



## Higher Education and Membership of Voluntary Groups

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# Higher Education and Membership of Voluntary Groups —A Perspective on Gender Difference

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**Abstract** This research uses the British National Child Development Study to examine the effect of higher education on individual membership of voluntary groups and organizations. Gender difference in the education effects is given emphasis. We apply parametric and nonparametric econometric methods to isolate the influences of confounding variables. There is strong evidence of education endogeneity in the female sample and we observe negative education effect on women's group membership. Education endogeneity does not cause serious estimation bias in the male sample. Higher education is a significantly positive determinant of men's group membership. Further investigations from a mid-life perspective reveal that the boost of female participation in the workforce and their attitudes towards employment are key factors in the negative association between higher education and women's group membership. Our research provides clues for the divergence in the enrolment in higher education and social participation behavior in Western countries.

**Keywords:** membership; voluntary groups; higher education; endogeneity; gender differences

**JEL Classification:** C31, I23, Z13

## 1. Introduction

This research examines the effect of higher education on individual membership of voluntary groups and organizations of or relating to community living and welfares<sup>1</sup>. Membership of voluntary groups is a general indicator of social participation and an important indicator of social capital (Glaeser, 1999; Paxton, 1999; Putnam, 2000). Voluntary groups facilitate people's effective involvement in community life and promote sense of community. Voluntary groups can act as a resource for the people involved by increasing access to information and facilitating the transmission of knowledge (Gamson, 1992; Hughey et al., 1999; Dekker and Uslander, 2001). 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 (House et al., 1988; Thoits et al., 2001). A high level of voluntary participation raises civic norms among people and strengthens the foundations of a democratic society.

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<sup>1</sup> These voluntary groups and organizations are outside the political arena and the workplace (i.e. unions, parties, voting and lobbying groups). We do not consider religious groups as subjects of voluntary organizations although they are often related to community living and welfares.

Education is regarded as a major factor in increasing individual social capital and promoting social participations; it is widely believed that people with higher level of education are more likely to join voluntary groups. Glaeser et al. (1999) assert that the most robust predictor of social participation, measured by the probability of being a group member, is years of schooling. Putnam (1995a, 1995b, 2000) and Uslaner (1998) also claim that high-educated people are more likely to join social organizations and participate in social engagements more frequently. The exact degree of the education influence is, however, an under-studied topic. Few empirical studies have attempted to isolate the real effect of education from the influences of confounding variables.

The divergence in the transitions of higher education and social participation behavior in Western countries also creates a puzzle on the exact relationship between education and membership of voluntary groups. Over the second half of the 20<sup>th</sup> century, most Western countries have experienced an evolution from an elitist higher education system to a mass higher education system and the average education level of people has increased dramatically. More than one in five adults in OECD countries have received tertiary education. If education promotes social engagement, we should also have seen a substantial rise in social participation level in Western countries. It appears from many social reports that more people are disengaged from civic life and social ties nowadays as they belong to fewer voluntary groups and they do less voluntary work (Knack, 1992; Putnam, 1995a, 1995b). With the exception of the Scandinavian countries and Japan where levels have remained relatively stable, there seems to be a common pattern of declining organizational activity across industrialized democracies during the 1980s and 1990s (Leigh, 2003).

The changing gender attitudes and the rapid entry of women into the labor force are considered as a cause for the decline of social participation levels (Putnam, 1995a, 1995b; Taniguchi, 2006). Women are traditionally the main force in the voluntary sector related to community affairs (McPherson et al., 1982; Taniguchi, 2006; Enns et al., 2008). Over the past several decades, high-educated women have entered the labor market in large numbers as the gap in access to higher education between men and women has narrowed or even disappeared. Most of them, however, have to facilitate reconciliation of work and family life as they are still responsible for most of the domestic work. This could divert their time, interest and energy in joining voluntary or community organizations. In this perspective, the gendered patterns of workforce participation and social participation are important factors in the association between education attainment and voluntary participation level.

In this paper we quantify the effects of higher education on individual membership of voluntary groups for a British cohort born in 1958, using the rich data from the National Child Development Study (NCDS). The membership outcome is a binary indicator denoting an individual's current affiliation with one or more community-based voluntary groups. These voluntary groups include environmental groups, charity groups, PTA, residents group, and other volunteering groups<sup>2</sup>. We also attempt to shed some insights into the divergence in the transitions of higher education and social participation behavior in Western countries.

To address these two topics with informed articulation, we proceed in three stages in the empirical studies. Gender difference in the education effects is given emphasis as we perform analysis for men and for women separately in each stage. In the first stage, we isolate the influences of education endogeneity and identify the average treatment effect (*ATE*) of higher education. In the second stage, we present robustness tests on the distributional and functional form assumptions, missing data in key covariate and education measurement. In the third stage, we provide further investigations of the education effects in which we examine whether status of employment and attitudes towards workforce participation are important factors in the associations between education attainment and group membership of voluntary organizations.

In the next section we give a brief illustration of the bivariate probit and control functions probit, which tackles the endogenous relation between a binary treatment variable and a binary outcome variable. The third section presents summary descriptions of the NCDS dataset and quantifies the education effect on the membership outcome. The fourth section provides robustness tests on the education effects and provides further investigations on the roles of employment status and occupation attitudes. The fifth section draws conclusions and offers policy implications

## 2. Evaluation methods

This section offers a brief illustration on the bivariate probit and the control functions probit. We employ these regression methods to handle the potentially endogenous relation between a binary variable for education attainment ( $T_i = 1$  if individual  $i$  undertake higher education,

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<sup>2</sup> These groups are established to facilitate people's effective involvement in community life, to improve the living environment or teaching quality, and to increase social well-being. PTA and residents group membership require for specific hurdles, i.e. being a tenant or having children and there may be effective auto-enrollment in these groups. We offer additional analysis on the membership outcome in which PTA and residents groups are excluded and we find identical effects for higher education.

$T_i = 0$  otherwise) with a binary variable for membership outcome ( $y_i = 1$  if individual  $i$  has joined at least one voluntary group,  $y_i = 0$  otherwise). In a basic framework

$$T_i = 1(T_i^*(Z_i, \nu_i) > 0) \quad (1)$$

$$y_i = 1(y_i^*(T_i, X_i, \eta_i) > 0) \quad (2)$$

Where  $T_i^*$  and  $y_i^*$  are the latent variables.  $T_i^*$  depends on the observed covariates set  $Z_i$  ( $Z_i$  includes the exogenous variable set  $X_i$  and excluded variable  $z_i$  such that  $Z_i = (X_i, z_i)$ ) and unobserved factor  $\nu_i$ ;  $y_i^*$  depends on education choice  $T_i$ , exogenous variables  $X_i$ , and unobserved factor  $\eta_i$ . Assuming additive separability between observables and unobservables for both latent variables, and a cumulative standard normal distribution for the conditional probability in each equation, we obtain a standard bivariate specification

$$\Pr(T_i = 1) = \Phi(f(X_i, z_i) + \nu_i) \quad (3)$$

$$\Pr(y_i = 1) = \Phi(m(X_i, T_i) + \eta_i) \quad (4)$$

$$(\nu_i, \eta_i) \sim N(0, 0, 1, 1, \rho_{\nu\eta}) \quad (5)$$

$\rho_{\nu\eta}$  is a correlation matrix between the unobservable components in treatment and outcome equations. Define  $m(X_i, T_i) = b_0 + m_0(X_i) + \beta(X_i)T_i$  and the average treatment effect (*ATE*) is specified as

$$\begin{aligned} ATE &= EY_{T=1} - EY_{T=0} \\ &= E[\Phi(b_0 + m_0(X_i) + \beta(X_i))] - E[\Phi(b_0 + m_0(X_i))] \end{aligned} \quad (6)$$

In a homogeneous return specification where  $\beta(x_i)$  and correlation matrix  $\rho_{\nu\eta}$  are constrained to be constant across individuals undertaking a higher education, the average treatment effect is specified as

$$ATE = E[\Phi(b_0 + m_0(X_i) + \beta)] - E[\Phi(b_0 + m_0(X_i))] \quad (7)$$

When  $\rho_{\nu\eta}$  is non-zero, which indicates the existence of endogenous regressor, there would be endogeneity bias in the estimate of  $\beta$  if we perform a OLS or probit estimation based on equation (4). Econometric techniques are needed to eliminate the potential endogeneity bias.

The bivariate probit produces a consistent estimator of  $\beta$  in a homogeneous return specification (Wooldridge, 2002; Bhattacharya et al., 2006). The BVP approach has been widely used in medical evaluation to reduce the bias due to self-selectivity in the treatment choice. It is a simultaneous equation model that controls for endogeneity in the likelihood of the joint sets of the treatment and outcome distribution. Bhattacharya et al. (2006) have an

inclusive comparison on the performances of the probit, two-stage probit (or two-stage least squares) and bivariate probit models. They show that the bivariate probit is the only method to produce a consistent estimator when there is an endogenous treatment.

