Oxford Development Studies

ISSN: 1360-0818 (Print) 1469-9966 (Online) Journal homepage: http://www.tandfonline.com/loi/cods20

Education and the Poverty Trap in Rural China: Closing the Trap

John Knight , Li Shi & Deng Quheng

To cite this article: John Knight , Li Shi & Deng Quheng (2010) Education and the Poverty Trap in Rural China: Closing the Trap , Oxford Development Studies, 38:1, 1-24, DOI: 10.1080/13600810903551595

To link to this article: https://doi.org/10.1080/13600810903551595

Oxford Development Studies,
Vol. 38, No. 1, March 2010

Education and the Poverty Trap in Rural China: Closing the Trap

JOHN KNIGHT, LI SHI & DENG QUHENG

ABSTRACT *This is an ambitious attempt to view the relationships involving education and income as forming a system, and one that can generate a poverty trap. The setting is rural China, and the data are from a national household survey for 2002, designed with research hypotheses in mind. The paper shows how and why the returns to education vary according to household and community income. It examines the effects of education on income, innovation, health and happiness, and shows how education can be important in helping people to escape from various dimensions of poverty. The results are brought together to form an empirical model of a poverty trap, and the implications for poverty analysis and for educational policy are considered.*

1. Introduction

The objective of this paper, together with the closely linked companion paper (Knight *et al.*, 2009), is to show that education and poverty are closely related in numerous ways, and that the interactions among a set of poverty-related and education-related variables are capable of generating a vicious circle of educational deprivation and income poverty, and also a virtuous circle of positive interaction between education and income. The companion paper provides evidence that poverty has an adverse effect on both the quantity and the quality of education that a child in rural China receives. Our hypothesis in this paper is that education can help to raise households out of various dimensions of poverty. The argument is framed within a five-equation model, used in both papers. The underlying ideas are not new (see e.g. McMahon, 1999, 2007), but the estimation of the model using microdata may well be new.

The data set that we use is the rural component of the national household survey for China, relating to 2002, which was designed by an international team including the authors and organized and administered by the Institute of Economics, Chinese Academy of Social

John Knight, Department of Economics, University of Oxford, Manor Road Building, Oxford OX1 3UQ, UK. Email: john.knight@economics.ox.ac.uk

The research was conducted while Li Shi and Deng Quheng were visiting the Department of Economics, University of Oxford, from Beijing Normal University and the Institute of Economics, Chinese Academy of Social Sciences, respectively. We thank Nina Fenton for her research assistance, Chris Colclough for his support, and the editors and two referees for very helpful comments. We are grateful to the UK Department for International Development (DfID) for financial support through John Knight's membership of the Research Consortium on Educational Outcomes and Poverty (RECOUP), which is based partly at the Centre for the Study of African Economies in the Department of Economics, University of Oxford.

ISSN 1360-0818 print/ISSN 1469-9966 online/10/010001-24

DOI: 10.1080/13600810903551595

Sciences (IE, CASS). In addition to the main “Rural Household Questionnaire”, there was an “Administrative Village Questionnaire” and a “Social Network, Village Affairs and Living Quality” questionnaire. Both of these latter questionnaires contain questions that were introduced especially for current purposes.

Section 2 provides relevant background and hypotheses for the analysis to come. Section 3 reports the empirical results, proceeding systematically under seven subheadings. In Section 4 all the results of this and the companion paper are brought together to form an interrelated system that can constitute a poverty trap, and it is asked whether education can provide an escape from the trap. Section 5 draws conclusions for methodology, for research, and for policy.

2. Background and Hypotheses

The companion paper provides evidence of wide variation in educational expenditure according to household prosperity. When households were classified into income per capita terciles, the ratio of expenditure per pupil of the top to the bottom tercile generally exceeded two to one. Regression analysis showed that, at each educational level, household educational expenditure per enrolled child rose with household income per capita, with county income per capita (a proxy for public subsidy), and with the county average of local government expenditure per head of population (an alternative proxy). Private expenditure appeared to be complementary to, rather than a substitute for, public expenditure, so adding to the variation in educational quality based on the level of community prosperity. However difficult it might be to measure, the quality of education raises policy issues no less important than the quantity of education in rural China.

There is a considerable empirical literature on the effects of education on income in rural China, from which we can construct our hypotheses. Education became increasingly important as rural economic reform evolved. The returns to education rose on account of the changing structure of rural economic activity, both in farming and in the new non-farm activities. For instance, Yang (2004) examined the contribution of education to rural incomes during the period of factor market liberalization 1986–95, when the relaxation of controls permitted households to reallocate resources from agricultural to non-agricultural activities. Using panel data for Sichuan Province, he found that households with a better-educated member responded to the new opportunities by devoting more labour and capital to non-agricultural activities that yielded higher returns, and that this contributed to the growth of their household incomes. A panel of rural households and workers for the years 1988–96 was used to argue that education became increasingly important as a determinant of opportunities and income (Zhang *et al.*, 2002). At the first stage of the analysis, a logit analysis estimated the determinants of off-farm work. In 1988 the coefficients of the education variables were insignificant but the village dummy coefficients were important. By 1996 the education terms had become positive, significantly so, and substantial, whereas villages had no reliable effect. At the second stage, the education terms were not significant as determinants of non-farm income in 1988, but they had become positive and significant by 1996.

Knight & Song (2003, 2005, chapter 8) investigated Chinese peasant choices among three activities: farming, local non-farming and migration. Their source was a rural labour force survey conducted in eight provinces in 1994. The picture they obtained was one of peasants having a powerful economic incentive to diversify or move entirely out of agriculture but being constrained in various ways from doing so. The marginal return to non-farm labour—whether in local or migrant activities—was much higher than the very low marginal return on the farm. Moreover, workers who specialized in non-farm activities worked many more days a year than specialist farmers, so enabling them to be more fully employed. Education sharply raised the probability of access to both non-farm activities. These results suggest that education increases the incomes of rural people by improving their access to non-farm activities, in which conditional incomes are generally higher and in which the conditional returns to education are also higher.

Relationships can be important at the level of the community as well as that of the household or the individual. The way in which some Chinese villages are caught in poverty traps and some manage to escape is documented by Knight & Li (1997), who examined several villages in two counties of Hebei Province in 1994. Villages that were close together geographically could nevertheless be far apart economically. The explanation provided was in terms of factor immobility and processes of cumulative causation. Although a good natural resource base helped to initiate the process, the main cause of differential village development was non-farm sources of income: migration and village industry. Both were constrained and the easing of constraints involved path-dependent cumulative processes. For instance, migration required a village network of information and contacts, and village industrialization depended on the accumulation of local skills through a process of learning-by-doing and on the reinvestment of profits. The need for self-reliance meant that village expenditures on infrastructure and education depended heavily on the existence of non-farm activities in the village, but education could itself be important for generating non-farm activities.

In the companion paper (Knight *et al.*, 2009) we set up a system of interdependent equations. They are not simultaneous equations in the sense that they are not all contemporaneously determined, involving as they do some relationships running from one generation to another. They illustrate the nature of the vicious and virtuous circles that can generate a poverty trap or offer an escape from it. Where EP is parental education, EC is community education, YC is community income, Y is income, EN is educational enrolment in years, EQ is educational quality, HE is health, HA is happiness and an asterisk indicates that the variable is likely to be exogenous, we have five equations, each dependent on some of the others:

$$EN = EN(EP^*, EC^*, YC^*, EQ, Y, HE) \tag{1}$$

$$EQ = EQ(Y, YC^*) \tag{2}$$

$$Y = Y(EN, EQ, HE) \tag{3}$$

$$HE = HE(Y, EN) \tag{4}$$

$$HA = HA(Y, EN, HE). \tag{5}$$

The model draws its inspiration from McMahon (2007), in which a dynamic model of endogenous growth is used to examine education externalities and incorporate indirect returns to education arising from the education of others, including previous generations.

