only indirectly through its effect on the decision to practice physical exercise. In particular, four different variables (IV) are included in this group. The first two are the following time-lagged exercise variables: On average, minutes per day an individual spent doing exercise during the previous weekend,[1] measured at the first wave; and whether practising physical activity was a hobby for the student at the first wave. We also consider two additional instruments: whether a student's school had a swimming pool at the second wave; the student's height, measured in centimetres, was at the first wave. A swimming pool is a good proxy for access to general sports facilities as its construction is generally more expensive than alternative facilities. Therefore, the availability of sports services where students spend most of their time is, in principle, a good predictor of the probability of practising sports. At the same time, it does not directly impact academic performance as which school to attend is determined by geographical proximity, academic scores, and random allocation in China (Guan & Tena, 2021; Xu, 2000). Height is a common instrumental variable used in the literature. It is plausible to assume this variable is associated with the probability of doing exercise but not with academic outcome (Rees & Sabia, 2010). Here, we report estimation results with the four proposed instruments. However, our conclusions are robust to the choice of any of them.

In our estimation approach, we started from basic models in which confounders and instrumental variables and residuals between exercise and academic outcomes are allowed to be correlated. Other covariances are omitted. Score tests (Lagrange multiplier tests) are applied for the statistical significance of the constrained

[1] We cannot distinguish the exercise participation between weekdays and weekends in the second wave. This information is only offered in the first wave.

parameters; see Sörbom (1989) and Wooldridge (2010, 421-428). Based on the tests, more covariances between different residuals are linked to improving the model fit. The double arrow dotted lines in Fig. 2 represents a sketch of the connection.

All components of the model depicted in Figure 2 are jointly estimated. However, for clarity of exposition, we present and discuss results sequentially. In particular, latent variables regarding the main groups of leisure activities are formed as a weighted average of their components. Detailed information about this estimation is reported in Appendix Table A1. Table 2 shows the estimated effect of confounders and IV on *Exercise* in each of the three SEM models. It can be observed that the four IVs are significant with the expected sign. Among the set of confounders, results indicate that other things equal, girls, students with non-agricultural hukou and students in high-rank schools and high-income families practice more physical exercise on average.

Table 2
Determinants of Exercise

	SAA	OAP	Cognition
Lag exercise in weekend	0.002***	0.002***	0.002***
	(8.78)	(7.77)	(8.67)
Lag exercise hobby	0.175***	0.178***	0.170***
	(4.37)	(4.38)	(4.20)
Swimming pool	0.428***	0.391***	0.443***
	(4.02)	(3.46)	(4.12)
Lag height	0.035***	0.040***	0.035***
	(11.91)	(11.79)	(11.95)
Age	-0.024	-0.021	-0.021
	(-1.10)	(-0.97)	(-1.00)
Male	-0.268***	-0.269***	-0.263***
	(-7.16)	(-7.19)	(-7.06)
Rank school	0.162***	0.163***	0.160***
	(7.16)	(7.21)	(7.10)
Agriculture hukou	-0.914***	-0.916***	-0.916***

	(-16.12)	(-16.13)	(-16.17)
Income	0.659***	0.659***	0.662***
	(15.32)	(15.32)	(15.40)
Poor health	-0.060	-0.060	-0.059
	(-0.82)	(-0.81)	(-0.81)
Constant	-2.872***	-2.883***	-2.939**
	(-4.83)	(-4.84)	(-4.94)
#Obs.	7197	7197	7197

Note: t statistics in parentheses, * p<0.1 ** p<0.05 *** p<0.01. Source: Own estimation using the CEPS database.

Now we turn our attention to the primary purpose of the analysis, the estimation of the direct and indirect effect of *Exercise* on the different measures of academic achievement considering the different mediating impacts of each activity. This information is shown in Table 3. The goodness of fit statistics (CFI>0.9; RMSEA<0.06) indicate that all of the three models fit well (Hu & Bentler, 1999).

Interestingly, *Exercise* exerts a significantly positive direct effect on academic outcome, which is consistent across the three measured measurements of academic achievement considered in the analysis and contributes to incentivising (reduce) positive (negative) habits in terms of academic achievement. Therefore, the total effect of increasing exercise each week by half an hour, obtained from the sum of direct effect and indirect effect, is 0.115, 3.002 and 0.781 on *SAA*, *OAP* and *Cognition*, respectively. These estimates are of small magnitude in all cases, which logically suggests that increasing physical exercise by itself cannot turn a student with poor academic outcome into an optimal one. However, the fact that this causal effect is highly significant suggests that managerial policies promoting physical exercise could have a relevant impact on academic outcome for the aggregate student population in China by promoting healthy habits and improving student's academic achievement.

