Does education promote social capital? Evidence from IV analysis and nonparametric-bound analysis

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Abstract This study uses the British National Child Development Study to examine the effect of educational attainment on social capital at the individual level. Social trust and membership of voluntary groups are considered as two basic indicators of social capital. We employ the IV analysis and nonparametric bound analysis to tackle the problem of education endogeneity. Both the approaches reveal that the OLS estimator of the educational effect suffers from an upward bias in the study of group membership. We do not observe any significant bias in the educational effect on social trust. Our empirical findings indicate that education has a positive influence in promoting social trust and membership of voluntary groups.

Keywords Education · Social capital · Instrumental variable · Nonparametric bound

JEL Classification C14 · I2

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Abbreviations

IV	Instrumental variable
MTR	Monotone treatment response
MTS	Monotone treatment selection
MIV	Monotone instrumental variable
NCDS	National Child Development Study

1 Introduction

This study examines the effect of education on social capital at the individual level. Social capital is an aggregate concept that encompasses the association networks, norms, and trust that facilitate collective interactions for mutual economic and social benefits (Putnam 1993, 1995, 2000; Coleman 1990). We focus on two commonly discussed indicators of social capital at the individual level—social trust and membership of voluntary groups. The presence of social capital is indicated by a high degree of trust in general people and a rich network resource for collective action (Putnam 2000).

Social trust denotes impersonal trust between random people and it differs fundamentally from personal trust by its extension to people on whom the trusting part has no direct information (Hardin 2003 p. 13; Delhey and Newton 2005; Paxton 2007). Social trust reflects a bond that people share across society, across economic and ethnic groups, religions and races. It provides the foundation for a cooperative spirit that brings people together for common and mutually advantageous purposes. Social trust contributes to economic growth and market efficiency (especially in e-commerce) by reducing the “transaction cost” involved in economic activity. High levels of social trust lead people to expect that others are cooperative and not opportunistic in social and economic exchanges, which help solve the free-rider problem in providing public goods. Knack and Keefer (1997) find that a one standard deviation increase of the national-level of social trust increases economic growth by more than one-half of a standard deviation. La Porta et al. (1997) show that social trust promotes the performance and character of political institutions.

Measurement of social trust is generally based on a standard survey question: “Generally speaking, would you say that most people can be trusted or that you can’t be too careful in dealing with people?” This operationalization of social trust has been widely used for more than four decades in empirical studies and surveys around the world. The survey question is controversial among some researchers for its abstract definition with respect to which “people” or what “stake” respondents have in mind and its difference with “trust” measured in experiment (Glaeser et al. 2000; Ermisch et al. 2009).

Albeit that the standard measurement of social trust is not consistent with “trust” measured by experiments, it provides useful information on respondents’ faith in other people. It is noteworthy that whether findings from current “trust” experiments generalize to public-goods experiments remains ambiguous (Anderson et al. 2004). From our perspective, social trust reflects “a belief in the benevolence of human nature in general.” A person’s trust on generalized others has different aspects and they do not form a single syndrome. It is far beyond being simply an indicator of the respondents’

interactions with their intimates. Based on this standard measurement of social trust, researchers produce strong evidence for the positive effects of social trust at the individual and societal level (see, e.g., [Knack and Keefer 1997](#); [Zak and Knack 2002](#)).

Affiliation with (one or more than one) voluntary groups is a general indicator of social participation and also an important indicator of social capital ([Glaeser et al. 1999](#); [Paxton 1999](#); [Putnam 2000](#)). These voluntary groups include all types of groups and organizations relating to community living and welfare. These groups and organizations are outside the political arena and the workplace (i.e., unions, parties, voting and lobbying groups).¹ The local and community aspects that social groups focus on can be private interest oriented, such as parent–teacher association, tenant associations, as well as purely altruistic interest-oriented—charity, environmental, and community volunteering.

Voluntary groups facilitate people's effective involvement in community life and promote a sense of community. Scientific research indicates that group members acquire organizational skills and expand their social ties in ways that positively impact their physical and mental health, as well as many other normatively desirable outcomes (e.g., [House et al. 1988](#); [Thoits and Hewitt 2001](#)). A high level of voluntary participation improves the living environment and social well-being, raises civic norms among people, and strengthens the foundations of a democratic society.

The interest in social capital has led to a proliferation of studies on its sources of origin and accumulation mechanisms. Education, according to [Putnam \(1995\)](#), [Putnam \(2000\)](#), [Brehm and Rahn \(1997\)](#), [Glaeser et al. \(1999\)](#), and [Alesina and La Ferrara \(2000\)](#), is one of the most important determinants of individual social capital. It reflects an orientation toward the future by strengthening human capital and social capital for economic and social development. It is the first nonfamilial context in an individual's life where moral and cognitive capacities are trained. During their education, students practice in a peer culture that shapes values such as reciprocity, respect, and trust. Students learn and develop the basic norms and responsibilities in society, as well as the functioning of democracy through civil education from schooling.

[Glaeser et al. \(1999\)](#) assert that the most robust correlate of social capital variables is years of schooling. Using the World Values Survey, they find a positive relationship between schooling and membership of organizations in almost every country. [Denny \(2003\)](#) claims that acquiring a 4-year university degree is associated with a 10% higher probability of an individual engaging in voluntary work. [Putnam \(1995, 2000\)](#) and [Alesina and La Ferrara \(2000, 2002\)](#) also show that more educated people are more likely to trust other people, and that they tend to join more social organizations and participate in group activities more frequently.

In studies on private returns to education, the endogeneity of schooling is always a difficult topic to tackle. A large number of empirical studies have shown that income and educational attainment can be simultaneously influenced by a wide range of unobservable terms, and that the omitted-variable problem could lead to an upward bias in the estimate of the educational effect. Similar problems can emerge in the investigation

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¹ Based on Max Webber's typology of social action ([\[1914\]](#), [1978](#)), activities in unions, parties, voting, and lobbying groups are instrumentally rational action, serving for the purpose of certain interest group. These group activities are defined as instrumental action.

of the relation between educational attainment and social capital. However, hitherto few empirical studies have attempted to isolate the real effect of education from the influence of confounding variables (Huang et al. 2009).

Dee (2003) employs 2SLS and bivariate probit, by exploiting possibly exogenous sources of variation in schooling that should otherwise be unrelated to civic outcomes in adulthood (i.e., the geographic availability of 2-year colleges as a teen and exposure to child labor laws as a teen), to estimate the impact of education on the probability of volunteering in social services and the impact on the number of affiliated groups. He confirms a substantial causal effect of schooling on most measurements of social participation. Changes in the compulsory schooling law have also been employed as an instrumental variable in the studies of education and social trust. Milligan et al. (2004), for example, apply this strategy in their study of the educational effect on trust and other civic outcomes. They do not observe any substantial difference between the estimates from the OLS and IV estimations.