Our model differs, however, in being amenable to estimation using survey-based microdata.

The companion paper examined the determinants of education, and estimated equations (1) and (2). In this paper, the effects of education are examined, and equations (3)–(5) analysed. Consider equation (3). The results reported above suggest that education raises the income of rural households not only by making their labour more productive within an economic activity, but also by providing access to activities in which both labour and education are more productive. The quality of education received as a child can raise the amount of human capital possessed, and current health can improve labour productivity. Income is hypothesized to improve heath, as is educational attainment, and educational attainment may improve the health of the individual and their household (equation (4)). Happiness, normally referred to in the literature as subjective well-being or satisfaction with life, may depend positively on income, education and health (equation (5)).

3. The Effects of Education

A potentially important link in the circle of deprivation is whether, and to what extent, the outcomes of education are less favourable for the poor than for the less poor. This effect can operate through both the lesser quantity and the poorer quality of education that they receive. We start by examining the effect of education on income. A simple aggregative estimation of equation (3) is likely to be a misleading guide to the benefits of education for poor people. It is necessary to delve more deeply, in order to understand the mechanisms by which education raises income and to examine the implications for the poor.

We proceed by stages. First, we show that farm and non-farm activities are very different in relevant respects, that income is higher in non-farm activities, and that education improves access to non-farm activities. Second, we show that the returns to education are higher within non-farm activities than farm activities. Third, by means of a methodology devised for the purpose, these estimates are used to conduct counterfactual exercises in order to show the effects on poverty of raising educational levels. Fourth, rates of return to education in the two activities are estimated for different subsamples to show that the returns are lower for poor households and poor communities. Fifth, in considering the reasons for the lower returns, we examine the relevance for China of the distinction—well established in the development literature—between "traditional" and "modern" farming, and also the role of education in fostering positive attitudes towards agricultural innovation.

3.1 Education and Allocation of Labour between Farm and Non-farm Activities

It is relevant to know how workers are allocated between farming and non-farming activities and, within the latter, between local and migrant activities. We classify farm workers and non-farm workers according to which activity they spend more time in, and local non-farm and migrant workers according to whether or not they are working in the county. Our purpose is to contrast poor households, and young workers, with others.

In the sample as a whole, the farm/non-farm percentage division is 64/36, and the local/migration division of the 36% is 22/14. However, there is a marked difference between the poorest and the richest third of households: 75% of the former are in farming but only 52% of the latter. There is little difference in the importance of migration but a large difference in the importance of local non-farm work: 12 and 34%, respectively. A similar pattern is found in comparing the poorest and the richest third of counties, except that there is a larger difference in migration (favouring poorer counties), probably reflecting the role of migrant networks in fostering migration. There is a heavy dependence on farming (73%) for the poorest half of households in the poorest half of counties. Non-farm activities are much more important for workers aged less than 30 years (accounting for 49% of them) than for older workers, especially migrant activities (30%). For workers under 30 in the poorest half of households in the poorest half of counties, local non-farm opportunities are rare but migration is common (28% being migrants).

A further indication that the distinction between farm and non-farm activities is important for income is provided by the association between household income per capita decile and the distribution of activities. The proportion of non-farm hours worked of total hours worked (equal to 37% overall) rises monotonically from 14% in the lowest decile to 65% in the highest. The reasons for this powerful association can be seen in Table 1. The ratio of the average return per hour of labour in non-farm activities to that in farm activities is 1.91. Estimates of the marginal returns per hour show the ratio to be far higher, at 11.92. Moreover, the ratio of the return per hour of labour in local non-farming to that in migration is 1.51 on average and 1.37 at the margin. These disparities are consistent with there being labour market segmentation and rationing of non-farm jobs, as argued by Knight & Song (2003, 2005, chapter 8). If so, does education assist households to earn non-farm income?

Educational decisions are liable to be based on the prospects currently facing young people. They face a roughly equal division of labour between farm and non-farm activities, and even those in poverty have reasonable prospects of non-farm employment. The role of education in determining whether people engage in farming or non-farming, and the returns to education in farming and non-farming, are therefore important issues. We explore them in turn, the hypothesis being that education can have both allocative and efficiency income benefits.

Table 2 reports the relevant results of a multinomial logit analysis to predict the determinants of activity choice, the reference activity being farming. Being healthy is important for both non-farm activities, but more so for migration. The proportion of workers in the county who are migrants and the proportion who work locally off-farm have

Table 1. Average and marginal returns per hour of labour in farming and non-farming, yuan per hour

		Marginal returns	
	Average returns	(1)	(2)
Farming	1.44	0.012	0.017
Non-farming	2.75	0.143	
of which: local non-farming	3.08		0.167
migration	2.04		0.122
Ratio of non-farming to farming	1.91	11.92	
Ratio of local non-farming to migration	1.51		1.37

Notes: The marginal returns per hour are based on income functions that contain productive fixed assets and farmland as well as hours worked in the different activities as the explanatory variables. All the coefficients in the income functions are significant at the 1% level.

Table 2. The determinants of activity choice among farming, local non-farming and migration, multinominal logit analysis

	Local non-farming		Migration	
	Coefficient	Marginal	Coefficient	Marginal
Male	1.397***	0.183	1.231***	0.067
Age	0.084***	0.013	− 0.021	− 0.003
Age squared	− 0.001***	− 0.0002	− 0.001***	− 0.0001
College	1.811***	0.355	0.997***	0.025
Professional school	1.583***	0.291	1.072***	0.046
High school	0.900***	0.146	0.680***	0.037
Middle school	0.657***	0.090	0.528***	0.029
Primary school	0.263***	0.035	0.346***	0.023
Healthy	0.174***	0.020	0.407***	0.025
Farm land (mu)	− 0.053***	− 0.007	− 0.048***	− 0.003
County migration density	2.266***	0.198	9.565***	0.672
County non-farm labour density	5.674***	0.796	3.326***	0.162
Mean value of dependent variables	0.221		0.142	
Pseudo R-squared	0.284			
Number of observations	22 220			

Notes: The criterion for classification between farm and non-farm activity is the predominant number of hours worked, and between local non-farming and migration whether the worker is in or out of the county. Farming is the reference activity (with coefficients equal to zero). Several explanatory variables were included in the specification but are not reported in the table, including whether the worker has children, has army experience, has suffered a natural disaster in the previous year, and lives in an officially designated poor county. In this and subsequent tables, ***indicates that a coefficient is significant at the 1%, **at the 5%, and *at the 10% level.

predictable effects: the migration of others greatly increases the chances of own-migration, possibly through network effects, and high non-farm labour density is a sign of local employment opportunities. Education raises the chances of being in either of the non-farm activities, but especially if it is local rather than outside the county. For instance, the marginals imply that high school rather than primary school completion increases the probability of migrant work by 33 percentage points and of local non-farm work by no less than 64 percentage points. Thus, education is a lifeline for young people who wish to escape from the farm, whether their motive is economic or social. Very similar general results are obtained from equivalent analyses conducted on the subsamples of workers in the poorest third of households and of workers aged less than 30 years.

3.2 The Economic Benefits of Education in Farm and Non-farm Activities

The benefits of education arise from two effects: an allocation effect and an efficiency effect. Our estimation strategy is as follows. It is necessary to instrument hours worked on account of its likely endogeneity: more hours may be worked if the returns are higher. We first estimate farm and non-farm working hours separately. A Tobit estimation is necessary owing to non-participation in an activity: the proportion of censored observations is 15% for farm and 54% for non-farm work. The instrumented hours variable can then be included in the second-stage income functions, which measure the benefits of education in farm and non-farm activities.

Consider first the non-farm equation, based on data for individuals currently working but under 65 years of age. The key explanatory variables are the education categories, chosen rather than years of schooling so as to permit non-linearities and to assist policy analysis. We regress working hours also on self-rated health status, gender, age, age squared, and the county average hourly wage in farm and non-farm work. Table 3 presents the results: the coefficients, the marginals, and the decomposition of the marginals into that part due to change in the number of hours worked given positive non-farm hours and that part due to change in the probability of working off-farm. Almost all the coefficients are highly significant.