The control functions probit (CFP) is a special case of the control functions (CF). The control functions (CF) method is generally applied to correct an omitted-variable bias in the study of treatment effect on continuous outcome. Because the probit specification can be derived from a model involving a latent variable  $y_i^*$  with a linear expression, the control functions probit produces a good approximate of the true *ATE* in a binary response model.

The principle inspiring the control functions method is to evaluate the treatment effects by controlling directly for the correlation between the treatment choice and the unobservable heterogeneity in the outcome equation (see, i.e. Heckman et al., 2004; Blundell et al.; 2005). The control functions method allows for outcome unobservables  $\eta_i$  to depend on the treatment  $T_i$ , and it models this dependence. The control functions probit (CFP) applies the same principle to identify the treatment effect on the binary outcome variable. Under joint normality of  $\nu_i$  and  $\eta_i$  in the treatment and outcome equations and a homogeneous return specification, the latent variable  $y_i^*$  is specified as

$$y_i^* = b_0 + m_0(X_i) + \beta T_i + \rho_{\eta\nu}(1 - T_i)\lambda_{0i} + \rho_{\eta\nu}T_i\lambda_{1i} + \delta_i \quad (8)$$

A consistent estimator of  $\beta$  is achievable in equation (8) with a continuous dependant variable  $y_i^*$ , where  $\lambda_{0i}$  and  $\lambda_{1i}$  are the standard inverse Mills ratios. In the binary response model, the estimate obtained from the control functions is merely an approximate of the true treatment effect because of the changes in the latent equation. Nevertheless, the CFP method provides a rather precise *ATE* estimate under the assumption of standard bivariate normality<sup>3</sup>. Compared to the BVP, which has a messy and time consuming, though doable maximum likelihood calculation, the CFP has a considerably lower calculation cost, especially when it comes to the estimation of standard error or confidence interval for the treatment effect that involves Monte Carlo simulation. The maximum likelihood calculation may not always converge in bootstrapping estimation.

The CFP, like the BVP, allows one to recover the *ATE* even when individuals select on the basis of unobservables, and one can examine the presence of treatment endogeneity by a

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<sup>3</sup> Our simulation exercises, which follows the same design applied by Bhattacharya et al. (2006), show that the CFP does considerably better than the probit and two-stage probit (or two-stage least square) in the identification of *ATE* and it produces an approximate estimate of the true *ATE*, while the BVP produces a consistent estimator. Details of our Monte Carlo simulations are presented in the appendix of the working paper.

test of the null hypothesis that  $\rho_{v\eta}$  equals zero. These two methods are major approaches in our evaluation to tackle endogeneity bias. Since the BVP and the CFP methods rely on certain distributional assumptions or functional form restrictions to identify average treatment effect, we will provide a nonparametric local average treatment effect (or LATE) analysis in the robustness tests on the relaxation of distributional assumptions and functional form restrictions.

### **3. Introduction of NCDS dataset and evaluation of education effects**

#### **3.1 NCDS Dataset**

Our dataset contains 9046 observations from the National Child Development Study (NCDS). The NCDS is a multi-disciplinary longitudinal study of all those living in the UK who were born in the week 3 to 9 March, 1958. The first three sweeps were carried out by the National Children's Bureau in 1965, 1969 and 1974. The following three sweeps were carried out by the Centre for Longitudinal Studies (CLS) in 1985, 1991 and 1999-2000. The NCDS is widely used in economics, social and health sciences research to examine the patterns of human development that follow the lifespan (McCulloch and Joshi, 2002; Case et al., 2005).

Table 1 provides summary statistics of the main variables in this study. Information on group membership is extracted from the 2000 survey, when the respondents were 42 years old. Information on higher education achievement is extracted from the 1991 NCDS survey based on their formal education experience and qualifications. There are noticeable differences between men and women in group membership and higher education attainment. Thirteen percent of men indicated that they were member of at least one voluntary group in the 2000 survey and around twenty-four percent of male respondents had received higher education by age 33. Women had a substantially higher participation rate in voluntary groups and a considerably lower rate in receiving higher education. Twenty percent of women indicated in the 2000 survey that they joined at least on voluntary group and less than eighteen percent of them had received higher education by age 33.

All covariates are extracted from the 1973-1974 survey except for the basic demographic information and prenatal/natal health information, which are extracted from the 1958 birth survey. The cohort members were 15-16 years old 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)<sup>4</sup> as well as a choice of further education. Parental socioeconomic covariates include indicators of parental education level and parental social class from the 1973-1974 survey. Other covariates of family backgrounds contain information of whether parent(s) changed (as a result of divorce, death etc.), and the number of siblings of respondent.

Academic ability and motivation in adolescence are crucial predictors for the highest education achievement in adulthood. Using the teacher's report in the 1973-1974 survey, we collect information of individual ability in Math and English, and whether the individual was absent from school for trivial reasons. We also collect, from the teacher's report, information of parental interest in education of their children, as well as certain school characteristics that consists of school enrolment, teacher/student ratio, expelled student ratio and availability of facility resource.

We include information on chronic conditions and physical height from the physician examination and parent-reported adverse illness as adolescent health indicators; we also include information of the smoking habit of mother during pregnancy, birth weight and level of breastfeeding from the 1958 survey as natal health indicators. To maintain a large and representative sample in concern on missing data in the key covariates, we follow the treatment of missing value adopted by Case et al (2003, 2005) in their health study of the same British cohort<sup>5</sup>. Case et al. (2003, 2005) and Feinstein et al. (2003) have shown that the initial sampling bias and sample attrition do not appear to be a problem for the 1958 cohort targeted by the NCDS. We will also show in our robustness tests that the estimates of education effects are not sensitive to missing data in covariates.

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<sup>4</sup> The General Certificate of Education or GCE is a secondary-level academic qualification that [Examination Boards](#) in the [United Kingdom](#) confer to students. The GCE traditionally comprised two levels: the [Ordinary level](#) (O-level) and the [Advanced level](#) (A Level). The A-level is usually taken by students during the optional final two years of [secondary school](#) (years 12 and 13, usually ages 16-18). The qualification is used as a sort of entrance exam for some universities. O-level was introduced as part of British educational reform in the 1950s alongside the more in-depth and academically rigorous [A-level](#).

<sup>5</sup> 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 non-missing 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 variable conditional on its value being observed.

Table. 1 Descriptive statistics of the main variables

<u>Variable</u>	<u>N</u>	<u>Mean</u>	<u>S.D.</u>	<u>Variable</u>	<u>N</u>	<u>Mean</u>	<u>S.D.</u>
<u>Outcome variable (age 42)</u>				<u>Treatment variable (age 33)</u>			
Male membership	4326	0.133	0.340	Male higher education	4326	0.236	0.424
Female membership	4720	0.200	0.400	Female higher education	4720	0.175	0.380
<u>Basic Demographics (birth)</u>				<u>Father economic status (age 15-16)</u>			
Male	9046	0.480	0.500	Professional	6286	0.057	0.233
Minority-Non White	9046	0.021	0.144	Managerial	6286	0.146	0.353
<u>Reading ability (age 15-16)</u>				<u>Mother economic status (age 15-16)</u>			
Excellent	7005	0.168	0.374	Professional	6730	0.005	0.054
Above average	7005	0.298	0.458	Managerial	6730	0.106	0.308
Average	7005	0.339	0.473	Non-manual-skilled	6730	0.220	0.414
Below average	7005	0.121	0.328	Manual-skilled	6730	0.048	0.214
<u>Math ability (age 15-16)</u>				<u>Manual-semi</u>			
Excellent	6961	0.118	0.323	Manual-semi	6730	0.119	0.324
Above average	6961	0.223	0.416	Manual-semi	6730	0.100	0.301
Average	6961	0.361	0.480				
Below average	6961	0.164	0.370				

### 3.2 Instrumental variables

The bivariate probit and control functions probit methods require for a valid exclusion restriction in their evaluation procedures. We construct such an instrument from the information of 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 length of schooling absence due to illness can be decomposed into systematic components and non-systematic components. 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 education achievement and possibly group participation behavior in adulthood.

The non-systematic components arise from haphazard events, such as accidents, illness (cold or throat) due to unexpected weather changes and other 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 non-systematic components, in the sense that these students might have been absent from school in the original class arrangement. The non-systematic 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 non-systematic components of the absence length are strongly correlated with respondent's grades of the O/A-level exams, and subsequently their chance of receiving higher education. A valid exclusion restriction is obtained for the membership outcome if the non-systematic 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 backgrounds, parental socioeconomic status, adverse health information from the birth survey and the adolescent survey 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 of natural mother during pregnancy) in the regression of the absence length. The intuition is that, if an individual has certain health problems, and misses some classes because of non-accidental or chronic illness, it is highly plausible that these interaction capture some systematic health problems.