Table 3

Effect of Exercise on SAA, OAP and Cognition

	SAA	OAP	Cognition
Exercise			
Direct effect	0.008***	0.242***	0.093***
	(4.91)	(2.73)	(4.10)
Indirect effect	0.107***	2.760***	0.688***
	(6.92)	(3.34)	(3.42)
Total effect	0.115***	3.002***	0.781***
	(7.35)	(3.57)	(3.82)
CFI[a]	0.9	0.9	0.9
RMSEA[b]	0.039	0.040	0.040
#Obs.	7197	7197	7197

Note: t statistics in parentheses, * p<0.1 ** p<0.05 *** p<0.01, [a] CFI indicates comparative fit index, [b] RMSEA indicates root mean squared error of approximation. Source: Own estimation using the CEPS database.

Table 4 presents the direct effect of *Exercise*, different mediators and confounders on *SAA*, *OAP* and *Cognition*. Other than physical exercise, devoting more time to *Study* and *Cultural activities* can also significantly positively affect *SAA* and *OAP* of students. Spending more time on *Cultural activities* can improve students' *Cognition*, however, studying more does not significantly improve children's *Cognition*. This is reasonable as cognition might be hard to train in the short run by school courses. Spending more time on *Harmful habits* and *Visual media* have significant adverse effects on academic outcome.

Moreover, other things equal, female students have significantly higher *SAA* and *OAP* levels, but not *Cognition*. Students from more affluent families have a significantly higher level of *SAA* and *Cognition* but not *OAP*. Age has a significantly negative effect on academic outcome. The most likely reason for this is that grade repeaters generally face more difficulty in learning.

Table 4

Direct effect of Exercise and mediators on SAA, OAP and Cognition

	SAA	OAP	Cognition
Exercise	0.008***	0.242***	0.093***
	(4.91)	(2.73)	(4.10)
Harmful habits	-0.146***	-9.561***	-1.653***
	(-9.24)	(-10.48)	(-7.31)
Visual media	-0.048***	-3.129***	-1.135***
	(-5.48)	(-6.14)	(-8.45)
Study	0.100***	9.651***	0.454
	(3.44)	(5.93)	(1.13)
Cultural activities	0.188***	3.280**	1.257***
	(7.63)	(2.35)	(3.67)
Age	-0.058***	-2.972***	-0.588***
	(-8.87)	(-8.49)	(-6.65)
Male	-0.135***	-8.693***	0.505***
	(-12.23)	(-14.17)	(3.27)
Rank school	-0.002	4.013***	0.711***
	(-0.25)	(10.09)	(7.12)
Agriculture hukou	-0.022	-3.444***	-0.241
	(-1.25)	(-3.33)	(-0.94)
Income	0.069***	0.797	0.497**
	(4.99)	(1.01)	(2.53)
Poor health	-0.065***	0.557	0.037
	(-3.02)	(0.46)	(0.12)
#Obs.	7197	7197	7197

Note: t statistics in parentheses, * p<0.1 ** p<0.05 *** p<0.01. Source: Own estimation using the CEPS database.

Table 5 presents the effect of *Exercise* on four groups of leisure-time activities (mediators). Under three models, *Exercise* significantly decreases students' time spent on *Harmful habits* and significantly increases students' time spent on *Visual media*, *Study* and *Cultural activities*. This is interesting, as the results suggest that doing physical exercise does not crowd out studying time but helps students allocate their time more efficiently.

Table 5

Effect of Exercise on time allocation of different groups of activities

	SAA	OAP	Cognition
Harmful habits			
Exercise	-0.004**	-0.003**	-0.003**
	(-2.21)	(-2.08)	(-2.02)
Visual media			
Exercise	0.007***	0.006***	0.006**
	(2.95)	(2.65)	(2.12)
Study			
Exercise	0.111***	0.112***	0.109***
	(11.66)	(11.57)	(11.52)
Cultural activities			
Exercise	0.506***	0.502***	0.509***
	(17.06)	(17.02)	(17.07)
#Obs.	7197	7197	7197

Note: t statistics in parentheses, * p<0.1 ** p<0.05 *** p<0.01. Source: Own estimation using the CEPS database.