We concentrate on the explanatory variables that are relevant to our hypothesis. The mean value of non-farm hours worked is 732 hours per annum (14.1 hours a week). With no education as the omitted category, the education dummy coefficients are all positive and rise monotonically with education level. For instance, having high school instead of primary school education raises hours worked by 345 hours, two-thirds of this rise being due to the increased chance of participation. Education appears to encourage or enable workers both to participate in non-farm activities and to work longer hours in them. A report of being in good health or very good health raises non-farm work by 109 hours. As expected, the county average non-farm wage raises hours worked and the corresponding farm wage lowers them. Two demographic variables, the number of children (aged under 16) and the number of old people (aged over 65) in the household, which should not influence household income directly, are included as instrumental variables so that instrumented hours can be included in the income equation to come.

Table 3. The determinants of hours worked in non-farm activities by individuals, Tobit estimates

			Due to:	
	Coefficients	Marginals	intensity	participation
Male	1099.45***	503.61	171.76	331.85
Age	17.30**	7.92	2.70	5.22
Age squared	−0.61***	−0.28	−0.10	−0.19
Healthy	237.34***	108.71	37.08	71.63
County farm wage	−37.79***	−17.31	−5.90	−11.41
County non-farm wage	74.95***	34.33	11.71	22.62
College	1412.63***	647.06	220.68	426.38
Professional school	1370.90***	627.95	214.16	413.78
High school	1038.34***	475.61	162.21	313.40
Middle school	724.69***	331.95	113.21	218.74
Primary school	284.99***	130.54	44.52	86.02
Number of children under 16	−57.30***	−26.25	−8.95	−17.29
Number of elderly over 65	−45.87	−21.01	−7.17	−13.84
Intercept	−2264.48***			
Mean value of dependent variable	731.74			
Pseudo R-squared	0.021			
Number of observations	22 172			
Number of uncensored observations	10 156			

Notes: The McDonald–Moffitt decomposition is conducted to separate the change in non-farm hours worked into that part due to change in the number of non-farm hours worked (if positive) and that part due to change in the probability of working non-farm hours (if zero). The sample comprises all persons who are currently working and aged under 65 years.

An equivalent estimation for farm hours worked by individuals is reported in Table 4. Again, the education dummies and the health variable are the most directly relevant. The equation differs only in that three household variables are added: the amount of farm land cultivated, productive fixed assets, and the total number of labourers on the farm. The mean value of the dependent variable is 956 hours per annum (18.4 hours a week). All the coefficients except productive fixed assets (a poor proxy for specifically farm equipment) are highly significant. With no education again as the omitted category, the education dummy variables are all negative and rise monotonically in negative value. For instance, having high school instead of primary school education reduces time worked on the farm by 110 hours, two-thirds of which is due to a lower probability of working on the farm. This is the most important result of Tables 3 and 4: as education increases, so workers switch strongly to non-farm work and weakly from farm work. This result indicates the allocative benefit of education.

Reporting good health increases farm work by 30 hours. As expected, a higher county average non-farm wage, by raising the household's supply price, reduces farm hours. We also include the predicted number of non-farm hours worked, as we expect non-farm work to be preferred if it can be obtained, and farm hours then to be adjusted. The coefficient is indeed significantly negative but its impact is small. The marginal has a value of well under unity, suggesting that, with many rural households suffering from underemployment, non-farm work can be expanded without contracting farm work equivalently or even substantially.

Table 4. The determinants of hours worked in farm activities by individuals, Tobit estimates

	Coefficients	Marginals	Due to: intensity	Due to: participation
Male	94.12***	80.20	51.58	28.62
Age	92.39***	78.72	50.96	28.28
Age squared	− 0.10***	− 0.85	− 0.55	− 0.31
Healthy	35.49**	30.24	19.53	10.84
Farm land (mu)	8.56***	7.29	4.71	2.61
Productive fixed assets ('000 yuan)	10.81***	9.21	5.92	3.29
Number of workers	− 37.03***	− 31.55	− 20.30	− 11.26
Predicted non-farm hours	− 0.46***	− 0.40	− 0.25	− 0.14
County non-farm wage	− 16.36***	− 13.94	− 8.98	− 4.98
College	− 488.48***	− 416.22	− 267.50	− 148.46
Professional school	− 399.48***	− 340.39	− 218.74	− 121.40
High school	− 158.80***	− 135.30	− 87.05	− 48.31
Middle school	− 133.98***	− 114.16	− 73.44	− 40.76
Primary school	− 29.27	− 24.94	− 15.99	− 8.87
Number of children under 16	26.65***	22.71	14.35	7.96
Number of elderly over 65	17.45	14.87	6.31	3.50
Intercept	− 380.30***			
Mean value of dependent variable	955.71			
Pseudo R-squared	0.034			
Number of observations	22 172			
Number of uncensored observations	18 892			

Notes: As for Table 3.

Table 5. The determinants of non-farm income of individuals, OLS estimates

	ln non-farm income	ln non-farm income	Absolute non-farm income (yuan)
Age	0.053***	0.058***	223.8***
Age squared	−0.0006***	−0.0006***	−2.37***
Healthy	0.108**	0.111***	213.2*
Non-farm hours (instrumented)	0.078***	0.082***	218.0***
College	0.600***	0.734***	4214.0***
Professional school	0.425***	0.548***	1986.9***
High school	0.235***	0.319***	1003.0***
Middle school	0.173***	0.233***	585.9***
Primary school	0.059	0.078	105.3
Intercept	4.780***	4.849***	−5413.4***
County proportion of adults 25–34 who completed high school	0.856		
County mean school fees	0.772***		
County proportion dissatisfied with secondary schools	−0.244		
Mean of dependent variable	7.628	7.628	3780
Adjusted R-squared	0.434	0.416	0.274
Number of observations	9513	9513	9513

Notes: The standard errors are corrected for clustering at the county level. The test for joint significance of the three variables representing quality of education in column 1, $F(3, 119) = 11.04$, is highly significant.

Table 5 reports the determinants of the non-farm income of individuals. Our dependent variables are absolute non-farm income, to assist the simulations to come, and also log natural non-farm income. Consider column 2: being healthy raises income by 12%. The coefficients on the education dummy variables, beyond primary school, are large and highly significant, and rise monotonically with education level. In the absolute income equation (column 3), the differences in coefficients show the marginal product of each education level. For instance, the marginal product of middle school is 481 yuan and that of high school is 417 yuan per annum. However, this understates the value of education to a worker because education also increases the number of non-farm hours worked. When the hours variable is excluded from the specification, the marginal product of middle school becomes 835 yuan and of high school 781 yuan per annum.

The first column of Table 5 introduces three proxies for the quality of education that workers had received, each measured at the county level: the proportion of young adults who completed high school, the mean level of school fees per pupil, and the proportion of households that expressed dissatisfaction with the quality of secondary education. Each variable has the expected sign, and each is statistically significant when introduced singly. When they are entered together, they are jointly highly significant but, owing to their collinearity, only school fees remain significant. An increase in the county mean fee by one standard deviation raises non-farm income by 11.5%; and if all three variables are increased by one standard deviation, the gain is 22.0%. This suggests that the quality of education improves productivity in non-farm activities.