The studies of Dee (2003) and Milligan et al. (2004) include two types of education measurement: a binary indicator of college entrance or high school graduates and a one-dimensional measurement of education in terms of highest education grade or years of schooling. In the social capital literature, the size of the effect of a marginal year of schooling seems to vary with the levels of education (Huang et al. 2009). A multilevel education measurement is more realistic and it may provide more information on the role of education in the formation of social capital.

Conventional IV method requires a valid instrument satisfying the mean independence conditions for its implementation. In empirical research, the credibility of mean independence conditions has often been subject to disagreement. The IV method also relies on strong distributional assumptions (such as normality assumption) or functional form restrictions (such as a homogenous return to education). A violation of these assumptions can result in different findings. Empirical researchers should be cautious about the robustness of distributional and functional form assumptions.

This article makes two contributions to the literature on education and social capital. Using the rich information from a British multi-wave survey of a cohort born in 1958, we consider both one-dimensional measurement and multilevel measurement of educational attainment in our empirical study. Secondly, we employ parametric and nonparametric evaluations methods to identify the causal effect of education on social trust and membership of voluntary groups.

The results of our empirical study suggest that people with a higher level of education are more inclined to trust people in general and they are more likely to become a member of voluntary groups or organizations, *ceteris paribus*. Both the IV estimation and nonparametric bound estimation suggest that it could cause a noticeable upward bias if education endogeneity is not accounted for in the study of group membership.

The remainder of this study is divided into four sections. Section 2 gives a simple illustration of the parametric and nonparametric evaluation approaches. Section 3 presents summary descriptions of the NCDS dataset and findings from the OLS estimation. Section 4 reports empirical findings from the IV estimation and nonparametric bound estimation. Section 5 draws conclusions.

2 Model framework and identification strategy

2.1 One-dimensional modeling of education

Measuring the impact of education on social capital is similar to measuring the monetary return to education. It falls neatly into the treatment evaluation literature. This article identifies the educational effect on social capital by the average treatment effect (ATE). The ATE of treatment ω compared to treatment θ measures the average causal difference in $y(\omega)$ and $y(\theta)$, the outcomes under treatment ω and treatment θ , i.e.,

$$\text{ATE}(\omega, \theta) = E[y(\omega)] - E[y(\theta)] \quad (1)$$

Both one-dimensional modeling and multilevel modeling are considered in this article to incorporate a finite set of highest schooling levels attainable by any given individual. In the popular one-dimensional education model (or one-factor model), it is assumed that education can always be aggregated into a single indicator, say years of schooling or ordered levels of educational attainment. In this framework, the highest education level attained by individual i is denoted by s_i . s_i is an ordinal variable and its value space has a finite set of $(J + 1)$ values (namely, $s_i = 0, 1, 2, \dots, J$). The observed outcome of this individual $y_i \in Y$ is specified as a function of the education variable s_i and observed covariates $x_i \in X$:

$$y_i = \beta s_i + m_o x_i + \eta_i \quad (2)$$

Equation 2 imposes a linear (and homogenous) relationship between educational attainment and outcome variable of interest, such that each additional level increase of educational attainment has the same marginal impact on the outcome. Let T denotes the treatment space (for educational attainment) with $J + 1$ ordered values. Provided that there is no correlation between the education variable s_i and the error term η_i , a correctly specified ordinary linear regression produces an unbiased estimate of β . The ATE of treatment ω (highest educational attainment being ω , $\omega \in T$) compared to treatment θ (highest educational attainment being θ , $\theta \in T$) can be directly obtained from the estimate of β , i.e.,

$$\text{ATE}(\omega, \theta) = E[y(\omega)] - E[y(\theta)] = \beta \cdot (\omega - \theta)$$

Ordinary linear regression produces a biased and inconsistent estimator of the educational effect β if there is nonzero correlation between the education indicator s_i and the error term η_i . Such correlation may arise due to omitted-variable bias, measurement error bias, or return bias (Blundell et al. 2005). The instrumental variable (IV) estimation is a popular method for obtaining a consistent estimate in the case of endogenous education variable. With a valid instrument that is correlated with the true measure of schooling and uncorrelated with the unobservables in the outcome equation, the conventional IV method identifies the educational effect in a two-stage procedure: in the first stage, the endogenous schooling variable is regressed on the excluded instruments and exogenous covariates in the equation of interest. In the

second stage, the endogenous schooling variable is replaced with its predicted values based on the first-stage regression.

2.2 Multilevel modeling of education

The one-dimensional modeling generally assumes a linear relationship between education levels and the outcome of interest. This assumption may not be realistic in some human capital studies. Individuals with the same number of years of schooling can have quite different education qualifications and the spacing between the values of an ordinal education variable may not be the same across the levels of the variable. In the social capital literature, the size of the effect of a marginal year of schooling seems to vary with the levels of education (Huang et al. 2009). A multilevel education model is considered to be more realistic and robust in this case.

In a homogeneous multilevel education model, y_i , the observed outcome for individual i , is specified as a function of a set of mutually exclusive and exhaustive education variables s_{ij} ² and observed covariates x_i

$$y_i = \sum_{j=1}^J \beta_j s_{ij} + m_o x_i + \eta_i \quad (3)$$

Provided that there is no correlation between the education variables s_{ij} and the error term η_i , a correctly specified ordinary linear regression produces an unbiased estimate of β_j ($j = 1, 2, \dots, J$) from which $\text{ATE}(\omega, \theta)$ can be directly obtained, such that

$$\text{ATE}(\omega, \theta) = E[y(\omega)] - E[y(\theta)] = \beta_\omega - \beta_\theta$$

where $\beta_\omega = 0$ ($\beta_\theta = 0$) if $\omega = 0$ ($\theta = 0$).

The multilevel model contains a set of J exclusive binary education indicators, researchers may have to handle J binary endogenous variables when the education variables are correlated with the error term in the outcome equation. Conventional IV estimation may not successfully identify the causal effect for all the endogenous dummy variables and it is not an easy task for researchers to interpret the findings from the IV estimation with multiple endogeneous regressors. Moreover, conventional IV estimation relies on strong functional form assumptions, such as homogeneous treatment effect or additive separability in the error term, to identify the treatment effect. Recently, robust estimators of treatment parameters based on nonparametric or semiparametric identification procedures have received a lot of interest.

² $s_{ij} = 1$ if level j is the highest schooling level attained by individual i and $s_{ij} = 0$ if level j is not the highest level. Since the treatment space T contains $J + 1$ education levels, the outcome equation contains J mutually exclusive dummy variables. Schooling level 0 (leaving school without appropriate qualification) is used as the reference treatment.