6. Extended analysis

6.1. Endogeneity of leisure-time activities.

A general problem with SEM regards the specification of the model to identify structural parameters. More specifically, results in the previous section assume that leisure-time activities are meditators through which physical exercise indirectly affects academic outcome. This is consistent with the hypothesis that human capital formation by investing time in acquiring education and other activities precedes the observation of educational development (Becker, 1965). However, it is also possible to adopt a more conservative approach by assuming that academic outcome and all the different leisure-time activities are simultaneously determined. In order to take this point into account, we modify the structure of the SEM models by allowing for correlated residuals between each of the different leisure-time activities and response variables. This model is conceptually distinct from the one defined in the previous section as the four activities are no longer mediators between *Exercise* and academic output but additional response variables. In this framework, we can only estimate the direct effect of *Exercise* on academic performance and its impact on activities that are correlated with educational outcome.

The estimation results of these models are almost identical to those reported above, but their interpretation is very different. More specifically, the total effect of increasing exercise by half-hour per week obtained from the direct impact are all statistically significant and of magnitude 0.115, 3.002 and 0.781 on *SAA*, *OAP* and *Cognition*, respectively, which are the same as those in the baseline model. Moreover, exercise still increases the amount of time devoted to *Visual media*, *Study* and *Cultural activities* while it decreases the time dedicated to *Harmful habits*. Although we cannot infer causality, *Study* and *Cultural activities* are positively correlated with academic output, while *Harmful habits* and *Visual media* are negatively associated with the response variable.

6.2. Endogeneity of physical exercise

Endogeneity of physical exercise is a common concern in this type of analysis. Although a distinctive aspect of this research, compared to related SEM papers in the literature (Aadland et al., 2017) is the use of IVs to deal with the endogeneity issue, this could not be enough. For this reason, we consider two additional experiments to deal with this issue. The first one includes an additional confounder in the baseline model to explain *Exercise*: *Conscientiousness*. This variable indicates how persistent the student is in his/her studies and hobbies.[2] Therefore, it is, in principle, a relevant predictor of both treatment allocation (endogeneity) and academic outcome. Final effect estimates, shown in the first three columns of Table 6, indicate a positive impact of exercise on academic outcome, consistent with the baseline model.

Table 6
Impact of Exercise on academic outcome under two alternative approaches to further deal with the endogeneity of Exercise

	First estimation[(1)]			Second Estimation[(2)]		
	SAA	OAP	Cognition	SAA	OAP	Cognition
Direct effect	0.007***	0.176**	0.087***	0.011***	0.002	0.074***
Indirect effect	0.097***	2.160***	0.611***	0.158***	0.023	0.401**
Visual media	-0.0003***	-0.016***	-0.006**	-0.001***	-0.0003***	-0.009***
Study	0.010**	0.980***	0.038	0.011**	0.013***	-0.027
Cultural activity	0.087***	1.168*	0.575***	0.123**	0.009	0.414**
Negative habits	0.0005**	0.028**	0.005**	-0.021	0.0001	0.0009
Total effect	0 .104***	2.335***	0.698***	0.169***	0.025	0.475**
CFI[(a)]	0.9	0.9	0.9	0.9	0.9	0.9
RMSEA[(b)]	0.041	0.041	0.041	0.040	0.040	0.040
#Obs.	7192	7192	7192	7197	7197	7197

Note: * p<0.1 ** p<0.05 *** p<0.01, [(a)] CFI indicates comparative fit index, [(b)] RMSEA indicates root mean squared error of approximation, [(1)] Conscientiousness added as a determinant of physical activity, [(2)] An additional instrumental variable based on parents expectations. Note that there is a lower number of observations due to missing values in conscientiousness. Source: Own estimation using the CEPS database.

In a second experiment, we explore further the use of instruments to identify the direction of causality between *Exercise* and academic outcome. Thus, the new SEM

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[2] Concientiousness is defined as the sum of four variables indicating the degree of agreement with the following four statements 1) try best to go to school even if was not feeling very well or had other reasons to stay at home; 2) try best to finish even the homework dislike; 3) try best to finish homework, even if it would take quite a long time; and 4) persist in interests and hobbies.

has a similar path to the baseline SEM except for two issues: 1) Another direct effect from academic outcome to exercise is generated, and 2) a new instrumental variable affecting the academic outcome is further considered. In particular, we use parents' expectation of their child's highest education level as such an instrument variable. This variable takes values ranging from 1 to 9, with a higher value indicating a greater parents' expectation. This IV exerts a significantly positive impact on students' academic performance ($p<0.01$). In addition, it is reasonable to assume that it should not directly affect children's physical exercise participation. Estimation results are reported in the last three columns of **Table 6**. The impact of *Exercise* on *OAP* is less evident. Although this new model imposes a substantial modification in the SEM structure (transmission path becomes a loop), we still observe a positively significant impact of *Exercise* on *SAA* and *Cognition*.

