Associations between Levels and Rates of Change of Health with Schooling in China

by

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Abstract

This paper uses ordered probit regression through maximum likelihood estimation (MLE) to test how steep the health-schooling gradient is in China, and uses OLS regression to find if the gradient is attributable to steeper declines in health with age for less educated people. Using self-reported health (SRH) as the main health measurement, this paper find an increase in years of schooling increases the average predicted probability of achieving good or excellent health, and reduces the average predicated probability of fair or poor health. Lastly, the paper also finds that changes in health levels over time is similar for high-educated people and low educated people.

Keywords: health, schooling, gradient, China

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1. Introduction

As Chairman Mao once said “the body is the capital of the revolution,” clearly pointing to the importance of health. Health is a key human capital and can influence the amount of time people spend on production (Grossman, 1972). People are born with certain levels of health as endowment, and health declines after a certain age (Grossman, 1972). Education can be viewed as an investment in human capital (Grossman, 1972), and it plays a crucial role in shaping people’s behaviour.

In 1986, as Xie and Mo (2014) explained in their paper, China implemented the 9-year compulsory education law to eliminate illiteracy. The law has three features: it is nation-wide, compulsory, and tuition free. Children at age 6 begin to attend elementary school normally for 6 years, followed by 3 years of middle school, and leave school at age 15 (Xie & Mo, 2014). They can continue their study after graduating from middle school if they wish, but 9-year is the minimum. Many provinces implemented the law immediately after it came in to effect, but some were unable to due to financial reasons and lack of resources (Xie & Mo, 2014). Until 2011, the 9-year education has been universally achieved (Xie & Mo, 2014). The law increased average years of schooling dramatically from below five years prior 1985 to more than eight years (Zhang, Zhao, Zhao, Zhang, & Wang, 2004). After the goal of 9-year compulsory education has been achieved, the extension of 12-year free education was being discussed. The Ministry of Education of China encourages regions with financial capability to adopt this plan, while they do not see this as the country’s option due to the fiscal reason (Li, 2009). In 2007, Zhuhai city becomes the first one to offer 12-year compulsory education (Yang, 2009). Later, in 2008, Hong Kong started 12-year free education scheme (“Hong Kong,” 2007).

This paper addresses the question of how steep the health-schooling gradient is in China? Moreover, is the gradient attributable to steeper declines in health with age for the less educated people?

2. Literature Review

There is an abundant literature which studies the relationship between education and health. It is well documented that a significant correlation exists between education and health (Clark & Royer, 2013). This correlation can be caused by three possibilities (Grossman, 2008; Lleras-Muney, 2005; Xie & Mo, 2014): education has an impact on health, health has an impact on education, or unobserved factors can affect both education and health in same direction. The first possibility can be explained by Grossman's well-known paper published in 1972, where health and education are viewed as human capitals, and in his model, health can be increased by investments such as medical care (Grossman, 1972). Education, or knowledge, decides the productivity of producing these investments (Grossman, 1972). Hence, education has a positive impact on health (Grossman, 1972). Grossman (2008) provides a reason for the second possibility which can be explained by people with poor health attending school less than people with good health, and this could affect their school performance. Thus, poor health negatively affect years of schooling (Grossman, 2008). The third possibility, unobserved factors, can be explained by time preference (Fuchs, 1980). According to Fuchs (1980), time preference can be thought as the "trade-offs between current costs and future benefits" (p. 3). In other words, people with low time discount rate today are impatient for the future.

The most common way to empirically find a causal effect of education on health is via the instrumental variable (IV) method. The IV method works by finding a variable that only has impact on education but not health (Xie & Mo, 2014). If change in the IV changes health, this can only be because education has a causal effect on health. This causal relationship has been studied by many researchers in different countries with contrasting results (Arendt, 2005; Lleras-Muney, 2005; Xie & Mo, 2014). Lleras-Muney (2005) uses the change of compulsory schooling laws in the US between 1915 and 1939 as instruments, and finds that education has a significant causal effect on adult mortality and that compulsory schooling laws has a significant impact on educational attainment (Lleras-Muney, 2005). However, Arendt (2005) uses the Danish school reforms as instruments, self-reported health (SRH) and body mass index (BMI) as health measurements, and was not able to find a causal effect as the null hypotheses of no causal effect could not be rejected (Arendt, 2005). Clark and Royer (2013) use compulsory schooling laws changed in Britain in 1947 and 1972, applying with regression discontinuity method, and find that education has no causal effect on either monthly mortality, SRH, or smoking, although change in the laws has a strong impact on educational attainment and wage (Clark & Royer, 2013).