2.3 Nonparametric bound analysis

Our study employs a nonparametric technique to obtain the bounds on the causal effect of multiple educational attainments on social capital. [Manski \(1997\)](#) and [Manski and Pepper \(2000\)](#) introduced in the nonparametric bound analysis the monotone treatment response (MTR) assumption, the monotone treatment selection (MTS) assumption, and the monotone instrumental variable (MIV) assumption. Based on these relatively weak assumptions one can effectively tighten the bounds on the causal effect of the treatment. In current years, the number of studies applying a nonparametric bounding method has been growing ([Blundell et al. 2007](#); [Gundersen and Kreider 2009](#); [Hill and Kreider 2009](#); [De Haan 2010](#)).

This section presents a simple introduction of the MTR, MTS, and MIV assumptions and the nonparametric bounds on the ATE based on these assumptions. For a response function $y_i(\cdot) : T \rightarrow Y$ which maps treatments $t \in T$ (the treatment space is again a ordered set with $J + 1$ values) into outcome $y_i \in Y$, individual i has a realized treatment (the realized highest education level) $s_i \in T$ and a realized outcome $y_i \equiv y_i(s_i)$. Both y_i and s_i are observable. The latent outcomes $y_i(t)$, $t \neq s_i$ are not observable. [Manski \(1989\)](#) reveals that it is possible to identify bounds on $E[y(t)]$ without adding any assumptions if the support of the dependent variable is bounded, such that $Y = (\underline{y}, \bar{y})$. The no-assumption bounds are written as

$$\begin{aligned} E[y|s = t] \cdot P(s = t) + \underline{y} \cdot P(s \neq t) \\ \leq E[y(t)] \leq E[y|s = t] \cdot P(s = t) + \bar{y} \cdot P(s \neq t) \end{aligned} \quad (4)$$

The monotone treatment response or MTR assumption states that for each individual

$$t_2 \geq t_1 \Rightarrow y(t_2) \geq y(t_1) \quad (5)$$

The monotone treatment selection or MTS assumption states that for each $t \in T$

$$\mu_2 \geq \mu_1 \Rightarrow E[y(t|s = \mu_2)] \geq E[y(t|s = \mu_1)] \quad (6)$$

where μ_1 and μ_2 are values in the ordered set T . $s = \mu_2$ indicates the realized treatment has a value of μ_2 .

The MTR and MTS assumptions differ from one another. [Manski and Pepper \(2000\)](#) illustrate that the MTR and MTS assumptions interpret the verbal assertion that “wages increase with years of schooling” in different ways. The MTR interpretation indicates that “each person’s wage function is weakly increasing in conjectured years of schooling.” The MTS interpretation indicates that “persons who select higher levels of schooling have weakly higher mean wage functions than do those who select lower levels of schooling” ([Manski and Pepper 2000](#)). Although the MTS and MTR interpretations of the statement “wages increase with years of schooling” are distinct, they are not mutually exclusive. When imposed together, the two assumptions can have substantial identifying power. It follows from the combined MTR–MTS assumptions that

$$\begin{aligned}\mu_2 \geq \mu_1 &\Rightarrow E[y|s = u_2] = E[y(u_2)|s = u_2] \\ &\geq E[y(u_2)|s = u_1] \geq E[y(u_1)|s = u_1] = E[y|s = u_1]\end{aligned}\quad (7)$$

Under the combined MTR–MTS assumptions, one can obtain the MTR–MTS bounds³:

$$\begin{aligned}&E[y|s < t] \cdot P(s < t) + E[y|s = t] \cdot P(s = t) + E[y|s = t] \cdot P(s > t) \\ &\leq E[y(t)] \leq E[y|s = t] \cdot P(s < t) + E[y|s = t] \cdot P(s = t) \\ &\quad + E[y|s > t] \cdot P(s > t)\end{aligned}\quad (8)$$

With an instrumental variable z_{IV} , which has a finite set M , satisfying the mean independence conditions, the sample is divided by the value of the instrumental variable. One can obtain an IV-lower bound on $E[y(t)]$ by taking the maximum lower bound over all sub-samples (for all $m \in M$) and an IV-upper bound by taking the minimum upper bound over all sub-samples:

$$\begin{aligned}&\max_{m \in M} (E[y|s = t, z_{IV} = m] \cdot P(s = t|z_{IV} = m) + \underline{y} \cdot P(s \neq t|z_{IV} = m)) \\ &\leq E[y(t)] \leq \min_{m \in M} (E[y|s = t, z_{IV} = m] \cdot P(s = t|z_{IV} = m) \\ &\quad + \bar{y} \cdot P(s \neq t|z_{IV} = m))\end{aligned}\quad (9)$$

Combining the MTR–MTS assumptions, one can tighten the IV bounds and obtain the following MTR–MTS–IV bounds:

$$\begin{aligned}&\max_{m \in M} (E[y|s < t, z_{IV} = m] \cdot P(s < t|z_{IV} = m) \\ &\quad + E[y|s = t, z_{IV} = m] \cdot P(s = t|z_{IV} = m) \\ &\quad + E[y|s = t, z_{IV} = m] \cdot P(s > t|z_{IV} = m)) \\ &\leq E[y(t)] \leq \min_{m \in M} (E[y|s = t, z_{IV} = m] \cdot P(s < t|z_{IV} = m) \\ &\quad + E[y|s = t, z_{IV} = m] \cdot P(s = t|z_{IV} = m) \\ &\quad + E[y|s > t, z_{IV} = m] \cdot P(s > t|z_{IV} = m))\end{aligned}\quad (10)$$

In many cases, an instrumental variable that satisfies the mean independence conditions is hard to find. Instead of assuming mean-independence, [Manski \(1997\)](#) and [Manski and Pepper \(2000\)](#) introduce a weaker assumption to allow for a weakly monotone relation between the instrumental variable and the mean outcome function ([Manski and Pepper 2000](#)), such that:

$$m_1 \leq m \leq m_2 \Rightarrow E[y(t)|z = m_1] \leq E[y(t)|z = m] \leq E[y(t)|z = m_2] \quad (11)$$

The difference between the IV assumption (mean independence assumption) and the MIV assumption is straight-forward in wage-education functions. To use measured ability as an IV for schooling is to assume that measured ability has not direct impact in the wage function other than via schooling. To use measured ability as an MIV is

³ For a full derivation of the MTR–MTS bounds see [Manski \(1997\)](#) and [Manski and Pepper \(2000\)](#).

to assume that “persons with higher measured ability have weakly higher mean wage functions than do those with lower measured ability” (Manski and Pepper 2000). In the study of the private return to schooling it is reasonable to assume that measured ability is an MIV but not that it is an IV.