Farm income is defined to include non-marketed income: goods produced and consumed at home are valued by applying a county-level producer price to the quantity

Table 6. The determinants of farm income of households, OLS estimates

	ln farm income	Absolute farm income (yuan)
Farm land (mu)	0.042***	245.8***
Productive fixed assets	0.041***	257.3***
Proportion of workers healthy	−0.024	54.1
(Instrumented) hours worked by members with:		
College	0.029*	79.9
Professional school	0.047***	272.7***
High school	0.037***	167.8***
Middle school	0.031***	141.4***
Primary school	0.028***	97.0***
No education	0.017***	19.3*
Intercept	7.548***	2255.0***
Mean of dependent variable	8.161	5375.8
Adjusted R-squared	0.183	0.215
Number of observations	8603	8603

Notes: Farm land is measured in mu, productive fixed assets in thousand yuan, and hours worked in thousand hours. Hours worked are instrumented using the equation reported in Table 4.

of each good consumed. As farming is a household activity and a household contains workers of different educational levels, a different specification of the income function is required. In addition to farm land, productive fixed assets and the proportion of household workers who are healthy, we include the number of (instrumented) farm hours worked by household workers at each education level. The differences in the coefficients on these education-specific hours variables thus provide the marginal product of each education level.

Table 6 reports the results. As expected, farm land and productive fixed assets raise farm income. Poor health does not have an adverse effect, probably because there is plenty of underemployed household labour to draw on. All the education variables of interest are positive, highly significant and rise with education level. The exception is college education: very few college graduates remain in the rural areas, and those who do remain are unlikely to farm except as a hobby. The marginal product for 1000 hours of farm work of middle school is 44 yuan and of high school 26 yuan (column 2). To make these figures comparable to those for non-farm activities, we multiply up in the ratio 1519 (the average number of non-farm hours worked) to 1000: the marginal products become 67 and 40 yuan, respectively. Clearly, the marginal product of education in farming is much lower than in non-farming. There are efficiency benefits of education in both farm and non-farm activities, but they are considerably greater in the latter.

3.3 Simulating the Effects on Poverty of Raising Educational Levels

It is possible to make use of the estimates in Tables 3–6 to conduct a simulation analysis. The counterfactual question being posed is: What are the effects on the incidence of income poverty of improving the educational level of the rural labour force? We recognize that this is a simplistic exercise. We abstract from the long time lag between educational expansion and the consequent improvement in the income generation process, and from all the other relationships involving education and poverty for which this paper educes evidence. We also ignore the possibility that the intervention will alter the estimated

Table 7. Simulation analysis: the effects on measures of income poverty of improving the education of the labour force

	Actual case	Middle school the minimum	High school the minimum
Average farm income	1275	1206	1174
Average non-farm income	1017	1411	2069
Average other income	432	432	432
Average overall income	2592	3050	3675
Average farm hours	649	608	564
Average non-farm hours	458	555	700
Poverty rate (%):			
$1 a day	10.9	2.5	0.4
$2 a day	43.0	27.0	8.4

Notes: The simulations are based on the equations reported in Tables 3–6. The first simulation assumes that workers without education or only primary school are raised to middle school completion. The second assumes that all workers with less education are raised to high school completion. The $1 and £2 a day criteria are converted into 2002 prices in rural China: 925 yuan and 1850 yuan, respectively. Income is household net income per capita per annum.

relationships, e.g. by increasing competition for non-farm jobs among the educated, and the possibility that the economy will change before those being educated enter the labour market, e.g. by increasing the availability of non-farm jobs. Although these two effects will tend to counteract each other, our assumption that the chances of non-farm employment at each educational level remain unchanged is a strong one.

We use two poverty lines, corresponding to the $1 a day and $2 a day concepts. Converted into the 2002 prices in rural China, these become 925 yuan and 1850 yuan per capita per annum. Table 7 shows the results of this exercise. The first column reproduces the actual situation. It reports actual average farm income, non-farm income, other income and overall income. The mean numbers of farm and non-farm hours are also shown. Finally, it shows the actual proportion of rural households for which income per capita is under the $1 a day line (10.9%), and the proportion under the $2 a day line (43.0%).

The first simulation is to assume that those with no education and those with primary education had completed middle school, i.e. compulsory education. Our methodology is to calculate a simulated income for each household worker whose level of education is assumed to rise. The worker is given the estimated change in farm and non-farm hours for their new educational level (obtained from Tables 3 and 4) and the estimated marginal product per hour of their additional education in each of the two activities (obtained from Tables 5 and 6). The combination of the allocative and efficiency effects is to reduce "headcount" poverty to 2.6% ($1 a day) and 27.3% ($2 a day). Our other simulation is to assume that every worker with education below high school instead had completed high school. The poverty rates fall dramatically, to 0.5% ($1 a day) and to 9.0% ($2 a day). These benefits stem from a reallocation of labour towards non-farm activities and the higher returns to education in such activities.

3.4 Explaining Differential Returns to Education

The estimated returns to education in rural, or farming, activities in the developing world tend to be positive but low in absolute terms and in relation to the returns in urban, or non-farming, activities. Phillips (1994), in a meta-analysis of the returns to education in farming in developing countries, covering 30 studies and 59 data sets, estimated an average rate of return to an additional 4 years of schooling of 9.5%, implying an annual return of 2.4%. In China, Li & Zhang (1998) found the returns to a year of education for farmers in Sichuan Province in 1990 to be 3.3% (average household education) or 2.7% (highest household education). We shall show our own estimates of the return in farming to be variously 1.5% (all rural households, however little they farm), 3.2% (traditional farming households) and 4.8% (modern farming households) a year. The returns to education for farmers appear to be relatively low, both in China and more generally in poor countries.

The returns to education can be lower for poorer households either because the quality of their education is inferior or because their opportunities or resources are inferior. These adverse effects can operate at the household level or at the community level. Poor households may be unable to afford high-quality education and may be limited in their economic opportunities by lack of resources, of information, and of ambition. In poor counties the quality of educational provision may be low, local economic opportunities may be scarce, and the local resource base or infrastructure may be weak. We hypothesize that poor households, and households in poor counties, face lower returns to their education.

Table 8 shows the estimated returns to a year of schooling in farming, non-farming and combined activities, distinguishing between different subsamples according to household or county income per capita. It is not clear what education variable should be used in the case of household production because knowledge is in principle transferable and available within the household. After experimentation we decided to use the greatest years of education among the farm workers (for farm income) and among all workers (for combined income) in the household. Conditioning variables are kept to a minimum because of the possibility that education works partly through them. In the sample as a whole the return to a year of education is much lower in farming (1.5%) than in non-farming (10.8%), and for household income as a whole (6.4%). The overall return corresponds to a weighted average of the two component returns, with the weight on non-farming rising with

Table 8. The returns to education in farm, non-farm, and combined activities, by income category

	Farm	Non-farm	Combined
Whole sample	0.015***	0.108***	0.064***
Poorest third of households	0.006	0.060***	0.020***
Richest third of households	0.017**	0.081***	0.045***
Poorest third of counties	0.005	0.086***	0.047***
Richest third of counties	0.019*	0.068***	0.064***
Poorest half of households in poorest half of counties	0.008	0.070***	0.033***
Richest half of households in richest half of counties	0.021***	0.079***	0.054***

Notes: The non-farm equations use individual data and the farm and combined equations use household data. In the farm equations the dependent variable is ln household farm income per capita and the explanatory variables are maximum years of education among workers engaged in farming, maximum age among workers engaged in farming and its square, cultivated land (mu) and ln productive fixed assets. The inclusion of the variable input, farm hours, makes very little difference to the estimates of returns. In the non-farm equations the dependent variable is ln individual income and the explanatory variables are years of education, age and age squared. When ln non-farm hours is included, all the coefficients fall, reflecting education's influence on the probability and extent of non-farm work. In the combined equations the dependent variable is ln household income per capita and the explanatory variables are maximum years of schooling among workers in the household, maximum age among workers in the household, ln cultivated land (mu) and ln productive fixed assets.

educational level. Our estimate for non-farming is similar to those (6.4% for off-farm work and, among workers under 35 years, 9.7% for local and 11.7% for migrant work) made from a 2000 survey in six provinces by De Brauw & Rozelle (2007).