One may expect that a student might play truancy from school in the name of illness because of their distaste for schooling or poor relations with other school children, and the predicted residuals might not be excluded from the membership equation. We believe this should not be a problem because in the decomposition process we will control for the teacher's perspective of whether the respondent was absent from school for trivial reasons. We also include (teacher-reported) academic ability, relations with other children, parental interest in education of cohort member and information of school resources in the outcome equation. All covariates in the membership outcome equation are included in the decomposition of the absence length. The rich information included in the instrument construction should minimize the potential influence of fabricated illness on the validity of the non-systematic components.

As relevant covariates are included in the regression of the absence length, we obtain its predicted value—ideally the systematic components, and its predicted residual—ideally the non-systematic components. Statistical proofs of the validity of the instrumental variable are presented in table 2. Part A of table 2 provides the test statistics for the correlation between the respondent’s mid-life health status and the instrument, namely, the predicted residual variable of the absence length. For comparison, similar correlation tests are also performed for the absence length and for the predicted value of the absence length. It is straight-forward that the absence length and its predicted value are strongly correlated with the health conditions at age 33 and age 42, while the instrument has no significant correlation with the health conditions in adulthood. These statistics provide strong support to our design principle adopted in this research that the non-systematic components are not supposed to have a lasting health influence over the life span.

Part B of table 2 provides evidence for our argument that the predicted non-systematic components of the absence length have an impact on group membership only via respondent’s exam grades. We break down the membership outcome by the number of A-levels that the respondent had passed (as grades of entrance exam) by age 20. Then we perform correlation test for the instrument and the residual value of the membership outcome unrelated to the number of passed A-levels. Similar correlation tests are applied for the absence length and for the predicted systematic components of the absence length. Once again the absence length and its predicted value are strongly correlated with the residual value of the membership outcome unrelated to the number of passed A-levels, while the instrument has a trivial correlation with the residual value of the membership outcome.

Table. 2 Test statistics on the validity of the instrumental variable

	Absence length		Systematic term		Non-systematic term	
	coef.	p-value	coef.	p-value	coef.	p-value
A. Correlation with mid-life health						
General health status at 32-33	- 0.09	0.00	- 0.11	0.00	0.01	0.30
General health status at 41-42	- 0.10	0.00	- 0.11	0.00	0.01	0.40
No. Chronic illnesses suffered at 32-33	0.07	0.00	0.11	0.00	- 0.00	0.84
No. long-standing illness suffered at 41-42	0.07	0.00	0.10	0.00	0.01	0.42
B. Correlation with residuals of membership						
Membership residuals unrelated to exams	- 0.03	0.03	- 0.04	0.00	- 0.00	0.90

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

Figure 1 and figure 2 offer additional proof of the validity of the instrumental variable. Figure 1 depicts the kernel density (with bandwidth of 0.1) of the residual value of the absence length for voluntary group participants and non-participants in the control group, namely, the low-educated group. Figure 2 depicts the kernel density (with bandwidth of 0.1) of the residual value of the absence length for voluntary group participants and non-participants in the treatment group, namely, the high-educated group. Provided that the instrument only impacts membership outcome via education choice, the kernel densities of the residual value of the absence length should not be diverting for voluntary group participants and non-participants in the same education group. It is straight-forward in figure 1 and figure 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 voluntary group participants and non-participants and it can be regarded as a applicable exclusion restriction in the membership equation.

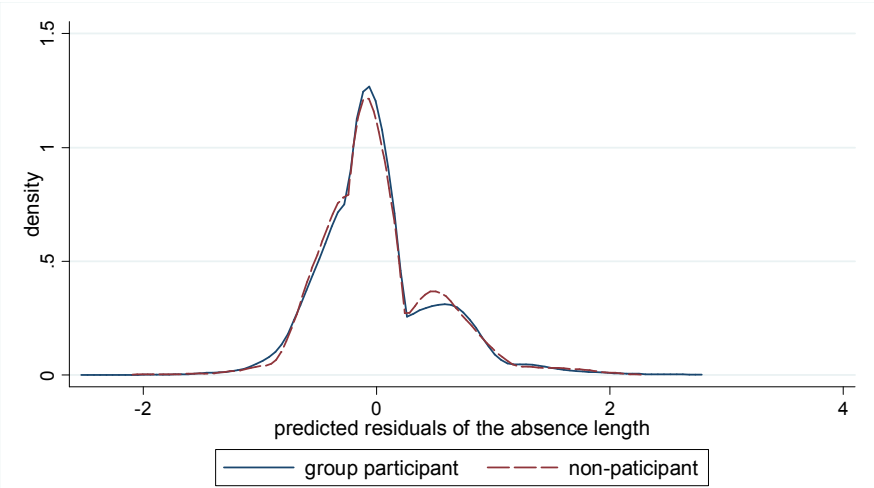


Fig.1. Kernel densities of the predicted residuals of the absence length - control group

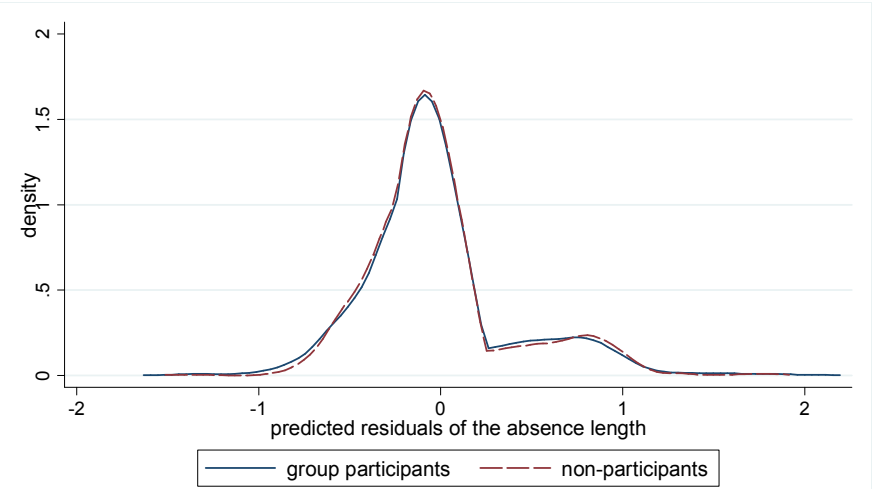


Fig.2. Kernel densities of the predicted residuals of the absence length - treatment group

### 3.3 Evaluation of education effects

We apply the probit, bivariate probit and control functions probit to assess the average treatment effect (*ATE*) of higher education attainment on membership of voluntary groups. The gender difference in the education effects is given emphasis as we perform each estimation for men and for women separately.

The results are presented in table 3. A statistically significant estimate of the average education effect, in terms of probability change, is found for both men and women in the probit model. The estimated *ATE* is 0.104 for men and 0.145 for women. In the BVP and CFP methods, however, the *ATE* estimates show sizeable divergence between men and women. The estimated *ATE* turns negative in the female sample. It is -0.070 in the BVP analysis and -0.063 in the CFP analysis. The estimated *ATE* is significantly positive across all specifications in the male sample. The estimates obtained from the endogeneity models are relatively larger than that from the probit model.

The CFP method provides a good approximate estimate as the BVP method at a much lower computational cost. Both the BVP and the CFP methods allow endogeneity tests and these tests strongly reject the hypothesis of a zero correlation term  $\rho_{v\eta}$  in the female sample. We find no statistical evidence for education endogeneity in the male sample.

Table 3 Analysis of higher education and group membership

	<i>ATE</i> (probability change)		Endogeneity test
	coef.	s.e.	p-value
Male			
Probit	0.102	0.015***	-
Bivariate probit	0.167	0.082**	0.331
Control functions probit	0.171	0.084**	0.401
N	4326		
Female			
Probit	0.145	0.021***	-
Bivariate probit	- 0.070	0.061	0.006
Control functions probit	- 0.063	0.060	0.002
N	4720		

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level. The coefficients and standard errors are reported from bootstrapping (500 repetitions).

The membership outcome under examination in table 3 is a binary indicator denoting an individual's current membership of at least one of the community-based voluntary groups. PTA member and residents group are also included as outcome groups. These groups, however, require for specific hurdles, i.e. being a tenant or having children, and there may be effective auto-enrollment in these groups. We replicate the analysis on a modified membership outcome in which PTA and residents groups are excluded. We present the regression results in table 4. It turns out that the estimates are relatively smaller in the male sample. Nevertheless, the findings from the replicated analysis are similar with those from the previous analysis in general.