With an instrumental variable z satisfying the MIV conditions, one can again divide the sample into sub-samples by the value of the instrument and obtain bounds for each sub-sample. For the sub-sample where the instrument has a value of m ($m \in M$) we can obtain a new lower bound, which is the largest lower bound over all the sub-samples where $m_1 \leq m$ ($m_1 \in M$). Similarly, we can obtain a new upper bound by taking the smallest upper bound over all sub-samples where $m_2 \geq m$ ($m_2 \in M$). Without additional assumption one can obtain the MIV bounds by laws of iterated expectations (Manski and Pepper 2000):

$$\begin{aligned} \sum_{m \in M} P(z = m) \cdot \left[\max_{m_1 \leq m} \left(E[y|s = t, z = m_1] \cdot P(s = t|z = m_1) + \right. \right. \\ \left. \left. \underline{y} \cdot P(s \neq t|z = m_1) \right) \right] \\ \leq E[y(t)] \leq \sum_{m \in M} P(z = m) \cdot \left[\min_{m_2 \geq m} \left(E[y|s = t, z = m_2] \cdot P(s = t|z = m_2) + \right. \right. \\ \left. \left. \bar{y} \cdot P(s \neq t|z = m_2) \right) \right] \end{aligned} \quad (12)$$

Under the combined MTR–MTS assumptions, one can obtain the MTR–MTS–MIV bounds

$$\begin{aligned} \sum_{m \in M} P(z = m) \cdot \left[\max_{m_1 \leq m} \left(\begin{aligned} &E[y|s < t, z = m_1] \cdot P(s < t|z = m_1) + \\ &E[y|s = t, z = m_1] \cdot P(s = t|z = m_1) + \\ &E[y|s > t, z = m_1] \cdot P(s > t|z = m_1) \end{aligned} \right) \right] \\ \leq E[y(t)] \leq \\ \sum_{m \in M} P(z = m) \cdot \left[\min_{m_2 \geq m} \left(\begin{aligned} &E[y|s = t, z = m_2] \cdot P(s < t|z = m_2) + \\ &E[y|s = t, z = m_2] \cdot P(s = t|z = m_2) + \\ &E[y|s > t, z = m_2] \cdot P(s > t|z = m_2) \end{aligned} \right) \right] \end{aligned} \quad (13)$$

The object of interest is to identify $ATE(\omega, \theta)$, the average treatment effect of treatment ω compared to treatment θ ($\omega, \theta \in T$). Suppose ω is larger than θ , the upper (lower) bound of the average treatment effect ($ATE(\omega, \theta) = E[y(\omega)] - E[y(\theta)]$) is identified by subtracting the lower (upper) bound on $E[y(\theta)]$ from the upper (lower) bound on $E[y(\omega)]$.

A disadvantage of the nonparametric bound analysis is that these bounds are less informative about the effect of interest than a precisely and consistently estimated point estimate based on a set of rather strong assumptions. However, the nonparametric bound analysis offers sharp upper and lower bounds on the treatment effect with a couple of relatively weak nonparametric assumptions. It is thus more applicable in empirical studies and its estimation results are more robust to functional form and distributional assumptions.

3 Data description and OLS estimation

The rich data of a British cohort born in 1958 from the National Child Development Study (NCDS) enable us to perform a comprehensive investigation of the educational effect on social capital at the individual level. The NCDS is a multi-disciplinary longitudinal study of all those living in the UK who were born in the week between March 3 and 9, 1958. The first three sweeps were carried out by the National Children's Bureau in 1965, 1969, and 1973–1974. The following three sweeps were carried out by the Centre for Longitudinal Studies in 1981, 1991, and 1999–2000.

Table 1 provides summary statistics of the NCDS dataset sample. The summary statistics include reported year, number of observations without missing data, mean and standard deviation of each variable. The sample used in this article contains 8,606 observations.⁴ Each wave of the NCDS did not necessarily have identical questions. The social trust variable is extracted from survey 1991 and the membership affiliation outcome is extracted from survey 2000, when cohorts were at the age of 33 and 41, respectively. 68% of the cohort members indicate that most people can be trusted and 17% of them are reported to be affiliated with at least one social group related to community or social welfare. The multiple-measurement of educational qualifications based on the 1991 survey includes four binary indicators for “no qualification,” “O-Level qualifications,” “A-Level qualifications” and “college degree”.⁵ Therefore, the one-dimensional education measurement has four-ordered values in accordance with the multilevel measurement.

Covariates are extracted from the reports of parents, teachers, and medical staffs in the survey 1958, 1965, 1969, and 1973–1974. The cohort members were 15–16 years of age during the 1973–1974 survey. They were approaching the end of compulsory education (secondary education was compulsory for all pupils between the ages of 11 and 16 in the UK). They would be faced with O/A-Level examination(s) as well as a choice of further education. To maintain a large and representative sample with respect to missing data in the covariates, we follow the treatment of missing values adopted by Case et al. (2003, 2005) in their health study of the same British cohort.⁶

⁴ The cohort population is 17,409 as reported in the birth survey, but there is attrition among each survey, only 11,000–12,000 observations remain since survey 1974 when cohorts were at the age of 16. Attrition does not appear to be systematically associated with family backgrounds, such as parental socioeconomic status (a detailed discussion can be found in the article of Case et al. (2003, 2005)).

⁵ The General Certificate of Education (GCE) is an academic qualification that *Examination Boards* in the *United Kingdom* conferred to students from the 1950s to the 1980s. The GCE comprised the *Ordinary Level* (O-Level) and the *Advanced level* (A-Level). The O-Level is normally taken by students of age 16; the A-Level is usually taken by students during the optional final 2 years of *secondary school* (years 12 and 13 or age 16–18). The A-Level qualification is used as a standard entry qualification for assessing the suitability of applicants for academic courses in UK universities.

⁶ For each of these covariates, observation with missing data is coded as 0. A new dummy indicator is created for the existence of missing value in the covariate (1 for observation with nonmissing value and 0 otherwise). We interacted each of the covariates with its missing-value indicator and retain them in our analysis. The estimated coefficients therefore represent the estimated effect of the variables conditional on their value being observed. Our robustness tests show that the estimates of education effects are not sensitive to missing data in covariates.