Particularly, Xie and Mo (2014) use China's 9-year Compulsory Education Law implemented in 1986 and Provisions on the Prohibition of Using Child Labor in 1991 as instruments, and spouse's education as an alternative instrument, find no causal effect of education on health by using Chinese data. I am going to argue that their IV estimates results are problematic for the following reasons. First, as the authors state in the paper, their F statistics for the pool sample on SRH by using the law as an instrument is below the conventional cut-off (Xie & Mo, 2014). Especially, the F statistics for the male subsample are not at all statistically significant, and male subsample has very large robust standard errors regardless of the health measurement used (Xie & Mo, 2014). The robust standard errors are about the same size as that of the coefficients for the gender pooled sample, and are larger than that of the coefficients for the female subsample (Xie & Mo, 2014). These results indicate that there could be an under-identification problem. Second, the spouse's education could be a biased instrument. As the authors mentioned in the paper, couples share the same interests (Xie & Mo, 2014). This means they could also share the same time preference. So, the high correlation between spouse's education level could be driven by this unobserved factor, hence it will be biased. Additionally, since SRH does not have a unit, interpreting the OLS partial effect of one unit change in schooling associated with a percentage change in SRH is misleading. Although I do not agree on their use of instruments, I follow their work on running the OLS regression to find the correlation between years of schooling and health outcomes.

Stabile and Currie (2003)'s study on socioeconomic status (SES) and child health provides me some idea for my model as well. They use Canadian youth data, and find that health shocks have an indifferent impact on high SES children and low SES children in the long-term. In my research, I treat high educated people as "high SES" and low educated people as "low SES", and I test how health status changes over time for high educated people and low educated people.

My research contributes to the study of the relationship between education and health from two perspectives. First, I use data from China, whereas the majority of the existing literature uses data from developed countries, such as the US, the UK, Canada, and European countries. Second, I focus on the gradient, where the existing literature pay more attention on the causal effects.

3. Methodology

I use two models to answer the two research questions. The first part of this section will explain how I find the health-schooling gradient, and the second part will show how I find the rate of change of health. All models in this paper only take people age 25 and above into account, as schooling is usually already complete and rarely changes for them (Culter & Lleras-Muney, 2006).

My main dependent variable, self-reported health (SRH), is ordered and categorical. Therefore, it is ideal to use a nonlinear regression model rather than OLS. Among the nonlinear regression models, such as probit, logit and Weibull, I assume that population is normally distributed, so I choose an ordered probit model for this study. Consequently, the Maximum Likelihood Estimation (MLE) is applied in this paper. Since probit is a nonlinear regression, its coefficients are not marginal effects (Greene, 2003), so I first use the OLS regression from Xie and Mo (2014) to see the degree of correlations between schooling and health status, and then use the ordered probit regression to find marginal effect.

$$y_{it}^{*} = \theta S_{it} + X_{it}\beta + \varepsilon_{it} \tag{1}$$

Equation (1) is the latent regression (Greene, 2003). y_{it}^{*} is the latent variable, in this case, the unobserved health status. In contrast, y_{it} is the observed health status. So y_{it} is subset of y_{it}^{*}. S_{it} is years of schooling, θ is the correspond coefficient. X_{it} is the independent variable vector including all other demographic factors such as age, marital status, and job status. β is the corresponding coefficient vector of X_{it}. ε_{it} is the error term, *i* stands for unique individual, and *t* stands for specific survey year. I will go through the model first, and present the details on y_{it} and X_{it} later. As I assume the population is normally distributed, which means the latent variable y_{it}^{*} follows a normal distribution, and it is normal conditional on the covariates. SRH as the key health indicator is a 4-point scale: excellent, good, fair, and poor. Based on the theory of latent regression from Greene (2003), I assume people's response on SRH (y_{it}) will be excellent if their underlying health status (y_{it}^{*}) over a certain threshold μ_i, based on the demographics people have. That is,

$$Pr(y_{it} = Excellent \,|X_{it}, S_{it}) = Pr(y_{it}^{*} > \mu_i|X_{it}, S_{it}) \quad (2)$$