Table 4. Analysis of higher education and modified group outcome

	ATE (probability change)		Endogeneity test
	coef.	s.e.	p-value
<b>Male</b>			
Probit	0.069	0.013***	-
Bivariate probit	0.081	0.117	0.988
Control functions probit	0.063	0.070	0.927
<b>N</b>	4326		
<b>Female</b>			
Probit	0.110	0.018***	-
Bivariate probit	- 0.055	0.046	0.005
Control functions probit	- 0.072	0.035*	0.001
<b>N</b>	4720		

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level. The coefficients and standard errors are reported from bootstrapping (500 repetitions).

So far we have applied the BVP and CFP methods to tackle education endogeneity and to identify the causal effect of higher education on membership of voluntary groups. We show that it could lead to misleading conclusions if women's choice of higher education is treated as an exogenous variable. We also show that there is a sizeable difference, quantitatively and qualitatively, in the education effect between men and women. Higher education does not seem to promote female membership of voluntary groups. We observe a negative estimate of the education effect in the endogeneity models. As for male membership, higher education has a

strongly positive effect and the probit regression produces the same conclusion as the BVP and CFP methods. These results are consistent with the findings from our meta-analysis on education and social capital (Huang et. al. 2009). In the meta-analysis we confirmed that education endogeneity and gender differences are importance causes of the variation in the estimated effects of education on participation in social groups.

The findings that high-educated women are less motivated in joining voluntary groups offer an explanation for the divergence in the transition of higher education and social participation in many Western nations. Women's networks are traditionally more informal due to their lower participation levels in formal work organizations. They tend to participate in smaller, more peripheral organizations and activities with a focus on domestic or community affairs (Taniguchi, 2006; Enns et al., 2008). Participation in these voluntary groups would not be promoted by the increase of average education level over the population or by the increase of gender equality in higher education opportunity, when higher education adversely impact female membership of voluntary groups.

The findings from the female study contradict, however, the common saying that schooling promotes social cohesion and strengthens citizenship. Further investigation is essential in search of the potential explanations of the negative education effect.

#### **4. Robustness tests and further investigations**

In the first part of section four we perform robustness tests on the relaxation of distributional and functional form assumptions by adopting a nonparametric evaluation approach. We also check whether the education estimates are sensitive to missing value in key covariates and sensitive to alterations in education measurements. In the second part of the section we provide further investigations from a mid-life perspective to obtain additional insights on the education effects.

##### **4.1 Robustness tests**

The BVP and the CFP approaches rely on certain functional form assumptions, such as bivariate normality, constant treatment effect or additive separability in the error term, to identify average treatment effect. Estimation of local average treatment effect (LATE) relies on much weaker assumptions and nonparametric or semi-parametric method can be easily integrated in the analysis procedure.

The general identification of LATE comes from a binary instrument that induces exogenous selection into treatment for the sub-population of compliers, where the compliers



are all individuals whose choice of treatment would change if the instrument were modified exogenously (Imbens and Angrist, 1994; Angrist et al., 1996). Recently there have been great efforts in introducing covariates in LATE estimation because instruments may require conditioning on a set of covariates to be valid (e.g. Hirano et al, 2000; Abadie, 2003; Frölich, 2007). As a robustness test on the relaxation of distributional and functional form assumptions, we apply the nonparametric LATE method proposed by Frölich (2007) to evaluate the effect of higher education on membership of voluntary groups. The binary instrument in our nonparametric LATE analysis is defined on the sign of the residual variable or predicted non-systematic components of the absence length ( $z_{LATE} = 1$  if  $z > 0$ ,  $z_{LATE} = 0$  otherwise<sup>6</sup>).

Full information of the instrument is required in our nonparametric LATE estimation. We do not include observations with missing value of the absence length. The restricted dataset contains seventy six percent of the observations in the full dataset. For comparison, we also apply the BVP and CFP methods to evaluate the education effects in the same dataset. It is shown in table 5 that the nonparametric LATE method produces qualitatively the same conclusion as the BVP and CFP methods. There are quantitative differences in the estimates as the LATE estimate is uncovered for the subpopulation that reacts on change of the binary instrument  $z_{LATE}$ . The standard error of the LATE estimate is not reported because it costs enormous time to compute. Analytic standard errors is instead reported through the estimation of asymptotic variance (Frölich, 2007; Frölich and Melly, 2008).

The estimates of *ATE* obtained by the BVP and CFP methods from the restricted dataset are the same as those obtained from the full dataset. We have also performed robustness tests on the restricted dataset with no missing observations on parental economic class, education or teacher-reported academic abilities. The estimates obtained from these restricted dataset are very similar to the estimates obtained from the full dataset. The outcomes from table 5 indicate that the estimates of the education effects are robust to distributional assumption and functional form restrictions, as well as missing data in key covariates.

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<sup>6</sup> The binary instrumental variable  $z_{LATE}$  indicates schooling absence due to non-systematic factor in illness. It has similar power and exogeneity as the original instrumental variable.

Table 5 LATE, BVP and CFP estimation in the restricted sample

	Male		Female	
	coef.	s.e.	coef.	s.e.
LATE estimation	0.252	0.507	-0.095	0.524
BVP estimation (bootstrapping)	0.182	0.056***	-0.050	0.052
CFP estimation (bootstrapping)	0.173	0.093*	-0.060	0.065
N	3239		3573	

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level.

Our measurement of higher education is based on information on formal education experience and qualifications reported in the 1991 survey. An academic sequence is imposed in the measurement of higher education for an unambiguous treatment analysis. Observations with a higher education have also received the preceding lower level of education. In other words, an A-level or equivalent qualification is a prerequisite for a higher education attainment and observations without A-level or equivalent qualification are categorized into the control group. This education sequence is a common procedure for people who have undertaken an academic route. It is not necessarily true, however, for people who have undertaken vocational routes.

The difference between the reported year (1991) of education variable and the reported year (2000) of membership variable also causes a concern for the measurement of education. Adult learning during this time interval may lead to a change in the education groups. Adult learning also plays an important role in contributing to the small shifts in attitudes and behaviors that take place during mid-adulthood (Feinstein et al., 2003). We may therefore not be able to identify the total effect of higher education with the education information from the 1991 survey.

Robustness tests are performed on the measurement of higher education. Part A of table 6 presents the results from the analysis in which the restriction on academic sequence is relaxed. An A-level or equivalent qualification is not a prerequisite for higher education. Part B of table 6 presents the results from the analysis in which we adjust the education measurement by accounting for the education qualifications respondents collected since the 1991 survey. Part C of table 6 presents the results from the analysis in which a new binary treatment variable is created to indicate whether respondents left fulltime continuous education before

age 20<sup>7</sup>. We do not provide the estimation results from the BVP method because its bootstrapping calculation does not always converge and simulated standard error cannot be obtained. Nevertheless, the education effects we quantify in the CFP regression (without bootstrapping) are virtually the same as the education effects we quantify in the BVP regression (without bootstrapping).

As we observe in table 6, the estimates of the average education effect based on the adjusted measurement of higher education are quite similar to each other. They are not substantially different from the estimates obtained in the previous analysis. We come to the same conclusions on gender-specific education effects and the same conclusions on the problem of education endogeneity in the female study.

Table. 6 Estimation on adjusted education measurement

	Male		Female	
A. Relax on education sequence				
	<i>ATE</i>	s.e.	<i>ATE</i>	s.e.
Probit	0.094	0.014***	0.121	0.017***
CFP	0.218	0.101**	-0.046	0.105
B. Inclusion of education qualification obtained since 1991				
	<i>ATE</i>	s.e.	<i>ATE</i>	s.e.
Probit	0.103	0.014***	0.123	0.016***
CFP	0.250	0.109**	-0.061	0.099
C. Binary treatment for age leaving fulltime continuous school (age $\geq 20$ )				
	<i>ATE</i>	s.e.	<i>ATE</i>	s.e.
Probit	0.091	0.019***	-0.126	0.022***
CFP	0.180	0.077***	-0.089	0.050*
N	4720		4326	

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level; The coefficients and standard errors are reported from bootstrapping (500 repetitions).

## 4.2 Further investigations

That high-educated women are less motivated to join voluntary groups offers an explanation for the divergence in the transition of higher education and social participation in many Western nations. The negative causality observed in the female study, however, contradicts

<sup>7</sup> The binary treatment variable is coded as 0 if respondent left fulltime continuous education before age 20; it is coded as 1 otherwise.

the common saying that education promotes social cohesion and strengthens citizenship. There may be some missing links in the association between higher education and voluntary participation.

The changing gender attitudes and the rapid entry of women into the labor force are potential causes for this negative association. Putnam (1996) and Taniguchi (2006) suggest that the movement of women into the labor force is playing a role for the decline of social participation levels. Traditionally, men of working age are expected to devote themselves to professional life and women are considered responsible for household welfare and child care, which are unpaid domestic responsibilities. Voluntary group participation is a common and reliable option for women to share social resources and exert their influence in the community. The boost of female (especially high-educated female) participation in the workforce could divert women's interest, time and energy available for participation in voluntary groups. Taniguchi (2006) claim that for men the relationship between paid work and voluntary participation would be more consistent with the notion of a non-zero-sum game, whereas for women this relationship would resemble the trade-offs implied in a zero-sum game.