Table 1 Descriptive statistics

Variable	<i>N</i>	Mean	SD
Social trust—1991	8,616	0.682	0.466
Group membership—2000	8,606	0.170	0.376
Gender-male—1958	8,606	0.474	0.499
Ethnicity-White—1958	8,606	0.981	0.137
Father education—1958	6,301	3.998	1.762
Mother education—1958	6,396	3.960	1.401
Scotland-birth—1958	8,606	0.100	0.300
Wales-birth—1958	8,606	0.055	0.228
London-birth—1958	8,606	0.179	0.383
Foreign birth—1958	8,606	0.047	0.209
Mother reads—1965	7,601	0.503	0.500
Scotland—1969	7,422	0.094	0.292
Wales—1969	7,422	0.056	0.229
London—1969	7,422	0.159	0.366
Siblings—1969	7,395	2.835	1.203
Siblings squared	7,395	9.484	7.520
Natural father—1974	6,515	0.880	0.325
Natural mother—1974	6,516	0.955	0.208
Chronics since 11—1974	6,337	0.126	0.331
Private school—1974	8,606	0.029	0.169
Lack facility—1974	8,606	0.100	0.299
Mother interest—1965			
Strong interest	7,685	0.424	0.494
Some interest	7,685	0.350	0.477
Little interest	7,685	0.118	0.321
Education information—1991			
Ordinal education level	8,606	1.312	0.980
No qualification	8,606	0.231	0.422
O-Level education	8,606	0.365	0.481
A-Level education	8,606	0.263	0.440
College education	8,606	0.140	0.347
Length of schooling absence due to illness—1974			
Less than 1 week	6,488	0.557	0.597
1 week to 1 month	6,488	0.346	0.476
1–3 months	6,488	0.067	0.250
More than 3 months	6,488	0.013	0.112
Father social class—1958			
Professional	7,845	0.045	0.207
Managerial	7,845	0.142	0.349

Table 1 continued

Variable	<i>N</i>	Mean	SD
Nonmanual-skilled	7,845	0.105	0.307
Manual-skilled	7,845	0.505	0.500
Nonmanual-semi	7,845	0.123	0.328
Manual-semi	7,845	0.080	0.271
School truancy and absence—1974			
Truancy—frequent	6,472	0.018	0.134
Truancy—less frequent	6,472	0.076	0.265
No truancy	6,472	0.905	0.293
Absence—certain	6,718	0.068	0.252
Absence—somewhat	6,718	0.133	0.339
No absence	6,718	0.799	0.401

Our measures of parental socioeconomic status contain indicators for parental education level and father's social class. Measures of family backgrounds consist of the number of siblings and whether parent(s) changed by 1974 (because of divorce, death, etc.). We include information on chronic conditions from the physician examination. Using the teacher's report in the 1973–1974 survey, we collect information on student truancy, student absence for trivial reasons, and certain secondary-school characteristics—source of school funding (private school vs. public school) and availability of facility resources. The quality of family interaction is an important determinant of the development of human capital and social capital. We collect information from the 1965 survey mother's interest in the education of her child and whether mother often read to her child.

Figure 1 presents connected lines for the average level of social trust and group membership by ordinal education values (0—no qualification, 1—O-Level, 2—A-Level, 3—College degree). This figure indicates positive and monotone associations between educational attainments and the two dimensions of social capital at the individual level. Education appears to have a larger effect on membership of voluntary groups than on social trust.

Table 2 presents preliminary findings from the OLS regression⁷ in which it is assumed that unobserved heterogeneities do not have a simultaneous influence on the educational attainment and social capital outcomes conditional on the rich information of individual development in childhood. We impose in the OLS model a linear and homogeneous relationship between educational qualifications and social capital outcomes. Then we use multilevel education indicators to relax the linear relationship.

The OLS estimations indicate a strong effect of education on both the dimensions of social capital. In the one-dimensional education model, the probability change due to an additional level increase of educational attainment is 3.7% point for the social trust outcome and 7.5% point for the membership outcome. In other words, individ-

⁷ Since social trust and group membership are measured by a binary indicator, we also use probit model to identify the average treatment effect of education. The estimates of the average treatment effect provided by the probit regression are no different from those provided by the OLS regression.

Fig. 1 Average level of social trust and group membership by education qualification

Table 2 OLS estimation

	Social trust			Group membership		
	Coef.	<i>t</i> value	Beta	Coef.	<i>t</i> value	Beta
Ordinal education level	0.037	6.32	0.078	0.075	16.14	0.195
O-Level qualification	0.022	1.56	0.022	0.061	5.63	0.079
A-Level qualification	0.055	3.57	0.052	0.107	8.80	0.126
College degree	0.117	6.15	0.088	0.252	16.66	0.231
Gender—male	−0.058	−5.75	−0.062	−0.082	−10.40	−0.109
Ethnics—White	0.167	4.23	0.049	−0.074	−2.36	−0.027
Education level of father	0.008	1.91	0.038	0.010	3.11	0.061
Mother little interest	−0.071	−3.82	−0.048	−0.029	−1.99	−0.024
<i>N</i>	8,606			8,606		

Estimates of the covariates are reported from the one-dimensional OLS model

uals with a college degree, other conditions (in early life) being equal, have a higher probability of trusting people in general and joining voluntary groups than individuals without any of these education qualifications by 11 and 23% points.

In the multilevel education model, individuals with a college degree, A-Level qualification and O-Level qualification as their highest educational attainment have a higher level of social trust than individuals without any of these education qualifications by 12, 5.5, and 2% points, respectively. Individuals with a college degree, A-Level qualification, and O-Level qualification as their highest educational attainment have a higher probability of joining voluntary groups than individuals without these education qualifications by 25, 12, and 6% points, respectively. These linear models show that education has a substantially larger effect on membership of voluntary groups than on social trust.

The findings from the multilevel education model suggest a strictly monotone relationship between educational attainments and social capital outcomes. The estimates

produced by the multilevel education model moderately deviate from the estimates produced by the one-dimensional education model. Its estimated marginal effect of O-Level qualifications and A-Level qualifications is relatively smaller than the corresponding marginal effect reported by the one-dimensional model. The multilevel education model and the one-dimensional model have similar estimated marginal effects of college degree. Overall, the findings from the multilevel education model are more robust although we do not observe strong evidence against a linear relationship between ordered education levels and social capital.

Gender, ethnicity, father's educational attainment, and mother's interest in the education of her child are the only covariates with a statistically significant effect in both outcome equations of social capital. According to the standardized (beta) estimates and their corresponding statistical significance, education achievement turns out to be the most influential factor in determining both the dimensions of social capital.

4 IV estimation and nonparametric bound estimation

The OLS model may produce a biased and inconsistent estimate of the educational effect when the choice of educational attainment and social capital are simultaneously influenced by unobserved heterogeneity specific to the individuals. For example, it is possible that children with good relations with their parents, peers, and teachers because of their inherent personality traits or academic capacity are able to obtain a higher level of education and have a higher level of social capital in adulthood. These individual characteristics in childhood usually turn out to be unobservable to researchers.

In the one-dimensional education measurement, the IV method (2SLS) is employed to reduce the bias in the point estimate due to unobservable heterogeneities. In the multilevel education measurement, nonparametric bound analysis, which does not rely on delicate functional or distributional assumptions, is employed to identify the bounds on the causal effect of each educational qualification on social capital outcomes.