There are three thresholds for the 4 outcomes in SRH. For poor, fair, and good SRH, the same logic applied:

$$Pr(y_{it} = Poor \,|X_{it}, S_{it}) = Pr(y_{it}^{*} < \mu_1|X_{it}, S_{it}) \quad (3)$$

$$Pr(y_{it} = Fair \,|X_{it}, S_{it}) = Pr(\mu_1 < y_{it}^{*} < \mu_2|X_{it}, S_{it}) \quad (4)$$

$$Pr(y_{it} = Good \mid X_{it}, S_{it}) = Pr(\mu_2 < y_{it}^{*} < \mu_3|X_{it}, S_{it}) \quad (5)$$

The marginal effects in this paper refers to the change of probability for each SRH outcome to stay in the same group as schooling increases by one year. It shows the impact of schooling on underlying health status. It also gives me the predicted probability of the sample size. This can be done by using cross-sectional data. Taking good SRH status as an example, that is:

$$\frac{d\, Pr(Good|X_{it}, S_{it})}{d\, S_{it}} = \phi(\mu_2 < y_{it}^{*} < \mu_3)\times\theta \quad (6)$$

Where $\phi(.)$ is the standard normal density function (Greene, 2003). The marginal effect will not be a constant due to nonlinearity. The standard normal density (ϕ) of y_{it}^{*} decomposes to four parts for four SRH outcomes. The probability for the four parts must sum up to 1. Therefore, predicted probability change in one outcome will change the probabilities of the other outcomes simultaneously.

There are commonly two ways to calculate the marginal effect for nonlinear regressions (Greene, 2003). They are the marginal effect at means (MEM) and average marginal effect (AME) methods (Greene, 2003). MEM in my case is holding all variables in X_{it} at their sample mean level, and calculating the marginal effect by using (6). AME calculates marginal effect using equation (6) for every observation at their own X_{it} level, and divide the sum of marginal effects by the total observations. Because most variables in X_{it} are binary or dummy variables, sample means of these variables are meaningless. Hence, this paper use AME calculation to calculate the marginal effect.

$$y_{it} = \theta S_{it} + X_{it}\beta + \varepsilon_{it} \tag{7}$$

Equation (7) is the model I use to find the health-schooling gradient by OLS regression. The observed health status y_{it} is decided by the demographic factors the respondents have. In equation (7), where y_{it} is the dependent variable including health indicators such as: self-reported health (SRH), contraction of sickness, hypertension, heart attack, diabetes, apoplexy, and smoking. I follow Xie and Mo (2014)'s paper to use SRH as the main dependent variable. The original survey question asked for SRH is "Right now, how would you describe your health compared to that of other people your age?" (Xie & Mo, 2014, p. 6). The responses have 4 outcomes excluding people who answered with unknown: 1 being excellent, 2 being good, 3 being fair, and 4 being poor. To make the results easier to understand, I code excellent as 1, good as 0.67, fair as 0.33, and poor as 0. Besides SRH, sickness is being measured by answering the question "During the past 4 weeks, have you been sick or injured? Have you suffered from a chronic or acute disease?". Sick and all the rest health indicators are binary, they take value equal to 1 if the respondent has the related disease or behaviour, and 0 otherwise. S_{it} is schooling measured in years and range from 0 to 18 years. X_{it} is a set of explanatory variables including demographic factors such as: age, age square, urban, gender, insurance status, job status, marital status, and province the respondents live in. Xie and Mo (2014)'s paper provides me the framework for these explanatory variables. Urban is a dummy variable, it takes value equal to 1 if respondents live in city or suburban, 0 if respondents live in town, county capital city, or rural village. Gender is a dummy variable, with 1 being male, and 0 being female. Marital status is a dummy variable includes 5 categories: never married, married, divorced, widowed, and separated. Insurance status does not limit to a specific type of insurance, but simply asks "Do you have medical insurance?". Job status is also a dummy variable, with 1 being presently working, and 0 otherwise. β is the corresponding population parameters vector, and ε_{it} is the error term including unobserved factors which may affect health but are not included in the model. Although I am mainly interested in the relationship between schooling and health, there are other factors which affect health outcomes as well. So, I must include them in the regression to try to avoid the omitted variable bias problem. As I discussed in last section, there is a heterogeneity issue between schooling and health partly due to the unobserved time preference. However, it is hard to show that schooling has a causal effect on health levels without the instrumental variable method. Therefore, the results are based on a simplifying assumption of non-heterogeneity.