For the meantime, the traditional gap in higher education participation between men and women has narrowed or even disappeared. In the UK, women have outnumbered men in higher education programs since 1996 and they now make up almost 60 percent of the full-time student population. High-educated women may be more motivated, because of their education experience or profession expertise, than low-educated women to pursuit economic independence and regularity of collective participation. When high-educated women enter the labor market to obtain a return to their education and become more ambitious in competing in the workplace with men, the role of female participation in voluntary groups is adversely impacted in achieving personal values and fulfilling social responsibilities. High-educated women may also face greater time constraints for voluntary participation due to the intensification of labor force participation and the increasing economic pressure for dual-career families. Since most of these women continue to take main responsibility on domestic works i.e. child care and household work, they are under more pressure than men to balance career and social activities.

To obtain additional insights on the gender-specific effects of higher education, we provide two investigations via mid-life information. In the first investigation, we collect information of individual employment characteristics and individual attitudes towards workforce participation from the 2000 NCDS survey, and we apply the control functions method by gender to quantify the causal effect of higher education on these employment

variables and attitude variables. Information of individual employment characteristics consists of employment status, fixed working hours, weekend shift, night shift, etc; Information on individual attitudes towards workforce participation consists of individual perception on the priority of having a job, the importance of staying in job, the benefit of a working mother for the family and for the child.

The main findings from the control functions estimation are presented in table 7. This control functions estimation has the same model specification as the previous estimations. Part A of table 7 examines the education effects on individual employment characteristics. Higher education has a negative effect for males in workforce participation and a positive effect for females, although the estimates are not statistically significant. There are substantial gender differences in the education effects on fixed-time working, weekend working and night working. We find a strong and negative education effect in the male sample for being in a job with fixed working hours. The estimates of the education effects are also negative for working on weekends every week or working on night shifts frequently. In the female sample, we find a significantly positive effect of higher education on fixed-time working, weekend working and night working.

Part B of table 7 examines the education effects on individual attitudes towards workforce participation. High-educated women have a more positive attitude towards the priority of having a job and the importance of staying in job. They are more affirmative of the benefits of working mother. High-educated men are not more inclined than low-educated men to consider participation in the workforce as an indispensable factor of personal life, although they give more affirmative answers towards the benefits of working mother.

Our investigation indicates that higher education plays an important role in increasing female employment and developing a positive attitude toward female employment. High-educated women are indeed more motivated than low-educated women to pursue economic independence. This means the increase of women's education level could bring down the level of voluntary participation when there are trade-offs between female workforce participation and female voluntary participation.

Table. 7 Education effects on individual employment status and attitudes

	Male		Female	
	coef.	s.e	coef.	s.e
<u>A. Employment characteristics at age 42</u>				
Employed	-0.023	0.092	0.073	0.069
Fixed working hours required in job	-0.248	0.091**	0.152	0.084*
Work on weekend every week	-0.098	0.072	0.164	0.083**
Night shift often required	-0.004	0.080	0.146	0.078**
<u>B. Perception on female employment/family life</u>				
Any job is better than being unemployed	-0.017	0.225	0.321	0.191*
Important to stay in job even if unhappy	-0.235	0.224	0.308	0.183*
Mother and family benefit from a work mother	0.461	0.227**	0.404	0.197**
Child benefits from a working mother	0.252	0.228	0.344	0.187*

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level. Employment variables in Part A are binary indicator: 1=yes, 0=otherwise; Attitude variables in Part B are discrete variables with 5 categories: 0-strongly discrete, 1-discrete, 2-uncertain, 3-agree, 4-strongly agree

In the second investigation we break down the membership variable by the mid-life information on individual employment characteristics and individual attitudes towards workforce participation. We obtain the membership variation related to, or predicted by, these mid-life variables and membership variation unrelated to these mid-life variables. Then we apply control functions regression by gender, which has the same model specification as in the previous analyses, to assess the education effects on these membership variables respectively. The purpose of this design is find out whether female employment and attitudes towards female employment are the key channels via which the negative effect of higher education relates to female membership outcome.

When individual employment characteristics and individual attitudes towards workforce participation are both introduced as explanatory variables to break down the membership outcome, the probit model indicates that the value of the pseudo- $R^2$  is 0.082 for the male membership and 0.072 for the female membership. Therefore, these two categories of mid-life information account for nearly eight percent of the membership variance. In other words, nearly ninety-two percent of the membership variance cannot be explained by the contemporary employment characteristics or employment attitudes.

Standardized coefficients (beta coefficients) are reported in table 8 by gender for the education effects on the break-down of these membership variables. We also report the test

statistics (in terms of p-value) of the presence of education endogeneity by the control functions method.

Part A of table 8 examines the education effects on the membership variable predicted by individual employment characteristics, on the membership variable predicted by individual attitudes towards workforce participation, and on the membership variable predicted by both employment characteristics and employment attitudes. We observe strongly positive beta coefficients in each of the predicted membership variables. These coefficients are very similar, ranging from 0.287 to 0.310 ( $p$ -value $<0.01$  in each equation). When it comes to the predicted variables of female membership, the beta coefficients are significantly negative ( $p$ -value $<0.05$  in each equation). The control functions method indicates strong education endogeneity in the female sample. We come to the same conclusion on the gender-specific education effects and the same conclusion on the problem of education endogeneity for both the membership outcome and the break-down of the membership variable predicted by mid-life information.

Part B of table 8 examines the education effects on the break-down membership variable unrelated to individual employment characteristics, the education effects on the break-down membership variable unrelated to individual attitudes towards workforce participation, and the education effects on the break-down membership variable unrelated to either employment characteristics or employment attitudes. In the male sample, the beta coefficient of the education effect is practically 0.22 for each equation of the residual membership variables (unpredicted by mid-life information), and they have a significant statistical level. These beta coefficients are not much different to those obtained from the equations of the predicted membership variables. In the female sample, the beta coefficients are become uniformly positive in the residual membership variables. The null hypothesis of exogenous choice of higher education cannot be rejected in both the male sample and the female sample.

Table. 8 Education effects on membership variation broken down by mid-life information

Break-down membership	Male			Female		
	Beta estimates		Endogeneity	Beta estimates		Endogeneity
A. Predicted variation	coef.	s.e.	p-value	coef.	s.e.	p-value
Explained by employment	0.296	0.081***	0.219	-0.301	0.064***	0.000
Explained by attitudes	0.310	0.082***	0.194	-0.134	0.062**	0.000
Explained by both categories	0.287	0.080***	0.352	-0.268	0.061***	0.000
B. Residual variation	coef.	s.e.	p-value	coef.	s.e.	p-value
Unexplained by employment	0.224	0.087***	0.135	0.067	0.065	0.307
Unexplained by attitudes	0.221	0.086***	0.137	0.046	0.065	0.230
Unexplained by either categories	0.216	0.087**	0.125	0.088	0.065	0.350
N	4720			4326		

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level.

The estimation results in table 7 and table 8 indicate that female participation in the workforce and their attitudes towards employment are indeed the main channels via which higher education exerts a negative impact on the female membership outcome<sup>8</sup>. The beta coefficient is -0.268 ( $p$ -value<0.01) in the equation of the predicted variation in female membership, and it is 0.088 ( $p$ -value=0.18) in the equation of the residual variation in female membership where we isolate these main effects. We observe such remarkable difference in the education effects because higher education promotes female employment (especially for weekend working and night shift) and generates a positive attitude towards female employment, while female choice of, or preference for, employment diverts women's interest and energy in joining voluntary or community organizations. The beta coefficients are similar in the male sample because high-educated men do not have more motivation or probability of joining the workforce. The allocation of time between paid work and volunteer work is not entirely a zero-sum game for men.

<sup>8</sup> It has been shown that female employees can be under more pressure than male employees to balance career and civic activities (Tiehen, 2000; Taniguchi, 2006). Our correlation tests (presented in the appendix of the working paper) also show that female participation in the workforce and female occupation motivation are negatively associated with female membership of voluntary groups. There can be a reverse effect from participation in voluntary groups to participation in the workforce (or fixed-time working, weekend working, night shifts) and it is accommodated in the predicted membership variation. We believe this reverse effect, if existing, cannot dominate the effect from workforce participation and occupation time/shift, especially for women.



## **5. Conclusion**

This paper investigates the impact of higher education on group membership in voluntary associations. We show that simple regression could produce misleading conclusions on the causal relationship between higher education and female group membership due to the problem of education endogeneity. We observe sizeable differences in the education effects between men and women. Higher education adversely impacts female group participation while it has a strongly positive effect on male group participation.

