A SPORTING CHANGE: ON THE IMPACT OF SPORTS PARTICIPATION ON SUBSEQUENT EARNINGS

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ABSTRACT

Matching methods are used to conduct a causal analysis of the impact of participation in sporting activities while at university on subsequent earnings once graduated and in employment. The analysis employs an innovative longitudinal dataset, Futuretrack, which follows UK students from upper secondary education through higher education and on to the labour market. The results indicate a positive causal effect of sports participation on earnings of around 5 per cent.

1. Introduction

It is widely recognised that extra-curricular activities undertaken alongside education are associated with a range of positive outcomes. Establishing the causal effect of such activities is rendered difficult by the fact that participation is typically non-random. Indeed, randomised control trials in this context are impossible, since, by definition, extra-curricular activities often take place beyond the scope of the institution where an experiment might take place.

In this note, we take advantage of a new longitudinal source of data that allows a variety of causal analyses to be conducted. The data concern a cohort of young people in the United Kingdom progressing through upper secondary education, higher education, and on to the labour market. The cohort comprises those who were in upper secondary education in academic year 2005-06, and who applied to enter university the following year. The appealing and distinctive aspect of this particular data set is that it provides a considerable amount of information about individual students that can be used in matching, going well beyond the range of variables available in administrative data sets.

The remainder of this note is organised as follows. The next section provides a brief overview of relevant literature. The data are described and analysis conducted in the following section before the paper ends with a brief conclusion.

2. Literature

The recent literature has identified links between a range of extracurricular activities and a variety of positive outcomes. Barron et al. (2000) find evidence of a positive impact of sporting activity on both educational and employment outcomes, though the results are somewhat weakened by instrumenting athletic participation by a group of variables deemed to reflect industriousness. An alternative approach to instrumentation, taken by Hyuytinen and Lahtonen (2013) and by Cabane and Clark (2015) is to use sibling activity; these studies too provide evidence of a positive effect of sports. Other recent studies have used panel data to control for individual fixed effects, and confirm a positive impact of sports participation. For example, Lechner (2009) uses German Socio-Economic Panel data to establish that participation in sports raises earnings by at least 5 per cent. Likewise, Ewing (2007) uses data from the US National Longitudinal Surveys of Youth, and finds a persistent wage effect of around 6 per cent, in addition to various impacts on fringe benefits.

Youth participation in a more general set of activities that involve a response to challenge and that allow participants to develop social skills can also have positive long term impact. Dibben et al. (2017) find a positive and remarkably enduring relationship between participation in scouting/guiding activity in childhood and mental health outcomes. Further evidence, using a more robust identification strategy but widening the focus of interest beyond scouting, comes from Li et al. (2017), who find that academic outcomes are improved.

The present paper complements earlier work on the labour market impact of sports participation in university, but uses a different strategy to tackle the endogeneity issue. This is the focus of the next section.

3. Data and Analysis

Our empirical work utilises data from the Futuretrack study, a longitudinal dataset which followed students from their time in upper secondary school through to the period after they graduated from university. These students applied to study at UK universities through the Universities and Colleges Admissions Service (UCAS) system during academic year 2005-6. Futuretrack was funded by the Higher Education Careers Services Unit (HECSU) and the data collection was undertaken by Institute for Employment Research at the University of Warwick. This was, until Longitudinal Education Outcomes (LEO) data recently became available, the only source of data on higher education that followed students through higher education from a point before admission to one after graduation. Importantly in the present context, Futuretrack includes information about skills acquisition and use and about activities undertaken during higher education that are absent from the LEO data. The Futuretrack microdata are available from the UK Data Service (https://discover.ukdataservice.ac.uk/).

The Futuretrack survey was conducted in four stages. The first was in mid-2006 before students entered university, and focused on their motivations for applying to study at tertiary level. The second stage was undertaken in 2007 and contains information about students' early experience of higher education and about their activities out of class. The third stage was undertaken later during students' university experience, and contains more information about their time at university and their aspirations for the future. And the final stage, undertaken in late 2011 and early 2012, focuses on their experience since graduation, in particular on labour market outcomes and the extent to which their time at university equipped them for the world of work. This last stage provides information about earnings, hours of work, industry, occupation (job title), region, and firm size. The questionnaires also include a broad range of questions typical of individual surveys of this kind, for example, concerning gender, ethnicity, health and parental education. The Futuretrack survey has been used to examine a variety of issues in higher education, including the classification of graduate occupations (Purcell and Elias, 2013) and analysis of employment outcomes (Behle et al., 2015).

The key variable in the analysis that follows concerns whether the respondent participated in a sports society or club – either at university or otherwise – at the time of the second stage survey. Some 48.6 per cent of our sample did. The outcome variable is the natural logarithm of hourly wage, this being calculated by dividing annual income by the product of 52 and weekly hours normally worked.[1] Other variables used in the analysis are: educational attainment on entry to university (measured by the UCAS tariff[2]), subject of study (medicine, science/technology/engineering/mathematics, business and law, or other), class of degree awarded (first, upper second, lower second, other), gender, ethnicity (white, other), and a set of variables concerning skills taught at university. Observations for which no data are available on subject studied, UCAS tariff, or wage are excluded from analysis, leaving a sample size of some 3659.

[1] Annual income is before tax in current occupation at the time of the fourth stage of data collection. The variable is grouped and has 15 categories; £85000 is used for the top group, with mid-points used in all other cases. There are few observations in the top group.