Now I am going to explain the model I use to find the rate of change. This is conducted by using panel data. I define the change of SRH levels as:

$$\Delta h = h_{it+n} - h_{it} \tag{8}$$

For observation *i* who participate the survey in both year *t* and *t+n*, changes of SRH level for him or her is defined by the difference between the latest response on SRH level and the previous one. This difference can be either positive (better health), negative (worse health), or zero (no change in health). Regressing Δh on the explanatory variables in equation (7), gives:

$$\Delta h = \theta S_{it} + X_{it}\beta + \varepsilon_{it} \tag{9}$$

Although Δh takes the difference of SRH in two survey years, the explanatory variables in (9) are measured in wave *t* level. I assume the demographic factors does not change over time. The coefficient θ tells me how the change of SRH is due to schooling. If $\theta > 0$, it means health improves faster for high educated people than low educated people. If $\theta < 0$, it means health deteriorates faster for high educated people than low educated people. If $\theta = 0$ it means the rate of health change over time is similar for high and low educated people.

4. Description of data and summary statistics

The data used in this paper is collected by the China Health and Nutrition Survey (CHNS). CHNS is an ongoing program, which has collected longitudinal data since 1989 in nine waves, with 2011 being the latest wave available for use. Health related information are asked in the survey on individual, household, and community levels (http://www.cpc.unc.edu/projects/china), only individual level data is applied in this paper. Data used in this paper includes 9 provinces, ranging from northern China to the south. This diversity feature helps the results to be more general. Since my main health indicator SRH only exists before and including the 2006 survey, only data prior to and including 2006 will be applied in this paper. Specifically, I only use data from 2006 and 2000.

I merge the datasets by the observations' unique ID. In my study, there are 35,703 observations available for use in wave 2006 and 2000, but only about 9200 observations from wave 2006 for use in the marginal effect model, and about 4900 observations to use for the rate of change model due to missing observations. The summary statistics table on next page shows the main variables from the 2006 wave.

VARIABLE	OBS	MEAN	STD. DEV.	MIN	MAX
SRH	10,393	0.5536467	0.2664619	0	1
SCHOOLING	11,137	7.392835	4.580305	0	18
AGE	13,890	46.84507	15.44951	25	109
URBAN	18,827	0.2856005	0.4517119	0	1
GENDER	35,703	0.4801277	0.4996119	0	1
INSURANCE	11,741	0.4748318	0.4993874	0	1
JOB	9,912	0.5793987	0.4936805	0	1
MARITAL	9,762	2.099262	0.6398967	1	5

5. Results

Restate equation (7):

$$y_{it} = \theta S_{it} + X_{it}\beta + \varepsilon_{it} \quad (7)$$

Regressing SRH on equation (7) by OLS gives me Table 1 on the next page, which shows the correlation between years of schooling and SRH.