We further show that female participation in the workforce and their attitudes towards employment are key factors via which education attainment exerts a negative effect on the female group membership. Despite the changing gender attitudes and the rapid entry of women into the labor force over the past several decades, women continue to play a major role in running the household and giving care to family members (England, 2000; Taniguchi, 2006). This suggests that female employees from a two-career family may be under more pressure than male employees to balance career and social activities.

Because high-educated women are less likely to join voluntary groups and women are traditionally the main force in the voluntary sector related to community services, voluntary participation is not promoted by the increase of the education level over the population or by the increase of gender equality in higher education. Our findings provide a plausible explanation for the divergence in the transitions of higher education and social participation behavior in Western countries.

As women become an increasingly important element of the labor force, the role of female participation in voluntary groups is impacted adversely in terms of achieving personal values and fulfilling social responsibilities. More and more high-educated women are committed to work or motivated to pursue economic independence. This reflects a trend of increasing gender equality in the functioning of society.

The decline of female participation in voluntary groups, however, is not a desirable outcome from many perspectives. Workforce participation cannot replace the role of voluntary participation in raising common bonds and civic norms among people. The appreciation and recognition of community works are non-economic returns that paid-jobs do not yield. Participation in voluntary organizations is considered a distinctive cause for improving health status while stress from intensive work participation has been considered a key source of health problem in modern life. Many people choose to leave voluntary groups for paid works because of the economic pressure and they are hanging on the job although they do not like it.

Given the importance of voluntary participation and the development of higher education over the population, is there any solution to promote female participation in voluntary groups without compromising gender equality in employment or female economic independence? Our studies suggest that fixed-time working, weekend working and night shifts are important factors via which the adverse education effect goes to female membership. In this perspective, voluntary participation should benefit from the decline in weekend working or night working. Policy-makers can also promote voluntary participation by creating more jobs with flexible working hour. Restrictions in work intensity and weekly working hours, especially for working overtime, should also be beneficial for voluntary participation.

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## Appendix

### Appendix A. Coding of the outcome variables, treatment variable, covariates and mid-life information on employment status and employment attitudes

#### A. 1 Coding of indicator of membership of voluntary groups from the 2000 survey

The dummy indicator of joining social groups is coded as 1- being in at least on one of the following social group; and 0-otherwise.

Table A.1. Categories of Social groups

- 
- 
1. Environmental/charity groups
  2. Other charity/voluntary groups
  3. Parents/school organizations
  4. Tenants/residents associations
  5. Women's groups/institutes/library
- 
- 

#### A. 2 Classification of Higher education

**Qualifications for Higher education**—HNC/HND, SHNC/SHND; TEC/BEC or SCOTEC/SCOTBEC higher or higher national certificate or diploma; professional qualification; nursing qualification including NNEB; polytechnic qualification; university certificate or diploma; first degree; postgraduate diploma; higher degree.

**Adjustments to guarantee the sequential nature of the educational variable**—It is thus essential that higher education also have the preceding lower level of education, which is almost universally true of people who have undertaken an academic route and we impose this in our model. It is, however, not necessarily true for individuals who have undertaken vocational routes. If this is the case, we downgrade their qualification by one level to maintain our sequential structure. Specifically: if someone has a first degree or a postgraduate qualification, we assume they have all the lower qualifications; if someone has one of the other (i.e. vocational) higher education qualifications but not an A-level or equivalent qualification, we downgrade their qualification to the non-higher education.

### **A. 3 Explanatory variables in membership equation**

All covariates are extracted from the 1973-1974 survey except for the basic demographic information and natal health information, which are extracted from the 1958 birth survey. We also collect mid-life information from the 2000 survey to further investigate the gender-specific education effects.

Information from the 1958 survey:

1. Dummy indicator of parent-reported ethnic group: 1-white, 0-other.
2. Dummy indicator of midwife-reported being low birth weight infant: 1-less than 2500 grams, 0-other.
3. Dummy indicators of the mother-reported breastfeeding habit, whether she was breastfeeding for 3 months and whether she was breastfeeding for less than one month, reference group—breastfeeding for 3 months.
4. Dummy indicators of whether natural parents were younger than 20 in 1958: 1- at least 20 years old; 0-otherwise.
5. Mother-reported smoking behavior during pregnancy: 0-never, 1-seldom, 2-occasionally, 3-often.

#### **Information from the 1973-1974 survey:**

6. Six dummy indicators are created for respondent's self-reported number of siblings in 1974: no sibling, one sibling, two siblings, three siblings, four siblings, five and more than five siblings; reference group—no sibling.
7. Dummy indicator of whether father was employed in 1974; Six dummy indicators are created for father's social class in 1974 if employed: professional, managerial, non-manual skilled, manual skilled, semi-skilled, unskilled, unemployment; reference group—professional group.
8. Dummy indicator of whether mother was employed in 1974; Six dummy indicators are created for mother's social class in 1974 if employed: professional, managerial, non-manual skilled, manual skilled, semi-skilled, unskilled, unemployment; reference group—professional group.
9. Father's and mother's self-reported age left full time school with a range of 0-9: 0-under 13 years old; 9-23 years old or older; interaction of parental age left full time school is also created to capture influences of parental education.

10. Teacher-rated ability in math and five dummy variables for teacher-rated ability in reading at the age of 16: 0-little ability, 1-below average, 2-CSE 2-4 grade, 3-O-level or CSE 1, 4-A-level and higher. Interaction is created for teacher-rated abilities to capture effects of academic abilities.
11. Dummy indicator of parent-reported whether individual suffers non-accidence hospitalization since age 11: 1-yes, 0-otherwise.
12. Dummy indicator of physician-assessed chronic health conditions by age 16: 1-chronic conditions positive, 0-otherwise.
13. Dummy indicators of physician-reported whether the male cohort member lower than 160cm and the female lower than 150cm at the age of 16: 1-lower, 0-otherwise.
14. Dummy variable of parent-reported illness of asthma and bronchitis: 1-suffered from asthma and bronchitis, 0-otherwise.
15. Three dummy indicators of teacher-reported being absent from school for trivial reason: often absent for trivial reason; ever absent for trivial reason; never absent for trivial reason; reference group—never absent for trivial reason.
16. Three dummy indicators of parent-reported seriousness of aching or vomiting: often aching or vomiting, sometimes aching or vomiting, never aching or vomiting. Reference group—never aching or vomiting.
17. Teacher-reported number of pupils at school rounded by hundred; square number is also created in case of non-linear effect.
18. Teacher-reported teach/student ratio according to teacher-reported school enrollment and number of fulltime teachers.
19. Teacher-reported ratio of expelled student/total student.
20. Self-reported voluntary participation behavior at age 16: 0-never participating, 1-seldom participating, 2-occasionally participating, 3-often participating.
21. Five dummy indicators of teacher-reported parental interest in the education of their child (or survey respondent): over concern, very interested, cannot say, with some interest, with little interest; reference group—with little interest.
22. Parent-reported number of family members and its square term in case of non-linear effect.
23. Eight category indicators of the illnesses parent reported for the absence from school: bronchitis, asthma, convulsion, headache, emotional problem, abdominal pain, infectious disease, diarrhea and other illnesses except for score throat, accidental injury and cold. reference group—score throat, accidental injury and cold.



#### **A.4 Information from the 2000 survey—employment status and employment attitudes**

1. Dummy indicator of whether the respondent was employed: 1=yes, 0= otherwise.
2. Dummy indicator of whether the respondent was self-employed: 1=yes, 0= otherwise.
3. Dummy indicator of whether the respondent had a fixed-time job: 1=yes, 0= otherwise.
4. Dummy indicator of whether the respondent worked on weekend once a week: 1=yes, 0= otherwise.
5. Dummy indicator of whether the respondent work at night frequency: 1=yes, 0= otherwise.
6. Dummy indicator of whether the respondent had a permanent job: 1=yes, 0= otherwise.
7. Dummy indicator of whether the respondent work 40 hours or more than 40 hours a week: 1=yes, 0= otherwise.
8. Dummy indicator of whether the respondent had additional income: 1=yes, 0=otherwise.
9. The respondent agreed that any job is better than being unemployed: 0=strong disagree, 1=disagree, 2=uncertain, 3=agree, 4=strongly agree.
10. The respondent agreed that kids benefit if mum has job outside home: 0=strong disagree, 1=disagree, 2=uncertain, 3=agree, 4=strongly agree.
11. The respondent agreed that a mother and family happier if she goes out to work: 0=strong disagree, 1=disagree, 2=uncertain, 3=agree, 4=strongly agree.
12. The respondent agreed that mother should take time off work if a child is ill: 0=strong disagree, 1=disagree, 2=uncertain, 3=agree, 4=strongly agree.
13. The respondent agreed that important to hang onto job even if unhappy: 0=strong disagree, 1=disagree, 2=uncertain, 3=agree, 4=strongly agree.
14. The respondent agreed that pre-school children suffer if mum works: 0=strong disagree, 1=disagree, 2=uncertain, 3=agree, 4=strongly agree.