Our interest is in the contrast between the average, the poor and the rich. The estimates of the returns to schooling for income-based subsamples are subject to downward bias owing to truncation, but comparisons of the returns for the different income groups are valid. In all three cases, the return for the poorest third of households is lower than that for the richest third, being less than half in the farming and combined cases. For instance, the overall return to a year of education is a paltry 2.0% for the poorest third of households and 4.5% for the richest third. Poor households thus have less incentive than the non-poor households to invest in education. Households in the bottom third of counties face distinctly lower returns in farming than do those in the top third. There are differences in returns both for poor households and for households in poor counties, suggesting that the problem must be addressed at both household and county levels.

We search for the underlying reasons for the differential returns to education. The returns to education are likely to depend positively on the level of technology being used in the production process. Accordingly, they are likely to be greater not only in rural non-farming than in farming, but also, within the latter, greater in "modernizing" farming conditions than in a "traditional" farming environment. Argument in support of this hypothesis is to be found in, for example, Schultz (1975) and Cotlear (1989), and summary evidence in a meta-analysis that found an average return per year of schooling of 2.9% in modern farming and of 1.9% in traditional farming (Phillips, 1994).

We test the latter hypothesis in the following way. First, we identify "farming" households. Our criterion is that the household derives the majority of its income from farm activities. Second, we distinguish between modern and traditional farming households on the basis of their relative emphasis on the traditional farm activity, grain production. Our necessarily crude definitions are that households which obtain the majority of their farm income from grain production are "traditional" and those which obtain a minority are "modern". We then estimate a farm income function, with three key explanatory variables: average years of education of the household workers, a "modern" dummy variable and a modern × years of education interaction term. The dependent variable is log natural household farm income and the conditioning independent variables are land area used and productive fixed assets. Table 9 shows all the coefficients to be significant. Being a modern farming household adds 33% to income, and the rate of return to a year of education is 4.2%. However, when the modern × years of schooling interaction term is introduced, the coefficient on the interaction term is 2.1% per year. The implication is that the return to a year of schooling is 2.7% among traditional farmers and 4.8% among modern farmers. The inclusion of the potentially endogenous variable, farm hours worked, produces the same pattern, the difference in the return being a significant 1.6%. This is powerful evidence that education is more valuable for farming households that are able and willing to diversify away from traditional crops in China, as in many other developing countries.

Subsequent analysis has shown that our simulation analysis of the effects of increasing education on poverty—being based on average relationships in the sample as a whole—may be misleading. In so far as poor households face lower returns to education, the poverty gains will be overstated. In so far as young people face better prospects of non-farm employment, the poverty gains will be understated. Accordingly, we redid the simulation analysis: first, for the poorest third of households, and second, for households

Table 9. Returns to education in farming households: OLS estimates

Dependent variable: ln household farm income	(1)	(2)
Average years of schooling	0.042***	0.027***
Modern	0.284***	0.140**
Modern × average years of schooling		0.021**
Land (mu)	0.023***	0.023***
Productive fixed assets ('000 yuan)	0.019**	0.019***
Intercept	7.978***	8.084***
Mean of dependent variable	8.719	8.719
Adjusted R-squared	0.169	0.170
Number of observations	4719	4719

Notes: "Farming households" are those that derive a majority of their income from farm activities. "Modern farming households" are those that derive a minority of their farm income from grain production.

Table 10. Simulation analysis for the poorest third of households: the effects on measures of income poverty of improving the education of the labour force

	Actual case	Middle school the minimum	High school the minimum
Average farm income	769	718	698
Average non-farm income	334	443	596
Average other income	85	85	85
Average overall income	1072	1247	1379
Average farm hours	682	635	613
Average non-farm hours	262	324	410
Poverty rate (%):			
$1 a day	32.5	21.1	11.7
$2 a day	100.0	96.7	92.2

Notes: As for Table 7, except that the simulations are based on the specifications reported in Table 3–6 but estimated for the subsample of households in the lowest third of household income per capita. Income is household net income per capita per annum.

of which the head is aged less than 30 years. The results are different for two reasons. Not only are the values of the relevant characteristics of each subsample different from those of the sample as a whole, but also the equations are different. In both cases we re-estimated the equations in Tables 3–6—on which the counterfactual simulation analysis is based—using only the subsample observations.

Consider the simulation results for the poorest third of households (Table 10). The poverty rate is extremely high: 32% are below the $1 a day line and 100% below the $2 a day line. Assuming that all workers have completed at least compulsory education has a trivial effect on the poverty rate at the higher line but reduces the rate at the lower line by over a third. Giving all workers at least a high school education again has little effect on $2 a day poverty, but reduces $1 a day poverty by almost two-thirds. Despite the poverty trap, the poorest can be helped out of their poverty by education. The simulations for the subsample of young households are reported in Table 11. The baseline is quite similar to that for the sample as a whole: even though young individuals spend more time off the farm, their households actually work fewer non-farm hours. However, the simulated falls

Table 11. Simulation analysis for households with heads aged less than 30 years: the effects on measures of income poverty of improving the education of the labour force

	Actual case	Middle school the minimum	High school the minimum
Average farm income	1,158	1078	950
Average non-farm income	637	1282	2387
Average other income	440	440	440
Average overall income	2145	2800	3777
Average farm hours	663	663	513
Average non-farm hours	321	397	567
Poverty rate (%):			
$1 a day	16.8	1.8	0.4
$2 a day	52.6	24.7	5.2

Notes: As for Table 7, except that the simulations are based on the specifications reported in Table 3–6 but estimated for the subsample of households for which the household head is aged less than 30 years. Income is household net income per capita per annum.

in their poverty rates are somewhat greater than for the sample as a whole, reflecting the strong tendency for the educated young to find non-farm employment.

3.5 Education, Poverty and Innovation

Education may be important in fostering risk-taking behaviour in agriculture (Knight *et al.*, 2003), and low income may itself foster a culture of poverty in which enterprise, risk-taking and innovation are repressed. The survey contained a question asking respondents about their attitude to adopting new agricultural technology. The answers ranged from very positive to not at all positive. We created a dummy variable for "positive" or "very positive" replies, the other three replies being the reference category. In a binary logit equation, the explanatory variables are male sex, age and age squared, years of schooling of the respondent, and log natural household income per capita. We consider the subsample of "farming" households, i.e. with more than half of their income from farming. The hypothesis is that both the education and the income variables have positive coefficients.

Table 12 shows this indeed to be the case. If log natural household income per capita is used, the coefficient is positive and highly significant, and raising the income variable by one standard deviation increases it by 3.4 percentage points, or by 4.9%. However, causation is questionable. For instance, an inhospitable terrain may produce both poverty and a negative attitude. In the table we therefore instrument the income variable. The coefficient on income is reduced from 0.251 to 0.088 and ceases to be significant. Raising education from primary to high school significantly increases the probability of having a positive attitude to innovation by 13.1 percentage points, or by 19.6%. This result, also, is open to criticism: more able people may be both more educated and more positive about innovation. Correction of this potential bias would require a valid instrument for years of education. Nevertheless, the results of our attitudinal analysis suggest yet another link in the chain: low education and low income may be associated with the negative attitudes that are part of a "culture of poverty".

Table 12. The determinants of a positive attitude towards new agricultural technology, binary logit analysis

	Coefficient	Marginal
Male	0.082	0.017
Age	0.074***	0.015
Age squared	− 0.0008***	− 0.0002
Years of schooling	0.110***	0.023
ln household income per capita (instrumented)	0.088***	0.018
Intercept	− 2.167***	
Mean of dependent variable	70.00	
Pseudo R-squared	0.019	
Number of observations	4725	

Notes: ln household income per capita is instrumented using productive fixed assets, land, average years of schooling of household workers, number of farm hours worked, number of non-farm hours worked, number of household members, whether the terrain is mountainous, hilly, or plain, and a set of province dummy variables.