Table 1

	(1)	(2)	(3)
VARIABLES	Pool	Urban	Rural
Schooling	0.00654***	0.00430***	0.00731***
	(0.000675)	(0.00114)	(0.000859)
Age	-0.00829***	-0.00716***	-0.00803***
	(0.00126)	(0.00220)	(0.00154)
Age Square	2.91e-05**	2.78e-05	2.11e-05
	(1.18e-05)	(2.02e-05)	(1.47e-05)
Urban	-0.0166***		
	(0.00567)		
Gender	0.0328***	0.0270***	0.0355***
	(0.00545)	(0.00959)	(0.00664)
Insurance	-0.0134**	0.0132	-0.0267***
	(0.00558)	(0.0102)	(0.00691)
Job	0.0287***	0.0376***	0.0299***
	(0.00616)	(0.0112)	(0.00747)
Observations	9,161	3,105	6,056
R-squared	0.152	0.117	0.181

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Using the 2006 survey, Table 1 shows that one more year of schooling on average is associated with a 0.007 increase in SRH, holding everything else constant. This coefficient is statistically significant. This result is consistent with Xie and Mo (2014), where their coefficient of schooling on SRH is 0.008. Although it does not show on the table, I also control for the dummy variables of marital status and provinces. Age on average is associated with a negative impact on health, which matches my prior expectation. Being male is associated with a greater impact of 0.0328 in SRH than female. Currently having a job on average is associated with a positive increase in SRH. Also, note that having insurance on average has a negative impact on health relative to without insurance. A story can be told that people with insurance are more likely to be careless of their health because they think insurance can "save" them when bad things happen, in other words, they are more likely to run into the moral hazard problem. It's reasonable to think that people living in urban centres on average should have more education than people live in rural. So, I test the data on this demographic difference. The result shows that education has a slightly higher return on rural people than urban people.

One way to think about this result is that high educated people could be healthier than low educated people because of wage. High educated people are more likely to get high paying jobs, so high educated individuals have more choice on food and can afford better medical care. I would like to see if income mediates the effect of schooling on health.

Including annual wage into the regression, Table 2 on the next page shows that an increased annual wage of ten thousand Chinese Yuan on average is associated with a 0.002 increase in SRH, holding all other variables constant. However, this impact is insignificant both statistically and economically. Including wage into the regression decreases schooling's impact on SRH, but this could be due to the dramatic reduction in the sample size. Since wage is statistically insignificant, utilizing the same observations from regression (2) in (1) produces the third column, which shows that excluding wage does not make any real difference on schooling's coefficient for the same simple size. Hence, it is appropriate to exclude wage in the regression.

Table 2

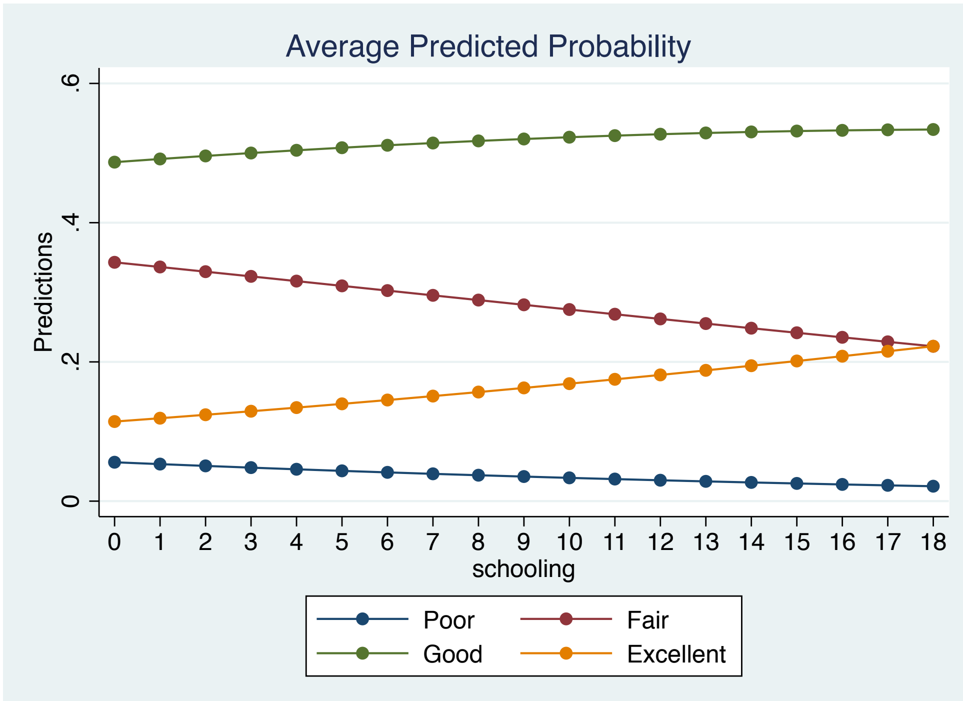
VARIABLES	(1) Pool	(2) Wage	(3) No Wage
schooling	0.00654***	0.00559***	0.00575***
	(0.000675)	(0.00122)	(0.00120)
Wage		0.00188	
		(0.00274)	
Observations	9,161	2,860	2,860
R-squared	0.152	0.108	0.107