4.1 Validity of the Instrumental Variable

The IV method requires a valid instrument in the evaluation procedures. We construct an instrument from the information on the *length of schooling absence due to illness* (or the *absence length* for brevity), which is reported in the 1973–1974 survey. From our perspective, the absence length can be decomposed into systematic components and nonsystematic components, when one can access a comprehensive set of information on individual development from childhood to adolescence. The systematic components arise from inherited health status and family factors, such as living conditions, nutrition intake, parental socioeconomic status, and parental role in the family. The systematic components are expected to have a lasting influence across the life span, impacting health status, education achievement, and possibly social capital in adulthood.

The nonsystematic components arise from haphazard events, such as accidents, illness (cold or throat) due to unexpected weather changes, and other random incidents.

For students with poor health or chronic conditions, class cancellation/re-arrangement due to adverse weather or provisional change in school programs can also be seen as the cause of the nonsystematic components, in the sense that these students might have been absent from school in the original class arrangement. The nonsystematic components are not supposed to have a lasting health influence over the life span, and they should not have any direct impact on voluntary participation behavior in mid-life.

Because of the timing of its occurrence, both the systematic and the nonsystematic components of the absence length are strongly correlated with the respondent's grades on the O/A-Level exams, and subsequently their chance of receiving higher education. A valid exclusion restriction can be obtained for individual social capital if the nonsystematic components can be separated from the systematic components. We achieve this design by regressing the absence length on relevant information and breaking down the dependent variable. Family background, parental socioeconomic status, and adverse health information in childhood are included in the regression to decompose the absence length. Besides, dummy variables are created for each type of systematic illness reported for the schooling absence except for throat, cold, periods, accidents, or injuries, and interacted with other adverse health factors (such as chronic illness, low birth weight, and the smoking habit of the natural mother during pregnancy) in the decomposition process. The intuition is that, if an individual has certain health problems, and misses some classes because of nonaccidental or chronic illness, it is highly plausible that these interactions capture some systematic health problems.

One may expect that students might play truancy from school in the name of illness because of their distaste for schooling, and the predicted residuals might not be excluded from the outcome equations of social capital. We believe that this should not be a problem in our study. In the decomposition process, we control for the teacher's report of whether the student was absent from school for trivial reasons and whether the student played truancy in the previous year. We also introduce information of parental interest in the education of their children, as well as certain secondary-school characteristics—source of school funding (private school vs. public school) and availability of facility resources. The rich information included in the instrument construction should minimize the potential influence of fabricated illness on the exogenous variation of the nonsystematic components.

With the decomposition of the absence length, we obtain its predicted value—ideally the systematic components, and its residual value—ideally the nonsystematic components. Statistical proofs of the validity of the instrument are presented in Table 3. This table provides the test statistics for the correlation between the respondent's mid-life health status and the instrument, namely, the residual value of the absence length. For comparison, similar correlation tests are also performed for the absence length. It is shown that the absence length is strongly correlated with the health status in adulthood, while the instrument has trivial or zero association. These statistics provide strong support for our design principle that the nonsystematic components are not supposed to have a lasting health influence over the life span.

Figure 2 offers additional proof of the validity of the instrument. It depicts the kernel density (bandwidth 0.1) of the residual value of the absence length (denoted by IV density in the figure) for trusters and nontrusters in each education group. Provided that the instrument only impacts social trust outcome via education choice, the kernel

Table 3 Validity comparisons for the instrument

Correlation with Health status in adulthood	Absence length		Residual value	
	Coef.	<i>P</i> value	Coef.	<i>P</i> value
General health status at 32–33	−0.09	0.00	0.01	0.44
General health status at 41–42	−0.10	0.00	0.01	0.67
No. Chronics suffered at 32–33	0.07	0.00	0.00	0.94
No. longstanding illness suffered at 41–42	0.07	0.00	0.01	0.45

Note: Indicator of general health status is discrete variable with 4 categories: 0—poor, 1—fair, 2—good, 3—excellent

Fig. 2 Kernel densities of the instrument for trusters and nontrusters by education level. **a** IV density for non-qualification, **b** IV density for O-Level qualifications, **c** IV density for A-Level qualifications, and **d** IV density for college degree

densities of the residual value of the absence length should not be diverting for trusters and nontrusters with the same educational attainment. It is straight-forward in Fig. 2 that the kernel densities are well overlapping for the same education group. Therefore, the distribution of the residual value of the absence length does not vary between trusters and nontrusters for any given educational attainment and can be regarded as an applicable exclusion restriction in the social trust equation. Likewise, the kernel densities are also overlapping for the same educational attainment for group participants

and nonparticipants (the distribution figure for group membership is not presented in the article; this figure is identical to the Fig. 2 and it is available upon request).

4.2 Feasibility of nonparametric assumptions

Nonparametric bound analysis requires a couple of relatively weak nonparametric assumptions in estimating the upper and lower bounds of the causal effect of educational attainment. In this study, the monotone treatment response (MTR) assumption requires that each person's social capital outcomes are a weakly increasing function of educational attainment. The monotone treatment selection (MTS) assumption requires that persons who select higher levels of schooling have weakly higher mean functions for the social capital outcomes than do those who select lower levels of schooling.

In the social capital literature, education has been considered one of the most important determinants of social capital (Putnam 1995, 2000; Glaeser et al. 1999; Alesina and La Ferrara 2000, 2002). Schooling cultivates social norms—the core of social capital. Though education is not the only factor that determines individual trust in people in general and personal involvement in voluntary organizations, it is a very powerful generator at the individual level, even after controlling for health, income, age, and gender (Putnam 2000). Furthermore, more educated people are less likely to live in a community where there are more social heterogeneities that have an adverse impact on social capital outcomes (Alesina and La Ferrara 2000, 2002).

An alternative perspective suggests that people with a higher level of education may have less time to participate in voluntary or community activities. However, the notion that the “opportunity cost of time” might reduce the interest and energy available for the involvement into social activities does not pose a severe challenge to the MTR–MTS assumptions. The decision to join a voluntary group is not identical to the decision on the frequency of participation in group activities. It is well accepted that more educated individuals enjoy more social respect and are able to access more social resources that facilitate the capability for group affiliation. We do not expect “opportunity cost of time” to be a substantial factor in the association between individual education and the two dimensions of social capital.

The available empirical evidence has provided an emphatic confirmation of the conventional view that education does promote social capital. Huang et al. (2009) conducted a meta-analysis on the estimates of the education effects from empirical literature and this meta-analysis confirms a significant return to education on both dimensions of social capital.