## Appendix. B Additional findings in empirical studies

### B.1 Robustness tests on missing data of key covariates.

Table B.1 Robustness tests on missing data of key covariates

	ATE (probability change)		Endogeneity test
	coef.	s.e.	p-value
A. Robustness test on male sample			
Excluding missing data of father education	0.188	0.109**	0.284
Excluding missing data of mother education	0.186	0.108**	0.271
Excluding missing data of father economic class	0.242	0.016**	0.141
Excluding missing data of mother economic class	0.153	0.103*	0.451
Excluding missing data of math ability	0.171	0.110*	0.349
Excluding missing data of reading ability	0.098	0.096	0.789
Excluding missing data of change of parent	0.152	0.110*	0.447
N	4326		
A. Robustness test on female sample			
Excluding missing data of father education	-0.054	0.067	0.018
Excluding missing data of mother education	-0.050	0.066	0.019
Excluding missing data of father economic class	-0.075	0.064	0.010
Excluding missing data of mother economic class	-0.060	0.064	0.012
Excluding missing data of math ability	-0.066	0.065	0.013
Excluding missing data of reading ability	-0.062	0.065	0.014
Excluding missing data of change of parent	-0.024	0.076	0.067
N	4720		

Note: \*Significant at 10% level. \*\*Significant at 5% level. \*\*\*Significant at 1% level. The coefficients and standard errors are reported from bootstrapping (500 repetitions).

## B.2 Pearson test for the correlation between membership outcome and mid-life information

Table B.2 Pearson test for the correlation between membership outcome and mid-life information

	Male		Female	
	coef.	s.e.	coef.	s.e.
A. Correlation with employment characteristics				
Employed	0.01	0.46	-0.03	0.04
Permanently employed	0.01	0.55	-0.06	0.00
Work on weekend every week	-0.05	0.00	-0.04	0.00
Fixed working hours required in job	-0.06	0.00	-0.03	0.04
Night shift often required	-0.05	0.00	-0.04	0.00
B. Correlation with employment attitudes				
Any job is better than being unemployed	-0.03	0.07	-0.07	0.00
Important to stay in job even if unhappy	-0.01	0.55	-0.04	0.01
Mother and family benefit from a working mother	-0.03	0.04	-0.01	0.37
Child benefits from a working mother	-0.03	0.08	-0.01	0.56

## Appendix. C Comparison of two-step probit, control functions and BVP in Monte Carlo exercise

### C. 1 Simulation design

We propose in the paper that the control functions method provides an approximate estimate of *ATE* that can be comparable to the estimate from the BVP method. It does not mean that the control functions method is sufficient to produce consistent estimate of *ATE*. Nevertheless, it does considerably better than the 2SLS and the two-stage probit in the identification of *ATE*. We will perform the Monte Carlo analogous to which has been applied by Bhattacharya et al. (2006). Their analysis demonstrates the limitations of the two-step procedure, such as 2SLS and two step probit and they argue in favor of using the multivariate probit rather than the two-step or linear probability model estimators.

In this simulation exercise, we draw a large random data set (5000 observations) according to a simple data generating process, and then apply the four different estimators to the same random data set. For the simulation, we repeat this step 1000 times and report the

average bias (in *ATE* and its corresponding coefficient) for the four estimators: 2SLS, TSP, BVP and CF. The simple probit is not considered in the simulation exercise because its insufficiency in handling endogenous treatment has been heavily exploited and the bias of its estimate obscures the scale in the comparison figures.

### *Data generating process*

- Both the dependent variable and the treatment are binary variables;
- The treatment is correlated with the error in the dependent variable;
- The instrument is powerful (correlated strongly with the treatment, but not with the error in the dependent variable, 0.5, determines the strength of the instrument.).

### *Basic model*

$$T_i^* = \gamma_0 + x\gamma_x + \nu_i$$

$$T_i = 1(T_i^* > 0)$$

$$y_i^* = m_0 + \beta T_i + b_x x_i + \eta_i$$

$$y_i = 1(y_i^* > 0)$$

$$(\nu_i, \eta_i) \sim N(0,0,1,1, \rho_{\nu\eta})$$

$T_i^*$  represents the index function generating the treatment  $T_i$ ,  $x_i$  represents the other regressor,  $z_i$  represents the instrument;  $\nu_i$  and  $\eta_i$  represents the error term in treatment equation and outcome equation respectively, and  $\rho_{\nu\eta}$  is the correlation coefficient between  $\nu_i$  and  $\eta_i$ . Coefficient  $\gamma_x$  determines the association between constant  $T_i$  and  $x_i$ ;  $m_0$  is the constant term in outcome equation that determines the average probability of  $y_i$  equaling one; treatment coefficient  $\beta$  reflects the influence of the treatment, correlation coefficient  $\rho_{\nu\eta}$  determines the correlation between the error terms in treatment and outcome equations, and correlation coefficient  $\rho_{z\eta}$  determines the power of the instrument. In our simulation exercise,  $\gamma_0$  is first imposed to be zero without loss of generality. We will examine the how each evaluation method performs in the case when the treatment  $T_i$  depends on  $x_i$  and in the case when the treatment  $T_i$  does not depend on  $x_i$ , with  $\gamma_x$  being 0 ( $T_i^* = \nu_i$ ) and being 0.5

( $T_i^* = 0.5x + v_i$ ) respectively. Correlation coefficient  $\rho_{z\eta}$  is imposed to be 0.5 so that we have a valid and strong instrument. We arbitrarily specify  $\rho_{v\eta}$  to be 0.2 (for comparison, we also try values 0.1 and 0.3, which lead to similar qualitative conclusion). In our main experiment, we vary  $\beta$  between 0 and two while holding  $m_o$  arbitrarily fixed at -1. In an alternative, we vary  $m_o$  while holding the true *ATE* arbitrarily fixed at 0.2 (more details can be seen in the study of Bhattacharya et al. (2006)).

We draw 5000 independent observations ( $v_i, x_i, z_i, \eta_i$ ) from a multivariate normal distribution:

$$\begin{pmatrix} v_i \\ x_i \\ z_i \\ \eta_i \end{pmatrix} \sim \text{MVN} \begin{pmatrix} v_i \\ x_i \\ z_i \\ \eta_i \end{pmatrix} \begin{bmatrix} 1 & 0 & \rho_{xz} & \rho_{v\eta} \\ 0 & 1 & 0 & 0 \\ \rho_{vz} & 0 & 1 & 0 \\ \rho_{v\eta} & 0 & 0 & 1 \end{bmatrix}$$

## C.2 Results

We first compare the performance of the four methods when  $T_i^* = v_i$  (the index function generating the treatment is also imposed to be independent of  $x_i$  in the study of Bhattacharya et al (2007)). Figure 1 shows the bias in *ATE* estimate and the bias in its corresponding coefficient estimate -  $\beta$  when we vary the value of  $\beta$  (we do not present the bias from  $\beta$  in OLS as it is enormously large compared to the biases in other methods). Figure 2 shows the bias in *ATE* estimate and the bias in its corresponding coefficient estimate when we vary the value of  $m_o$ .

The two-step probit does uniformly worse for all values of  $\beta$  and  $m_o$ . The TSP estimator is noticeably biased for the estimate of *ATE* and  $\beta$ , as the true *ATE* approaches 0.5 (or  $\beta$  approaches 2). Its bias in *ATE* or  $\beta$  is also substantially deviated from zero as it tends to underestimate the *ATE* or  $\beta$  when we vary the value of  $m_o$ . The BVP estimator produces unbiased estimates of *ATE* and  $\beta$  for all the values we try for of  $\beta$  and  $m_o$ . This is not surprising for our large sample, since it is considered a consistent estimator. The 2SLS and the control functions approaches appear to have good performance in the identification of the true *ATE*. Yet they are not unbiased and consistent estimator. The increasing of  $\beta$  or  $m_o$  ( $m_o$

is ranged from -3 to 0) tend to lead to larger bias for both the 2SLS and the control functions approaches in our simulation exercises.