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 in the appendix shows the associations of schooling on other health indicators such as hypertension, diabetes, and smoking. Although some of these correlations are statistically significant, almost all of them are economically insignificant.

Regressing equation (7) by ordered probit regression, and using AME through Maximum Likelihood Estimation, Figure 1 on the next page demonstrates the change of average predicted probability of schooling on SRH. The horizontal axis refers to schooling measured in year, ranging from 0 (no schooling) to 18 (normally equivalent to attained a Master's degree in China). The vertical axis represents the predicted probability by MLE for the four SRH outcomes. Since y_{it} (observed SRH) is a subset of y_{it}^* , y_{it} follows a normal distribution as well. Initially, around 11% of the distribution is predicted to be in poor health, 39% is predicted to be in fair health, 42% in good health, and 8% in excellent health. Increasing schooling by one year, a move on the horizontal axis from 0 to 1, the average predicted probability for good and excellent health slightly increase, and probability for fair and poor slightly decrease. Eventually, when schooling reaches 18 years, the average predicted probability of negative (fair and poor) outcomes is reduced by more than half of its original share, with 6.5% predicted to be in poor health, and less than 12% in fair health. Meanwhile, this corresponds to an increase of about 9% to the probability to be in good health, and 9.4%, to be in excellent health, nearly a two-fold increase. Tabulated summary results for the average predicted probability is in Table 4 in the appendix.

Figure 1



As much of the existing literature show, education has a positive correlation with health (Clark & Royer, 2013), and the earlier OLS result shows it is the case here given the data I have, therefore I expect less people in poor health. However, a 9.4% increase in excellent health is beyond my expectations. Ordered probit is a nonlinear regression, so the marginal effect is not constant, so the four lines in Figure 1 are nonlinear even though they may appear to be linear. Table 5 on the next page shows the average marginal effect of schooling on SRH. On average, one more year of schooling decreases the predicted probability of staying in poor and fair health by 0.4% and 0.6% respectively. In contrast, one more year of schooling on average increases the predicted probability by about 0.5% for both good and excellent health. All the marginal effects are statistically significant.

Table 5

	(1)	(2)	(3)	(4)
VARIABLES	Poor	Fair	Good	Excellent
Schooling	-0.00387***	-0.00633***	0.00515***	0.00505***
	(0.000417)	(0.000665)	(0.000544)	(0.000540)
Observations	9,161	9,161	9,161	9,161

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, the results show that schooling has a positive marginal effect on positive (good and excellent) SRH, and negative marginal effect on negative (poor and fair) SRH. Schooling benefits society as more people are likely to move to good and excellent health, and less people remain in poor and fair health.

Restate equation (9) for rate of change:

$$\Delta h = \theta S_{it} + X_{it}\beta + \varepsilon_{it} \quad (9)$$

Table 6 on the next page shows the impact of schooling on the rate of change of SRH by OLS regression. Unlike the results in Table 1, Table 6 shows schooling does not have any impact on the rate of change of health levels as the coefficient is statistically insignificant. Almost none of the results are significant at the 10% significance level. This means a change of health levels on average is similar for high educated people and low educated people.