Manski and Pepper (2000) suggest that Eq. 7 can be seen as a test of the joint MTS–MTR hypothesis. Under this hypothesis, the average outcome for the realized treatment must be a weakly increasing function of the realized treatment. Hence, the hypothesis should be rejected if $E[y|s = u]$ is not weakly increasing in u . The MTR–MTS hypothesis cannot be rejected in our NCDS dataset. Figure 1 has demonstrated a strictly increasing relation between the highest realized education level and the average outcome of individual social capital for each education group.

Imposing additional assumptions can tighten the MTR–MTS bounds. Both the IV (mean-independence) assumption and MIV assumption are introduced in our analysis to obtain the MTR–MTS–IV bounds and MTR–MTS–MIV bounds.

We create a discrete indicator with four categories for the predicted residuals of the absence length,⁸ which has been proved to be an applicable exclusion restriction in the outcome equations of social capital. With the new instrument, we can exploit the variation in the bounds over the four sub-samples and obtain tightened nonparametric bounds of the educational effect.

The credibility of mean independence conditions has often been subject to disagreement in empirical research. Instead of mean-independence conditions, the MIV assumption requires a weakly monotone relation between the instrumental variable and the mean outcome function. This article considers mother's interest in the education of her child as a monotone instrumental variable.⁹

In the social capital literature, family life is perceived as a bed-rock of social capital (Coleman 1988, 1990; Bourdieu 1993, p. 33; Putnam 1995, p. 73). Social capital is transmitted to children through time and effort invested by parents, through affective ties between parents and their children, and through clearly articulated guidelines on behaviors and moral value (Coleman 1988, 1994). According to Coleman (1988), parents' interest in the education of their children is a key indicator of intergeneration relation and a key determinant of the human capital and social capital stocks of the next generation.

In the NCDS dataset, we observe a strong association between parent's interest in the education of their children and parent's reading to and outing with their children in childhood, which are key indicators of the quality of family interactions. Since information on parent's interest is collected from teacher's reports and teachers generally had more interactions with mothers, this article uses mother's interest in the education of her child as a monotone instrumental variable. The MIV enables us to exploit the variation in the bounds over the sub-samples and obtain tightened bounds of the educational effect.

4.3 Empirical findings from IV estimation and nonparametric bound estimation

Table 4 provides the first stage estimation of the IV analysis implemented for the one-dimensional education model. Both ordinary linear regression and linear fixed effect regression are employed to estimate the power of the instrument. School fixed effects cannot be accounted for because the cohort sample in our study has 8,600 observations while there are roughly 4,000 secondary schools in the UK. Instead, we consider local fixed effect by local education authority code (of England and Wales) and standard regional code (of Scotland). The local education authority code and standard regional

⁸ This discrete indicator has four categories for the predicted residuals of absence length: no schooling absence, less than 1 week of schooling absence, 1 week of schooling absence, and more than 1 week of schooling absence due to nonsystematic health factors.

⁹ The monotone instrumental variable has four mutually exclusive categories: 0—mother with little interest; 1—mother with some interest; 2—merely mother with large interest; 3—both parents with large interest. We also obtain similar results with a three-category monotone instrumental variable.

Table 4 First stage analysis of IV estimation: predicting highest educational attainment

	Ordinary linear model			Local fixed effect model		
	Coef.	<i>t</i> value	<i>F</i> stat	Coef.	<i>t</i> value	<i>F</i> stat
IV—residuals of schooling absence	−0.085	−4.42	19.52	−0.081	−4.14	20.90
Gender—male	0.188	10.02		0.187	10.13	
Education level of father	0.043	5.82		0.041	5.80	
Education level of mother	0.096	10.85		0.095	10.65	
Truancy—frequent	−0.183	−2.28		−0.189	−2.33	
Truancy—less frequent	−0.278	−6.75		−0.276	−6.64	
Absence—certain	−0.548	−12.70		−0.548	−12.58	
Absence—somewhat	−0.388	−12.47		−0.392	−12.48	
Father professional position	0.683	11.14		0.668	10.95	
Father managerial position	0.456	10.30		0.456	10.14	
Father nonmanual-skilled	0.328	7.14		0.323	6.94	
Father manual-skilled	0.166	4.50		0.165	4.40	
Natural father by 1974	0.182	3.21		0.195	3.41	
Private school	0.218	3.84		0.217	3.77	
Mother little interest	−0.521	15.41		−0.522	15.14	
<i>N</i>	8,606			8,606		

code are recorded as a regional variable in the NCDS. There are 194 regional codes in our sample.

Table 4 shows that the instrument has strong explanatory power in the first stage estimation. The partial *F* statistics of the excluded instrument are 20 in each model specification. Thus the residual variable of absence length does not suffer from the problem of weak instruments. Table 3 also presents comprehensive results of the key covariates that have a statistical significance of 0.05 or smaller in the first stage analysis. The average education achievement of the male cohort is higher than that of the female cohort. Parental education and father social class (reference group—manual-unskilled position) are strong predictors of the education achievement of the next generation. Mother's interest in her child's education, the presence of natural father, and schooling motivation are strong predictors of the educational attainment.

Table 5 provides the second-stage results of the IV estimation. The IV estimate is 0.034 in the equation of social trust and 0.023 in the equation of group membership. The estimated effect of education on group membership varies substantially between the OLS analysis and the IV analysis. There is no noticeable difference in the OLS estimate and the IV estimate of the educational effect on social trust. Gender and ethnicity remain strongly significant in the IV estimations.

Table 6 reports on the (bias-corrected) estimates of the upper bounds of the education effect from the nonparametric bound analysis. Leaving school without an (appropriate) qualification is considered as a reference treatment in the one-dimensional and multilevel education models. For direct comparison with the point estimates,

Table 5 IV (2SLS) estimation in the one-dimensional education model

	Social trust		Group membership	
	Coef.	<i>t</i> value	Coef.	<i>t</i> value
Education level	0.034	0.78	0.023	0.24
Gender—male	−0.057	−2.26	−0.073	−3.61
Ethnic—White	0.167	4.13	−0.077	−2.39
Education level of father	0.008	1.17	0.015	2.91
<i>N</i>	8,606		8,606	

Table 6 Nonparametric upper bounds of the educational effect

	Social trust			Group membership		
	UB ATE	Bootstrap quantiles		UB ATE	Bootstrap quantiles	
	Coef.	0.10 LB	0.9 UB	Coef.	0.10 LB	0.9 UB
A. MTR–MTS–IV						
O-Level ATE(1,0)	0.065	−0.023	0.084	0.082	−0.029	0.101
A-Level ATE(2,0)	0.077	−0.004	0.094	0.148	−0.004	0.151
College ATE(3,0)	0.157	0.007	0.178	0.187	0.014	0.251
<i>N</i>	6,488			6,488		
B. MTR–MTS–MIV						
O-Level ATE(1,0)	0.043	−0.034	0.063	0.100	−0.045	0.113
A-Level ATE(2,0)	0.064	−0.014	0.084	0.121	−0.026	0.138
College ATE(3,0)	0.120	−0.007	0.149	0.231	−0.010	0.260
<i>N</i>	7,218			7,218		

The coefficients and quantiles are reported from bias-corrected bootstrapping (5,000 repetitions)

our nonparametric bound analysis aims at identifying the upper bounds of the ATE of different levels of education relative to leaving school without an (appropriate) qualification. Only the upper bound estimates of the ATE are reported because under the MTR assumption the lower bounds are never below zero while in empirical practice these limit points may yield nonpositive value. To give a range of the educational effect, we present in Table 6 the (bias-corrected) 0.1 bootstrap quantiles for the lower bounds and 0.9 bootstrap quantiles for the upper bounds of the ATE of each educational qualification.