3.6 Education, Poverty and Health

Individuals were asked to classify themselves on a five-rung health ladder, from very healthy to very unhealthy. A total of 84% reported being healthy or very healthy: we distinguish this group of adults aged 16–65 (taking a value of zero in the binary logit analysis) from the 16% whose health was so-so, bad, or very bad (taking a value of one). The explanatory variables are a dummy for male sex, age and age squared, a series of educational level dummies, and (instrumented) log natural income per capita.

All the variables predicting poor health have the expected sign and are significant at the 1% level (Table 13). The two variables of interest are the individual's education and the household's income. There is a significant fall in the chances of being unhealthy as education level rises. For instance, having completed high school instead of middle school reduces that probability by 2.5 percentage points, i.e. by 14.4%; and an increase in household income per capita by one standard deviation reduces it by 1.1 percentage points, i.e. by 6.5%. Thus, both income poverty and education poverty induce ill-health in adults.

Table 13. The determinants of health status among adults, binary logit analysis

	Coefficient	Marginal	Mean value	Standard deviation
Male	− 0.244***	− 0.0284	0.5273	0.4993
Age in years	0.058***	0.0067	38.21	15.25
Age squared	0.00002***	0.0000	1692.61	1296.24
Years of schooling	− 0.072***	− 0.0083	7.0926	2.9733
ln income per capita (instrumented)	− 0.192***	− 0.0222	7.7706	0.5076
Intercept	− 1.978***			
Pseudo R-squared	0.1518			
Proportion unhealthy (%)	17.38			
Number of observations	28 729			

Notes: The dependent variable takes a value of one if the respondent reports being so-so, unhealthy or very unhealthy, and of zero if healthy or very healthy. The omitted category in the dummy variable analysis is female. Very similar results were obtained from an ordered probit estimation using all five categories of health status.

However, a binary probit equation to predict ill-health among children aged 0–15 was unable to find links to the poverty or the education of their parents. Nevertheless, this may merely reflect an inadequacy in our dependent variable, as such effects have been found in other poor countries (Behrman & Lavy, 1994; Glewwe *et al.*, 2001; Grossman, 2006, pp. 619–20) and also in rural China. Using more appropriate data sets, both Jamison (1986) and Yu & Hannum (2006) found height-for-age and weight-for-age measures to influence grade attainment in rural China. The latter study also found that poverty raises the risk of low child nutrition; and that pupil test performance is improved by household better nutritional environment, household income level, and maternal educational attainment.

3.7 Education, Poverty and Subjective Well-being

Our final exercise is to examine the relationship between our central variables, education, income and health, and a variable that can be regarded as providing a broader criterion than any of these for assessing the quality of life: happiness or subjective well-being. We are encouraged in this exercise by the rapidly growing literature on the economics of happiness (including Helliwell, 2002; Frey & Stutzer, 2002, 2003; Graham, 2005; Layard, 2005; Kahneman & Krueger, 2006; Di Tella & McCulloch, 2006), which generally finds powerful regularities—involving statistically significant coefficients with the hypothesized signs—in many data sets. It is arguable that "subjective well-being poverty" is an encompassing concept into which income poverty and capabilities poverty can be incorporated (Kingdon & Knight, 2006). Our hypotheses are that, in improving subjective well-being, education, income and good health each help to reduce poverty defined in this encompassing sense. Any definition of poverty involves a value judgement on the part of the researcher, and subjective well-being poverty at least has the virtues of being based on individual choice, of concern for subjectively perceived misery, and of measurability.

Survey respondents were asked how happy they were: very happy, happy, so-so, unhappy, or not at all happy. We converted this information into two forms of dependent variable, a binary variable identifying those reporting themselves to be happy or very happy, and a cardinal variable ranging from very happy (equal to four) down to not at all happy (equal to zero). The independent variables of most interest in our subjective well-being functions are the respondent's years of schooling, a dummy variable indicating that the respondent reports being unhealthy, and log natural income per capita of the respondent's household. The conditioning variables are whether the current living standard is reported to be lower or higher than 5 years ago, age and age squared, and dummies for male sex, marital status and—to standardize for temporary effects—whether the respondent's current mood is good.

The choice of dependent variable makes no difference to the results, in line with the methodological conclusion of Ferrer-I-Carbonnel & Frijters (2004). In both cases the relevant coefficients are almost all significant (Table 14). The coefficient on years of schooling is positive. In the happiness score equation, raising education from primary to high school increases the score (mean value 2.68) by 0.036; in the logit equation it increases the probability of being happy or very happy by 3.0 percentage points, or by 4.8%. This is of course in addition to the indirect effects of education on happiness via income and health. In so far as causation runs from (past) education to (current) income and health, the full effect of education can be shown by omitting the latter variables. On their omission from the equation, the effect of education is more than doubled: the

Table 14. The determinants of subjective well-being, binary logit and OLS estimates

Happiness measure	Happy or very happy Coefficient	Marginal	Happiness score Coefficient
Years of schooling	0.020**	0.005	0.006**
ln income per capita (instrumented)	0.703***	0.162	0.278***
Poor health	− 0.573***	− 0.137	− 0.237***
Current living standard higher	0.742***	0.173	0.307***
Current living standard lower	− 0.357***	− 0.085	− 0.256***
Age	− 0.016	− 0.004	− 0.012**
Age squared	0.0003*	0.0001	0.0002***
Male	− 0.165***	− 0.038	− 0.061***
Married	0.487***	0.117	0.260***
Good mood	1.286***	0.301	0.506***
Intercept	− 6.464***		− 0.023
Mean of dependent variable	0.622		2.681
Pseudo/adjusted R-squared	0.142		0.212
Number of observations	8861		8861

Notes: The dependent variable is happy or very happy = 1, so-so, unhappy, or not at all happy = 0 (estimated using binary logit), or a cardinal variable with very happy = 4, happy = 3, so-so = 2, unhappy = 1, not at all happy = 0. The independent variables include dummies for current living standard that is higher than 5 years ago, and current living standard that is lower than 5 years ago, with the omitted category being current living standard the same; self-reported poor health, with other replies being the omitted category; and self-reported good mood, with other replies being the omitted category. ln household income per capita is instrumented using productive fixed assets, land, average years of schooling of household workers, number of farm hours worked, number of non-farm hours worked, number of household members, whether the terrain is mountainous, hilly or plain, and a set of province dummy variables.

additional education raises the happiness score by 0.114 and the probability of being happy by 7.1 percentage points, or by 11.4%.

When actual log natural household income per capita was used its coefficient had a significant positive value in the ordinary least squares (OLS) equation of 0.177. However, because income is potentially endogenous, we instrument the income variable in Table 14: the coefficient rises to 0.278, again highly significant. This rise suggests that some unobserved variable (such as a driven personality or high aspirations) adds to income but subtracts from happiness, or that instrumenting reduces attenuation bias caused by errors in the measurement of income. A rise in log natural income per capita by one standard deviation increases the happiness score by 0.127 and the probability of being happy by 7.4 percentage points, or by 11.9%. Being in poor health decreases happiness by 0.237 points and the probability of being happy by 13.7 percentage points, or by 22.0%.

4. Summary

4.1 The Interrelated System

Our first objective in this section is to present the various results in a systemic way, showing that, on account of their many interactions, the whole is greater than the sum of the parts. Only by considering all the relationships together can a coherent argument be developed. We take equations (3)–(5) as our theoretical framework.

Education is found to raise individual and household income. It does so through an effect on hours worked and on the income per hour, in farm and non-farm activities. The non-farm sector pays much better than does the farm sector, both on average and at the margin (Table 1). A rise in the education of a worker increases the number of hours worked in the non-farm sector (Table 2), and this is only slightly offset by a reduction in farm hours (Table 3). Standardizing for hours worked, the marginal products of high school and of middle school are substantial in non-farming (Table 4), and positive but lower in farming (Table 5). One of the ways in which education can raise income is by inculcating a positive attitude to innovation. Better educated farmers are more likely to have a positive attitude to adopting new agricultural technology (Table 12).