6.3. Disaggregated analysis

We analyse the impact of different exercise frequencies on academic performance and cognition. To do this, we disaggregate the *Exercise* variable into three treatment variables. They indicate whether students participate in physical exercise 2.5 hours or more (low level), 5 hours or more (medium level), or 7.5 hours or more (high level) per week. We find evidence of a positive impact of all exercise frequencies. In particular, estimation results shown in

Table **7** indicate that low and moderate exercise levels are especially beneficial for *Cognition*. However, the positive impact of high-frequency physical activity is more evident for *SAA* and *OAP*.

Table 7
The impact of different level of exercise on academic outcomes

	SAA			OAP			Cognition		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Direct effect	0.242***	0.486***	1.183***	-1.711	2.233	31.453*	2.136***	3.547**	5.429
Indirect effect	0.066***	0.065***	0.040***	2.012***	1.604***	-0.501	0.345***	0.270***	-0.140
Visual media	0.003**	-0.005**	-0.018***	-0.014	-0.369***	-1.216***	-0.017	-0.093***	-0.281***
Study	0.006***	0.008***	0.009***	0.578***	0.681***	0.831***	-0.004	-0.007	-0.008
Cultural activity	0.048***	0.062***	0.075***	1.023***	1.316***	1.496***	0.280***	0.376***	0.486***
Negative habits	0.008***	0.0002	-0.027***	0.426***	-0.023	-1.612***	0.087***	-0.006	-0.337***
Total effect	0.307***	0.551***	1.223***	0.301	3.838	30.952*	2.481***	3.817***	5.290
CFI[(a)]	0.9	1	1	0.9	1	1	0.9	1	1
RMSEA[(b)]	0.046	.	.	0.044	.	.	0.044	.	.
#Obs.	7197	7197	7197	7197	7197	7197	7197	7197	7197

Note: * p<0.1 ** p<0.05 *** p<0.01, [(a)] CFI indicates comparative fit index, [(b)] RMSEA indicates root mean squared error of approximation.

Source: Own estimation using the CEPS database.

The second disaggregation extension of our baseline specification regards estimating the specific impact of physical exercise on different academic subjects: *Math*, *Chinese* and *English*. This disaggregation is relevant as different subjects could be related to students' different abilities. The path model for this analysis is similar to Fig. 2 but replaces the response variable with each subject. Thus, we use the information reported by *SAA* and *OAP* in each of the three subjects to estimate three SEM models. Table reports these estimation results. Although the direct effect is only evident in *Math* and *English*, they show a positive and significant total impact of exercise on each of the three subjects under analysis.

Table 8

The impact of Exercise on different subjects

	Math	Chinese	English
Direct effect	0.012***	0.001	0.013***
Indirect effect	0.068***	0.076***	0.164***
Visual media	-0.001***	-0.0003***	-0.001***
Study	0.022***	0.012***	0.034***
Cultural activity	0.045**	0.064***	0.129***
Negative habits	0.001**	0.0005**	0.001**
Total effect	0.080***	0.077***	0.177***
CFI[(a)]	0.9	0.9	0.9
RMSEA[(b)]	0.040	0.039	0.040
#Obs.	7197	7197	7197

Note: * p<0.1 ** p<0.05 *** p<0.01, [(a)] CFI indicates comparative fit index, [(b)] RMSEA indicates root mean squared error of approximation. Source: Own estimation using the CEPS database.

We also study the different impact of physical exercise on academic outcomes on males and females. The measurement part of the model is constrained by default to be the same across the groups, whereas the remaining parts have separate parameters for each group. Standardised root mean squared residual (SRMR) between 0 to 0.08

indicates the model fit well in each group (Hu & Bentler, 1999). Estimation results of this analysis reported in Table shows an overall positive effect of exercise for both genders. However, the main difference is that a higher total *OAP* impact is observed for males and a higher *Cognition* impact for females.