The IV assumption and the MIV assumption are imposed on the MTR–MTS assumption to obtain the MTR–MTS–IV bounds and MTR–MTS–MIV bounds. The sample used in each nonparametric bound analysis is smaller than the full sample because there are missing data in the instrumental variable and the monotone instrumental variable. We repeat our linear regression and IV regression in the restricted samples as robustness tests. These regression estimates are not subject to the problem of missing data.

Part A of Table 6 reports upper bound estimate and its 0.90 bootstrap quantiles based on the MTR–MTS–IV assumptions. In the study of social trust, the point estimates from the multilevel OLS model (0.022 for O-Level, 0.055 for A-Level, and 0.117 for college degree) are clearly below the upper bound estimates and their 0.90 bootstrap quantiles. In the study of group membership, the point estimates from the multilevel OLS model (0.061 for O-Level, 0.107 for A-Level, and 0.252 for college degree) are not uniformly below the upper bound estimates. The OLS point estimate of the college effect is noticeably larger than the nonparametric upper bound estimate and marginally larger than the 0.90 bootstrap quantiles.

Part B of Table 6 reports the upper bound estimates and their 0.90 bootstrap quantiles based on the MTR–MTS–MIV assumptions. We obtain similar conclusions on the upper bounds of the educational effect on social capital outcomes. In the study on social trust, the point estimates from the multilevel OLS model are substantially below the upper bound estimates and their 0.90 bootstrap quantiles. In the study on group membership, the OLS point estimate of college education is once again larger than its upper bound estimate and it is identical to the 0.90 bootstrap quantiles of the upper bound estimate.

Since the nonparametric bound analysis does not necessarily require a valid instrument satisfying the mean independence assumption in the estimation and these nonparametric bounds are more robust to functional form and distributional assumptions, we are able to acquire useful information about the causal effect of multiple educational attainments and examine the sensitivity of the OLS estimates and the IV estimates in the one-dimensional education model.

In the study of group membership, the (one-dimensional and multilevel OLS) point estimates of college education are not uniformly below their upper bound estimates. Some point estimates even exceed the 0.90 bootstrap quantiles of the bounds. In the study of social trust the (one-dimensional and multilevel OLS) point estimates of each educational attainment are uniformly below their upper bound estimates. The nonparametric bound analysis produces similar qualitative conclusion as the IV analysis on the potential estimation bias. The IV point estimates of each educational attainment are below their upper bound estimates or 0.90 bootstrap quantiles. The nonparametric bound analysis provides useful information on the credibility of the OLS estimates and IV estimates.

In Table 6, we also present the (bias-corrected) 0.1 bootstrap quantiles for the lower bounds. These 0.1 quantiles are not necessarily positive. At first glance, the bound estimates and their quantiles may be less informative about the educational effect than the IV point estimates.

A further examination on the statistical significance of the estimates gives us a different conclusion. The IV analysis cannot provide a precise estimate of the educational effect even if its estimate is identical to the OLS estimate. In the IV estimation on social trust, the 0.9 confidence interval is $[-0.12, 0.19]$ for the marginal effect of an additional increase of educational attainment. In the IV estimation on social membership, the 0.9 confidence interval is $[-0.10, 0.15]$. The confidence interval for the effect of college (relative to no qualification) is three times the range of the confidence interval for the marginal effect. We cannot give definitive answer of the educational effect based on these confidence intervals. In the nonparametric bound analysis, combining

the 0.05 bootstrap quantiles of the lower bound and the 0.95 bootstrap quantiles of the upper bound, we obtain a much more informative range of the effect of each educational attainment. The ranges of the effect of A-Level and college education support the conventional view that education has a positive influence in promoting social trust and membership of voluntary groups.¹⁰

5 Conclusion

This article uses the rich information from the NCDS dataset to assess the causal effect of education on social capital at the individual level. Social trust and membership of voluntary groups are considered as two basic indicators of social capital. We consider the one-dimensional measurement and the multiple-dimensional measurement of educational attainment in our empirical study. The OLS estimations based on these education models suggest that individuals with a higher level of education are more inclined to trust people in general and are more likely to become a member of voluntary groups or organizations. A college education appears to have a relatively larger marginal effect on social capital outcomes.

Conventional IV method is applied to reduce the bias in the point estimate due to unobservable heterogeneities in the one-dimensional education model. Nonparametric bound analysis is applied to estimate the upper bounds of the causal effect of three educational attainments relative to leaving school without an (appropriate) qualification. These evaluation approaches reveal that the OLS estimators of the educational effect are subject to an upward bias in the study of group membership. We do not observe any significant bias in the estimated educational effect on social trust. These results are consistent with the conclusions from our meta-analysis on education and social capital (Huang et al. 2009).

The application of nonparametric bound analysis enables us to investigate the causal effect of multiple educational attainments and examine the sensitivity of the IV estimates in the one-dimensional model. In our study, the nonparametric bound analysis provides useful information on the credibility of the OLS estimates and IV estimates and confirms the positive effect of education, in particular, A-Level education and college education.

To conclude, this article provides two useful perspectives on the causal relationship between education achievement and social capital at the individual level. First, both one-dimensional and multiple-dimensional education models suggest a monotone relationship between educational attainment and social capital outcomes. Secondly, both the IV estimation and the nonparametric bound estimation suggest that it could cause an upward bias if education endogeneity is not accounted for in the study of membership of voluntary groups.

¹⁰ In the study of social trust, the range of the effect of A-Level education is $[-0.00, 0.10]$ and the range of the effect of college education is $[0.01, 0.18]$ based on the (MTR–MTS–IV) 0.05 bootstrap quantiles of the lower bound and the 0.95 bootstrap quantiles of the upper bound. In the study of group membership, the range of A-Level education is $[-0.01, 0.16]$ and the range of college education is $[0.01, 0.26]$ based on the (MTR–MTS–IV) 0.05 bootstrap quantiles of the lower bound and the 0.95 bootstrap quantiles of the upper bound.

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