As against these general benefits of education, the fact that the returns to schooling are lower for low-income households and low-income counties helps to create and maintain a poverty trap (Table 8). Similarly, the returns to schooling are lower for traditional farming households than for those engaged in "modern" farming activities (Table 9).

Counterfactual simulation exercises, based necessarily on strong assumptions, suggest that raising the minimum level of educational attainment in all households (Table 7), in poor households (Table 10) and in young households (Table 11) can each produce a substantial reduction in the headcount poverty rate.

We have indirect evidence that the quality of education that workers have received is a determinant of their income. If all three county variables that we take to proxy the quality of education obtained are together increased by one standard deviation, although farm income is unaffected, non-farm income is raised substantially (Table 5). Another pointer is the willingness of parents to spend more on the education of their children the higher is their own income per capita and the higher the income per capita, and the average village educational expenditure per capita, in the county (Knight *et al.*, 2009, tables 6 and 7). This suggests that parents perceive a benefit from improved educational quality. Nevertheless, the evidence that educational quality raises income is rather weak. Further testing should be a priority, e.g. by using data sets that measure value added directly by means of test scores.

Being in good health raises the income of the individual and of the household. Self-reported good health increases the number of hours worked by individuals in non-farm activities and in farm activities (Tables 3 and 4). Standardizing for hours worked, good health raises a worker's non-farm income (Table 5).

The education and the income status of adults have an effect on their health status. Both education beyond primary school and a rise in household income reduce the probability of ill-health (Table 13).

The logit equation predicting the determinants of subjective well-being implies that an increase in educational attainment directly raises the probability of being happy (Table 14). The increase is more than doubled if the indirect effects of education, working through its influence on income and health, are included as well. A conditional increase in the income per capita of the household similarly raises the chances of the respondent's being happy, and poor health reduces the chances. Thus, given that subjective well-being is a criterion for poverty, we see that providing education, increasing income and improving health can all reduce the risk of being in subjective well-being poverty.

4.2 Can Education Break the Poverty Trap?

We can now see why and how a poverty trap can exist. From the companion paper, we know that low income restricts investment in education by the household. It is not only the quantity of education but also its quality that suffers: the poverty of the household pulls down quality, as does the poverty of the community. Poor quality of education in turn deters enrolment. Low education of the parents encourages earlier dropout, as does low education in the community. These relationships set the poverty trap.

From this paper we know that both low quantity and low quality of education reduce the income benefits of education, and do so through several channels. Poor health status threatens income, and both low income and low education adversely affect health status. Low income, low education and poor health all reduce subjective well-being, which can be viewed as an encompassing indicator of poverty. Some of these relationships are contemporaneous but others are transmitted across generations, implying that household poverty can be persistent over the years. The inability of the poor to derive these benefits of education thus closes the poverty trap.

The interaction among the variables of equations (1)–(5), which has the potential to create a vicious circle, also has the potential to create a virtuous circle. Consider two possible shocks. First, assume an exogenous shock that raises the household's income. This has the potential to encourage enrolment and also to improve the quality of education demanded. Over a generation, these gains feed through into higher household income; this in turn improves health, which itself has knock-on effects on education and income. It also raises the quantity and quality of education of the next generation, with further indirect effects. Second, assume an exogenous shock that raises not only the income of the household but also that of its community. In addition to the consequences listed in the first example, there are benefits accruing from the greater public revenue of the community: higher quality of education, the possibility of a demonstration effect from a higher community enrolment rate, and the possibility of a higher rate of return to education as the structure of the local economy changes.

Consider a policy intervention from above that is intended to improve the quantity and quality of education and is aimed at poor households. It will take time for the benefit from the educational improvement to flow, in the form of increased household income, but eventually this rise will in turn improve health, with its beneficial effects, and also improve the quantity and quality of education received by the next generation. The same policy intervention might be aimed at poor communities rather than poor households. If all households in the community are targeted, in addition to the benefits accruing to each household described in the first case, there can be demonstration effects of the higher enrolment rate. If local governments are targeted, the intervention need not require the mediation of household demand to improve the quantity and quality of education supplied.

Given a positive exogenous shock or policy intervention, there are two possibilities. One is that the change may simply raise the position of the low-level equilibrium. The other is that interaction among the variables may set in train a process of cumulative causation and a virtuous circle generating a high-level equilibrium of both education and income. We cannot establish from our evidence that there are two equilibria and that a sufficiently large shock can move the system from one to another. Nevertheless, our findings of numerous positive relationships among a set of interacting variables opens up that possibility. In any case, nothing in our general argument or policy implications hinges on the issue of whether there are two equilibria or just one, movable, equilibrium.

5. Conclusions

This paper provides some empirical support—rather lacking in the literature—for the role of education in the persistence of, and potential escape from, a poverty trap. The complexity and simultaneous determination within an interrelated system of the many relationships hypothesized, together with the cross-section nature of our data set, make it difficult to identify causal effects, as opposed to associations, among our variables. There are three methodological defences: first, our results have been supported by plausible economic arguments; second, there is a trade-off between depth and breadth; and third, the objectives of the research make identification of the causal relationships less important.

Most research papers in economics test one or two hypotheses: the research and its conclusions are specific and narrow. Broader conclusions might be drawn by introducing these research relationships into a more general system—by placing the results in the context of the research literature on related topics—but there is a natural reluctance to venture out in that way. In this paper and its companion paper we have taken a different approach. Our hypothesis is a very general one, which in turn gives rise to many sub-hypotheses, each of which requires empirical testing. In arguing the case we have had to adopt a broader and therefore necessarily shallower approach than is conventional in the research literature. The trade-off is worthwhile because light cannot otherwise be thrown on an important general phenomenon viewed as a whole. Our combination of broad hypothesis and empirical estimation using microdata has not, to our knowledge, been attempted previously in this topic.

Identifying the causal relationships is less important in the present context than establishing that there is an interrelated and mutually reinforcing system of relationships. This set of relationships constitutes our evidence that an education poverty, income poverty trap can exist. Although unobserved heterogeneity poses a problem in measuring the effect of income on education and the effect of education on income, if omitted but correlated variables such as lack of personal "ability" or "a culture of poverty" are themselves determinants of poverty and of educational attainment, they simply strengthen the poverty trap.

Measurement of the effects of exogenous variation in a variable becomes important for understanding the underlying reasons for the problem, for assessing the effects of policy interventions, and in devising policies that will engineer an escape from the poverty trap. For instance, in the absence of a good instrument for schooling, we cannot be sure that education will have the powerful effects on income that are implied by our estimates. For that, further, more detailed, research is required. An underlying policy issue is whether expanding educational enrolment alone would be sufficient or whether this should be accompanied by complementary policy interventions. These might aim to raise the prospective rate of return to education by, for instance, improving the quality of schooling, or improving opportunities in the local economy, or weakening a debilitating culture of poverty.

If the social benefits of education extend beyond the perceived private returns, the difference constitutes externalities. Our attempt to build a system of interdependent relationships suggests that economic decisions to invest in education have indirect effects that are unlikely to be internalized or even recognized. For instance, investors in education may not take into account the indirect effects on the household such as those on health and happiness, the effects beyond one generation, and the effects on community income and enrolment; and migrants may not take into account the contribution to building migrant networks. Nor have we encompassed all the possible ways in which education can generate production externalities, e.g. the productivity of farm households can be raised by the education of other farmers in the locality (Weir & Knight, 2004, 2007, for Ethiopia). Among the education externalities that we have not been able to explore are potential effects on fertility choices, on attitudes towards change, and on civil society. The positive externalities, interactions and feedback accompanying educational decisions can assist the escape from a poverty trap. Unless they explore its externalities and indirect effects, economic researchers run the danger of undervaluing education in poor societies.