Table 6

VARIABLES	(1) Pool	(2) Urban	(3) Rural
Schooling	0.000697	0.000133	0.000989
	(0.00128)	(0.00219)	(0.00162)
Age	-0.00415*	-0.000450	-0.00593*
	(0.00252)	(0.00456)	(0.00307)
Urban	0.00671		
	(0.0104)		
Gender	0.00977	0.00739	0.0116
	(0.00937)	(0.0170)	(0.0113)
Insurance	-0.00298	0.0168	-0.0194
	(0.0124)	(0.0188)	(0.0172)
Job	-0.0139	0.00406	-0.0287*
	(0.0121)	(0.0213)	(0.0151)
Observations	4,922	1,484	3,438
R-squared	0.017	0.016	0.023

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6. Conclusion

Health and schooling are positively correlated in China, holding demographics constant, but the relationship is surprisingly shallow. Additionally, schooling has an insignificant economic impact on most health indicators such as hypertension and smoking. Wage has statistically no correlation on SRH given the data I have. If wage has nothing to do with health, and assuming that people value health a lot, then it would be more efficient for the government to invest more in education rather than to increase wages. Increasing years of schooling increases the average predicted probability in good and excellent health by about 9% for each additional year, and decreases the average predicted probability of fair and poor health. Lastly, changes of health levels over time is similar for high educated people and low educated people.

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Appendix

Table 3

VARIABLES	(1) SRH	(2) Sick	(3) Hypertension	(4) Heart Attack	(5) Diabetes	(6) Apoplexy	(7) Smoking
Schooling	0.00654***	-0.00372***	0.00235***	0.000173	0.000810**	-1.07e-05	-0.00544***
	(0.000675)	(0.00110)	(0.000806)	(0.000223)	(0.000372)	(0.000290)	(0.000988)
Age	-0.00829***	-0.00222	0.00372**	-0.000373	0.00122*	-0.00188***	0.00955***
	(0.00126)	(0.00204)	(0.00149)	(0.000414)	(0.000691)	(0.000540)	(0.00183)
Age Square	2.91e-05**	7.86e-05***	1.92e-05	8.41e-06**	-2.88e-06	2.47e-05***	-9.05e-05***
	(1.18e-05)	(1.92e-05)	(1.41e-05)	(3.90e-06)	(6.52e-06)	(5.10e-06)	(1.72e-05)
Urban	-0.0166***	0.0683***	0.0427***	0.00204	0.0194***	0.00382	0.0206**
	(0.00567)	(0.00921)	(0.00678)	(0.00187)	(0.00313)	(0.00244)	(0.00830)
Gender	0.0328***	-0.0255***	-0.000163	0.00163	0.00201	0.00795***	0.606***
	(0.00545)	(0.00886)	(0.00651)	(0.00180)	(0.00301)	(0.00234)	(0.00798)
Insurance	-0.0134**	0.0488***	0.0133**	5.29e-05	0.00719**	0.00139	-0.00345
	(0.00558)	(0.00909)	(0.00667)	(0.00184)	(0.00308)	(0.00240)	(0.00818)
Job	0.0287***	-0.0249**	-0.0455***	-0.00574***	-0.0147***	-0.00853***	0.00607
	(0.00616)	(0.0100)	(0.00736)	(0.00203)	(0.00340)	(0.00265)	(0.00902)
Observations	9,161	9,189	9,180	9,187	9,178	9,178	9,219
R-squared	0.152	0.083	0.103	0.012	0.026	0.022	0.410

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 4

VARIABLES	Poor	Fair	Good	Excellent
Schooling=0	0.107***	0.395***	0.423***	0.0750***
	(0.00474)	(0.00735)	(0.00705)	(0.00422)
Schooling=18	0.0425***	0.274***	0.514***	0.169***
	(0.00352)	(0.00892)	(0.00671)	(0.00808)
Difference	-6.45%	-12.1%	9.1%	9.4%
Observations	9,161	9,161	9,161	9,161

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1