Table 9
Impact of Exercise for males and females

	SAA		OAP		Cognition	
	Male	Female	Male	Female	Male	Female
Direct effect	0.005**	0.012***	0.104	0.288*	0.052*	0.157***
Indirect effect	0.106***	0.088***	4.159***	1.544	0.764***	1.008***
Visual media	-0.001***	0.0004**	-0.091***	0.021***	-0.026***	0.015***
Study	0.012***	0.005	1.198***	0.779***	0.109**	0.034
Cultural activity	0.097***	0.079***	3.191***	0.552	0.701***	0.912***
Negative habits	-0.002***	0.003***	-0.139***	0.192***	-0.021***	0.048***
Total effect	0.111***	0.100***	4.263***	1.832	0.816***	1.166***
SRMR(a)	0.052	0.053	0.053	0.053	0.052	0.053
CFI(b)	0.9		0.9		0.9	
RMSEA(c)	0.040		0.041		0.040	
#Obs.	7197		7197		7197	

Note: * p<0.1 ** p<0.05 *** p<0.01, (a) SRMR indicates standardised root mean squared residual, (b) CFI indicates comparative fit index, (c) RMSEA indicates root mean squared error of approximation. Source: Own estimation using the CEPS database.

6.4. The mediator effect of cognition

As discussed in the introduction, Aadland et al. (2017) analyse the effect of physical activity on academic performance using executive functions (which includes cognitive flexibility) as a mediator. This is an exciting idea as it can provide a more detailed explanation of how the impact of exercise is transmitted. Therefore, although the focus of the present paper is on the mediation factor of leisure time activities, we have also extended our SEM for this consideration. More specifically, in the new specification, physical exercise and leisure activities affect academic outcomes through their effect on *Cognition*, allowing for direct and indirect transmission of exercise. Therefore, exercise can directly affect academic outcome. It can also affect it indirectly through Cognition (*Exercise*-*Cognition*-academic outcome) and leisure-time activities (*Exercise*-four groups of activities-*Cognition*-academic outcome). This is consistent with hypothesis H4. As shown in Table 8, the total positive effect of *Exercise* on *SAA* and *OAP* remains under this specification. However, it only indirectly impacts *OAP* through its impact on the moderators. This is reasonable as *SAA* is related to students' subjective feelings. However, the improvement of objective academic performance is more associated with the progress of cognition.

Table 8

Impact of Exercise on academic outcomes with Cognition as a mediator

	SAA	OAP
Direct effect	0.007***	0.076
Indirect effect	0.128***	3.127***
Cognition	0.0008***	0.097***
Visual media	-0.0002**	-0.009**
Study	0.010***	0.991***
Cultural activity	0.1041***	0.502
Negative habits	0.0005**	0.022**
Visual media--Cognition	-0.0001**	-0.012**
Study--Cognition	0.0004	0.047
Cultural activity--Cognition	0.0128***	1.480
Negative habits--Cognition	0.0001 **	0.009**
Total effect	0.136***	3.204***
CFI[(a)]	0.9	0.9
RMSEA[(b)]	0.041	0.040
#Obs.	7197	7197

Note: * p<0.1 ** p<0.05 *** p<0.01, [(a)] CFI indicates comparative fit index, [(b)] RMSEA indicates root mean squared error of approximation. Source: Own estimation using the CEPS database.

6.5. Limitations

The complex structure of our econometric specification and the use of a cross-sectional study is a limitation of our analysis. It does not allow us to fully control for unobserved heterogeneity due to, for example, different classes or schools. However, we use school information among our confounding variables. More importantly, we consider instrumental variables, defined at the individual level, to deal with this potential source of endogeneity. We could not control for other relevant variables such as county-specific effects either, as this consideration affected estimation convergency.

Moreover, due to confidentiality reasons, the database does not inform about county names but only provides numerical integers associated with them. This prevents us from using area dummies too. Despite these concerns, our baseline model contains individual information such as lagged exercise and an extensive set of socioeconomic confounders that can potentially account for individual heterogeneity.

Another limitation of our research is that we do not consider nonlinear SEM models given the complexity of our estimation. These are exciting topics to explore in future research.

7. Concluding remarks

This paper explores the channels through which physical exercise affects academic outcomes using comprehensive information from Chinese school students,. We find that our treatment exerts a significantly positive effect on educational outcomes both directly and indirectly by incentivising habits that positively correlate with academic outcomes while discouraging other practices with a negative correlation. This result is robust to different measures of academic outcomes regarding subjective academic assessment, objective academic performance and cognition. Results are also general to different academic subjects, with *Chinese* the only exception where *Exercise* exerts only a positive indirect effect by affecting leisure activities.