We turn to the policy implications of our findings. The issue for the poor in rural China is not only the quantity but also the quality of education—although we have found it difficult to measure quality and thus its effects. There are huge differences in expenditure on the education of a child, both by local governments and by households, and these differences are in turn closely related to community and household income. The underlying problem for people in poor households, poor villages, or poor counties is the degree of fiscal decentralization to be found in rural society. Chinese peasants are effectively expected to "pull themselves up by their own bootstraps". The solution to the education poverty, income poverty trap requires institutional reform: greater fiscal centralization and equalization—a theme that has already been stressed by the authors (Knight & Li, 1999). There should be more redistribution of tax revenue from higher to lower tiers of government, and from lower tiers of government to households. These redistributions should be aimed primarily at the poor.

The evidence suggests that the interventions should be made both at the household level and at the local community level. Chinese policy-makers might wish to introduce a version of the so-called Progresa/Oportunidades scheme, pioneered in Mexico and subsequently adopted in several other Latin American countries. An advantage of such schemes is that they lend themselves to experimental interventions designed to measure their effects accurately: the findings so far have been promising (Skoufias & McClafferty, 2001; Schultz, 2004). The Progresa/Oportunidades scheme is intended to address extreme poverty by developing the human capital of the poor. It encourages enrolment by making conditional payments: it is necessary for parents to send their children to school. By contrast, in the Chinese conditions of high enrolment rates at primary and middle school levels and rationing of places at high school level, such a scheme could be adapted so as to promote the quality of education. Subsidies might be paid to households so that parents demand higher quality of education for their children; or alternatively, to the lower tiers of government, on condition that they take measures to improve the quality of education that they provide. In line with the estimates of Hannum & Park (2007), such subsidies might be earmarked for payments to encourage college graduates to teach in poor rural areas. To reduce middle school dropout, the perceived rate of return to completing middle school could be raised not only by grants to improve middle school quality but also by the subsidized provision of more high school and vocational training places for middle school graduates.

Since our survey, the Chinese government has indeed begun to move in this direction. As part of the recently declared policy of promoting the "Harmonious Society", the educational burden on rural households has been progressively lightened. In 2001 the central government began to provide free textbooks for poor pupils attending compulsory education (years 1–9) in officially designated poor counties. In 2005 it introduced a policy of also exempting them from the payment of tuition fees and of providing them with accommodation subsidies. Government funding for exemption from tuition fees was extended to all pupils in western provinces in 2006 and to all provinces in 2007. Thus there are no longer tuition fees for compulsory education in rural China. However, unless the public funds that trickle down to the poor villages do more than replace their loss of fee revenue, measures to improve the quality of education will also be needed.

References

Behrman, J. & Lavy, V. (1994) *Children's Health and Achievement in School*, Living Standards Measurement Study Working Paper 104 (Washington, DC: World Bank).

Cotlear, D. (1989) The effects of education on farm productivity, *Journal of Development Planning*, 19, pp. 73–100.

De Brauw, A. & Rozelle, S. (2007) Returns to education in rural China, in: E. Hannum & A. Park (Eds) *Education and Reform in China*, pp. 207–223 (New York and Abingdon: Routledge).

Di Tella, R. & McCulloch, R. (2006) Some uses of happiness data in economics, *Journal of Economic Perspectives*, 20(1), pp. 25–46.

Ferrer-I-Carbonnel, A. & Frijters, P. (2004) How important is methodology for estimates of the determinants of happiness? *The Economic Journal*, 114(497), pp. 640–659.

Frey, B. & Stutzer, A. (2002) What can economists learn from happiness research? *Journal of Economic Literature*, 30(2), pp. 402–435.

Frey, B. & Stutzer, A. (2003) *Happiness and Economics. How the Economy and Institutions Affect Well-being* (Princeton and Oxford: Princeton University Press).

Glewwe, P., Jacoby, H. & King, E. (2001) Early childhood nutrition and academic achievement: a longitudinal analysis, *Journal of Public Economics*, 81, pp. 345–368.

Graham, C. (2005) Insights on development from the economics of happiness, *World Bank Research Observer*, 20(2), pp. 201–232.

Grossman, M. (2006) Education and non-market outcomes, in: E. Hanushek & F. Welch (Eds) *Handbook of the Economics of Education*, Vol. 1, pp. 578–633 (Amsterdam: North Holland).

Hannum, E. & Park, A. (2007) Academic achievement and engagement in rural China, in: E. Hannum & A. Park (Eds) *Education and Reform in China*, pp. 154–172 (New York and Abingdon: Routledge).

Helliwell, J. (2002) How's life? Combining individual and national variables to explain subjective well-being, *Economic Modelling*, 20, pp. 331–360.

Jamison, D. (1986) Child malnutrition and school performance in China, *Journal of Development Economics*, 20, pp. 299–309.

Kahneman, D. & Krueger, A. (2006) Developments in the measurement of subjective well-being, *Journal of Economic Perspectives*, 20(1), pp. 3–24.

Kingdon, G. & Knight, J. (2006) Subjective well-being poverty versus income poverty and capabilities poverty? *Journal of Development Studies*, 42(7), pp. 1199–1225.

Knight, J. & Li, S. (1997) Cumulative causation and inequality among villages in China, *Oxford Development Studies*, 25(2), pp. 149–172.

Knight, J. & Li, S. (1999) Fiscal decentralization: incentives, redistribution and reform in China, *Oxford Development Studies*, 27(1), pp. 5–32.

Knight, J. & Song, L. (2003) Chinese peasant choices: migration, rural industry or farming, *Oxford Development Studies*, 31(2), pp. 123–147.

Knight, J. & Song, L. (2005) *Towards a Labour Market in China* (Oxford: Oxford University Press).

Knight, J., Weir, S. & Woldehanna, T. (2003) The role of education in facilitating risk-taking and innovation in agriculture, *Journal of Development Studies*, 39(6), pp. 1–22.

Knight, J., Li, S. & Deng, Q. (2009) Education and the poverty trap in rural China: setting the trap, *Oxford Development Studies*, 37(4), pp. 311–332.

Layard, R. (2005) *Happiness. Lessons from a New Science* (London: Penguin Books).

Li, T. & Zhang, J. (1998) Returns to education under collective and household farming in China, *Journal of Development Economics*, 56, pp. 307–335.

McMahon, W. (1999) *Education and Development. Measuring the Social Benefit* (Oxford and New York: Oxford University Press).

McMahon, W. (2007) An analysis of education externalities with applications to development in the deep south, *Contemporary Economic Review*, 25(3), pp. 459–482.

Phillips, J. M. (1994) Farmer education and farmer efficiency: a meta-analysis, *Economic Development and Cultural Change*, 43(1), pp. 149–165.

Schultz, T. P. (2004) School subsidies for the poor: evaluating the Mexican Progresa poverty program, *Journal of Development Economics*, 74, pp. 199–250.

Schultz, T. W. (1975) The value of ability to deal with disequilibria, *Journal of Economic Literature*, 13(2), pp. 827–896.

Skoufias, E. & McClafferty, B. (2001) *Is Progresa Working? Summary of the Results of an Evaluation by IFPRI*, FCND Discussion Paper No. 118 (Washington, DC: International Food Policy Institute).

Weir, S. & Knight, J. (2004) Externality effects of education: dynamics of the adoption and diffusion of an innovation in rural Ethiopia, *Economic Development and Cultural Change*, 53(1), pp. 93–114.

Weir, S. & Knight, J. (2007) Production externalities of education: evidence from rural Ethiopia, *Journal of African Economies*, 16(1), pp. 134–165.

Yang, D. (2004) Education and allocative efficiency: household income growth during rural reforms in China, *Journal of Development Economics*, 74, pp. 137–162.

Yu, S. & Hannum, E. (2006) Poverty, health and schooling in China, in: G. Postiglione (Ed.) *Education and Social Change in China: Inequality in a Market Economy*, pp. 53–74 (Armonk, NY: M.E. Sharpe).

Zhang, L., Huang, J. & Rozelle, S. (2002) Employment, emerging labour markets, and the role of education in rural China, *China Economic Review*, 13, pp. 313–328.