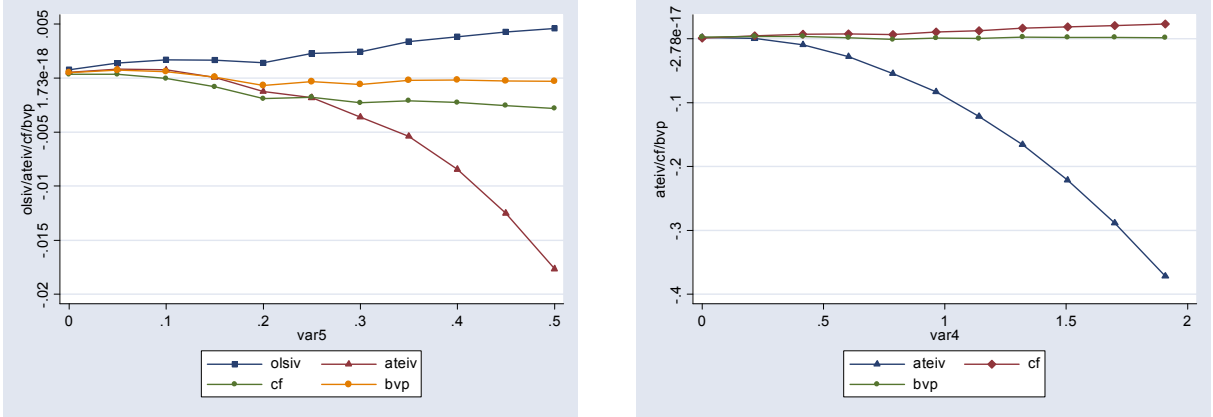


Figure 1. Bias in treatment estimate and bias in coefficient of treatment estimate

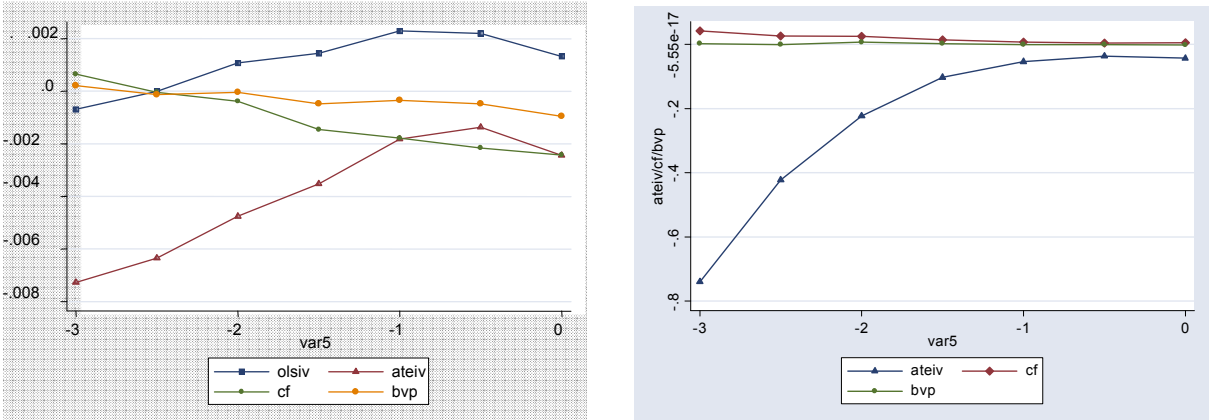


figure 2. The constant term and bias in treatment estimate and bias in coefficient of treatment estimate

In the previous setup, we assume  $T_i^* = v_i$ , such that the choice of the treatment  $T_i$  is independent of other covariates. This is an extreme case, however, since we rarely observe independent association between the treatment  $T_i$  and other observable covariates. To give a comprehensive illustration on the performance of the four estimators, we conduct a second

Monte Carlo simulation similar to the one just described, except that  $T_i^* = 0.5x_2 + v_i$

Figure 3 shows the bias in  $ATE$  estimate and the bias in its corresponding coefficient estimate when we vary the value of  $\beta$ . Figure 4 shows the bias in  $ATE$  estimate and the bias in its corresponding coefficient estimate when we vary the value of  $m_o$ . The performance of the BVP is not affected by the change of model setup. The BVP produces unbiased estimates of  $ATE$  and its corresponding  $\beta$  for all values of  $\beta$  and  $m_o$  we try. On the other hand, we find out the performance of the CF estimator is significantly superior to the 2SLS estimator and the TSP estimator. Similar to the setup where  $T_i^* = v_i$ , the CF provides an approximate estimate of  $ATE$  that can be comparable to the estimate from the BVP method.

Specifically, as shown in Figure 3, the TSP and the 2SLS estimators overestimate the  $ATE$  and its corresponding  $\beta$  for all **non-zero** values of  $\beta$ . The bias increases dramatically and becomes noticeably large (up to 0.05) as the true  $ATE$  approaches 0.5 or  $\beta$  approaches 2. Their performance in estimating the treatment changes substantially as  $m_o$  change. The TSP and the 2SLS estimator overestimate the  $ATE$  for  $m_o$  between 0 and -2 and then rapidly degrade with large negative bias as  $m_o$  decreases.

It is clearly shown that the performance of the BVP and the CF is not affected by the change of the generation of the random data sets. The BVP produces unbiased and consistent estimates of the  $ATE$  for all values of  $\beta$  and  $m_o$  we try. The CF produces an approximate estimate of the  $ATE$ , which is very close to that obtained from the BVP. Similarly, it cannot produce an unbiased and consistent estimator. The absolute value of bias in  $ATE$  or  $\beta$  is increasing moderately as the absolute value of  $\beta$  or  $m_o$  increases.

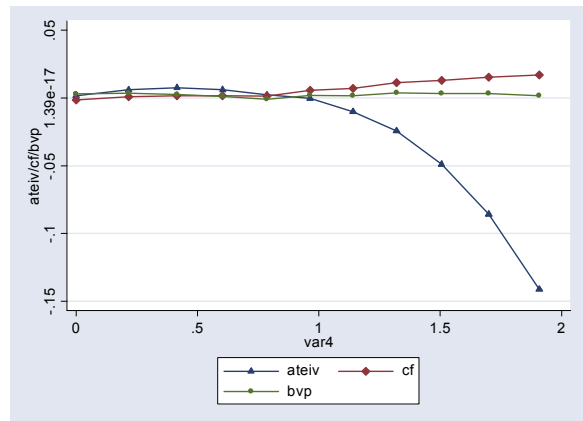
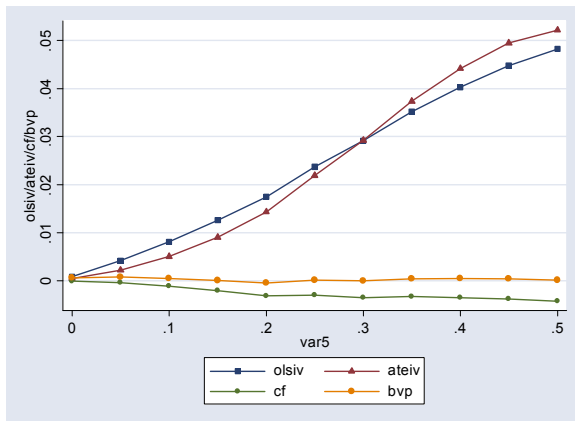


Figure 3. Bias in treatment estimate and bias in coefficient of treatment estimate

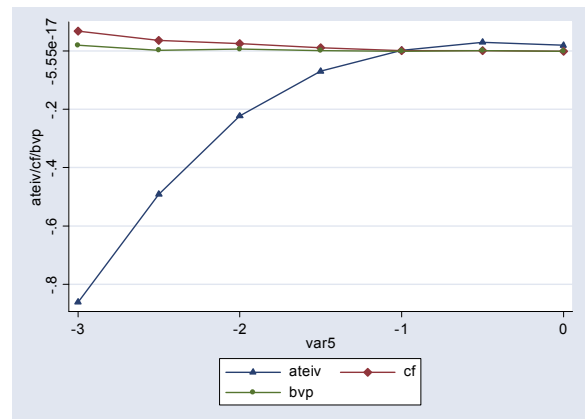
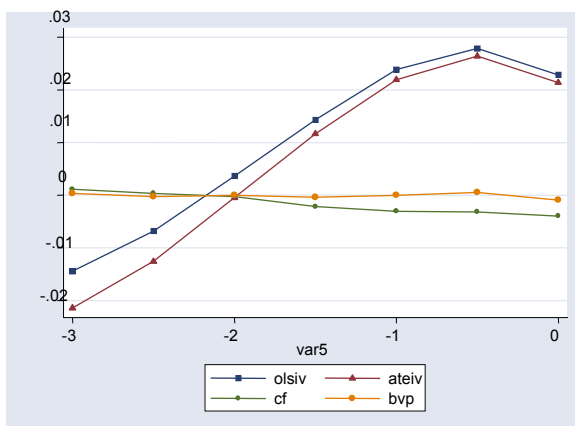


Figure 4. The constant term and bias in treatment estimate and bias in coefficient of treatment estimate

Our simulation exercise provides identical findings of which Bhattacharya et al. have proposed – the BVP estimator produces consistent estimates while the 2SLS and TSP are not sufficient to do so. Furthermore, our simulation exercise also confirms that the CF produces a close estimate of the true *ATE* that can be seen as a good approximate to that from the BVP.



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