We also found that the positive impact of physical activity on *Cognition* is less evident when it is practised with high frequency. At the same time, high-frequency exercise is more beneficial for *SAA* and *OAP*. Physical activity also positively impacts academic outcomes for both genders but in different ways, with *Cognition* and *OAP* more affected in girls and boys, respectively. Exploring the reasons for these differences is an exciting avenue for future research. Main conclusions about the positive effect of physical exercise are also robust to different considerations about the SEM structure regarding the role of mediators, treatment variable and channels of transmission.

Although the estimated individual impacts are minor, they can still have a crucial aggregate impact in a populous country like China. Policy decisions must confront total, rather than individual, costs and benefits of incentivising physical exercise in schools. Moreover, the contribution of physical exercise to promote positive leisure activities and reduce sedentary and harmful habits could be deemed as politically relevant. Thus, accurate policy analysis should take into account the effect of exercise not only on academic outcomes but also on a big group of variables such as, for example, crime, mental health and life expectancy. A joint policy evaluation of all these impacts should be worthwhile to consider in future research.

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Appendix

Table A1

Definition and factor loadings for observed items

Constructs	Variables	Definition	Factor loading		
			SAA	OAP	Cognition
SAA	Math	Difficulty of learning Mathematics	1		
	Chinese	Difficulty of learning Chinese	0.970***		
	English	Difficulty of learning English	1.942***		
OAP	Mathscore			1	
	Chinesescore			0.590***	
	Englishscore			1.021***	
Harmful habits	Curse	Frequency of cursing or saying swearwords	1	1	1
	Quarrel	Frequency of quarreling with others	0.969***	0.979***	0.985***
	Fight	Frequency of having a fight with others	1.000***	1.038***	1.039***
	Bully	Frequency of bullying the weak	0.564***	0.589***	0.593***
	Violent	Frequency of having a violent temper	0.911***	0.936***	0.944***
	Notconcentrate	Frequency of unable to concentrate on one thing	0.883***	0.871***	0.854***
	Skip	Frequency of skipping classes, being absent, or truanting	0.406***	0.426***	0.427***
	Copy	Frequency of copying homework from others, or cheating in exams	0.992***	1.022***	1.016***
	Smokeordrink	Frequency of smoking, or drinking alcohol	0.573***	0.597***	0.601***
	Netbar	Frequency of going to net bars or video arcade	0.766***	0.799***	0.801***
	Undersleep	Whether or not a student sleeps less than 8 hours every night	0.036***	0.030**	0.030**
Visual media	Time_Tv1	Time spent on watching TV on weekdays	1	1	1
	Time_Net1	Time spent on surfing the Internet or playing video games on weekdays.	1.708***	1.604***	1.448***
	Time_Tv7	Time spent on watching TV on weekends	0.478***	0.500***	0.530***
	Time_Net7	Time spent on surfing the Internet or playing video games on weekends.	1.616***	1.448***	1.232***
Study	Time_Teacher1	Amount of time doing homework assigned by teachers on weekdays	1	1	1
	Time_Teacher7	Amount of time doing homework assigned by teachers on weekends	0.812***	0.815***	0.811***
	Time_Pa1	Amount of time doing homework assigned by parents or cram school on weekdays	2.281***	2.261***	2.295***
	Time_Pa7	Amount of time doing homework assigned by parents or cram school on weekends	1.578***	1.564***	1.577***
	Time_Cram1	Amount of time taking schoolwork related cram school courses on weekdays	2.701***	2.681***	2.765***
	Time_Cram7	Amount of time taking schoolwork related cram school courses on weekends	3.388***	3.386***	3.476***
Cultural activities	Museum	Frequency of vising museums, zoos, science museums, etc. alone or with schoolmates	1	1	1
	Museum_Family	Frequency of vising museums, zoos, science museums, etc. with family members	0.740***	0.724***	0.724***
	Film	Frequency of watching films, shows, sports games, etc. alone or with schoolmates	1.270***	1.272***	1.274***
	Film_Family	Frequency of watching films, shows, sports games, etc. with family members	0.960***	0.957***	0.961***

Note: * p<0.1 ** p<0.05 *** p<0.01. Source: Own estimation using the CEPS database.