[2] The UCAS tariff awards points for qualifications earned in upper secondary education. For example, on the national Advanced level ('A level') qualifications, each A grade is worth 120 points, each B grade is worth 100 points, each C grade is worth 80 points, and so on.

The data on skill included in Futuretrack are detailed. Indeed the fourth stage survey gathers 11 separate measures of skills and capabilities developed on respondents' undergraduate course – specifically on written communication, spoken communication, numerical analysis, critical evaluation, research, presentation, innovative thinking, enterprise, teamwork, individual work, and time management. In the analysis that follows, we make use of the first three principal components of these measures – these broadly reflect hard skills (numeracy, critical evaluation etc.), soft skills (teamwork etc.) and communication skills respectively.[3]

In evaluating the impact of any variable on subsequent outcomes, it is necessary to consider causality. A naïve analysis that finds a positive correlation between earnings and sports participation cannot demonstrate causation, since both variables might simply be a response to other influences, for instance, non-cognitive traits such as motivation or determination. Care is therefore needed in choosing an appropriate estimation strategy. The method of propensity score matching (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008; Todd, 2010) allows the causal impact of a treatment – in this case sports participation – on an outcome variable – in this case subsequent earnings – to be evaluated by ensuring that treated individuals are compared only with untreated individuals who are, in respects other than treatment, similar.[4] In the present exercise, we match on a wide range of variables (the three skill measures, tariff, subject, degree class, gender and ethnicity), using a probit estimator to obtain propensity scores.

These propensity scores measure the predicted probability with which each respondent is treated. Comparing treated and untreated respondents who have similar propensity scores ensures a comparison of like with like, the random incidence of treatment being the only difference between each member of a pair being compared. A variety of methods can be used to select pairs. A common choice is to select (for each treated observation) the nearest (untreated) neighbour, with or without replacement. In order to ensure that the treated and untreated observations share a common support, the observations may (or may not) be trimmed. Alternatives to nearest neighbour matching include caliper matching (where a tolerance limit is imposed on the distance between pairs in a match), and methods where the comparator is a weighted average of observations rather than a single observation. The latter include kernel matching and the more general local linear matching approach, in which the weighting function used in the kernel is itself a function of the propensity score (Heckman et al., 1997). In these cases, a variety of distributions, such as the normal or the Epanechnikov (1969), may be used as the kernel. A further alternative is to match based on the distance between the set of variables used in the probit rather than by use of the propensity score; a commonly used example is a matching procedure devised by Rubin (1979) based on the distance measure of Mahalanobis (1936).

Given the number of alternative matching approaches available, we report results for a variety of these, thereby providing a robustness check on the results. In each case the average treatment effect on the treated (ATT – the mean difference between the outcome observed for the treated and untreated observations) is reported along with both the associated t statistic (which does

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[3] Principal components are obtained by transforming the set of observed variables into a set of constructed variables that are uncorrelated with one another, and thus the first few principal components capture the main sources of variation within the data.

[4] This allows for endogeneity due to selection on observables. There may be further endogeneity due to selectino on unobservables, but the nature of the data used in the present exercise do not allow further consideration of this.

not take into account the fact that the propensity score is an estimate) and a bootstrapped t statistic based on 50 replications.

Results are reported in Table 1. The ATT is varies somewhat across estimators, but is always positive and is typically around 0.05, suggesting a 5% wage premium associated with participation in sports. This is consistent with the findings of the received literature. In the case of most, but not all, estimators, the estimate is statistically significant at conventional levels; the exceptions are nearest neighbour matches models where selection from the control group is done with replacement. Trimming to ensure common support increases the significance of the estimated treatment effect.

Table 1 Average treatment effect on the treated, various matching indicators – the effect of participation in sports while at university on subsequent earnings

Matching estimator	**ATT**	**t statistic**	**z statistic**
Nearest neighbour (NN) with replacement	0.0360	1.53	1.57
NN without replacement	0.0961*	5.69	6.09
NN with replacement and 10% trim	0.0544	2.22	1.94
NN without replacement and 10% trim	0.0632*	3.56	3.63
NN with replacement and common support	0.0372	1.57	1.39
NN without replacement and common support	0.0948*	5.60	4.65
2 nearest neighbours with replacement	0.0533*	2.62	2.73
Caliper (maximum distance 0.2)	0.0894*	5.30	6.21
Kernel - Epanechnikov	0.0550*	3.17	3.22
Kernel - normal	0.0671*	3.93	4.22
Local linear – Epanechnikov	0.0499*	2.11	2.71
Local linear - normal	0.0497*	2.80	2.58
Mahalanobis	0.0663*	2.90	3.28

Note: Stata default values used for bandwidth, kernel type and caliper where not otherwise noted. The t statistic does not take into account the fact that the propensity score is an estimate, and so the z statistic, obtained using a bootstrap with 50 replications, is also reported. Where the common support is imposed, this is achieved by trimming treated observations with propensity scores outside the range of the corresponding scores for the control group. An asterisk denotes significance (on the z test) at better than 5%.

4. Conclusion

Previous analysis of the impact of sports participation on earnings have used a variety of identification strategies. The present paper is distinctive in taking a causal approach by using a variety of matching estimators. The analysis confirms the finding of other studies that the positive impact of participation in sport on earnings is around 5 per cent.

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