POOR HEALTH AND LABOUR MARKET OUTCOMES IN INDIA

by

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CONTENTS

1. INTRODUCTION

Overall human health has improved substantially over the past century. Various measures such as life expectancy, the rate of infant mortality, and the burden of disease indicate that people are living longer, healthier lives. While some nations have benefited more than others, these improvements have largely manifested across the world. One implication of a longer lifespan is an increase in the number of years that an individual can participate in the labour force. Additionally, longevity can induce people to undertake productivity-improving human capital investments which would otherwise be unappealing. These two forces underscore the idea that health improvements realized since the early 1900s have significantly affected one's economic value or "value of life.[1]" Curiously, in discussions of human capital, individual health has inspired considerably less interest from economists than has schooling. The idea of individual health as human capital has generated literature which is only a fraction of that pertaining to education. While there exists a substantial body of research relating health, income and human capital, it has largely framed the relationship as a one-way mechanism - by explaining better health as a consequence of higher income and increased levels of education.[2] The converse effect, that is, health's impact on labour-market outcomes and schooling, has been subject to less empirical scrutiny. Assessing this latter effect may be particularly important in nations with a higher prevalence of poverty. This is because ill-health may act as a poverty trap. Lower levels of health may make it difficult to accumulate other forms of human capital and, thus, may hinder the ascent from poverty. Additionally, as Strauss & Thomas (1998) suggest,

[1] Becker (2007) defines "value of life" as the NPV of one's expected earnings attributable to labour market and household activities. That is, the sum of one's discounted 'full income.'
[2] See, for example, Deaton (2008)

adults in poorer countries are more likely to be subject to maladies which may hamper productivity and these effects may be felt throughout one's lifetime. Thus, trying to ascertain how health affects individual outcomes may carry greater importance in such nations.

India is an interesting country to analyze because it holds the greatest number of individuals living in extreme poverty and, relatedly, has the largest absolute poverty gap. This implies that India has a lot to gain from the research and implementation of policies that enhance human capital. Assessing health's role in improving human capital and affecting labour-market outcomes at the micro-level may be an overlooked area and, therefore, is the focus of this paper. In particular, it may be of value to ascertain the economic loss associated with poor health.

Three techniques are used in this paper to estimate the economic cost of poor health: OLS, the instrumental variable (IV) method and propensity score matching (PSM). The first two techniques (OLS & IV) are used to estimate a Mincerian-type equation which incorporates health status and multiple socioeconomic status (SES) indicators.[3] The estimated equation is used to calculate foregone earnings attributable to poor health. The propensity score matching technique also provides us with estimates of forgone earnings. Once foregone earnings are calculated, the economic loss associated with non-labour market activities is estimated. Using these figures, total individual economic loss can be calculated (these can be found in Tables 4A, 5A and 6A in section 5).

The basic OLS model indicates that the economic loss due to poor health is roughly INR 300,000 for men (5 times the average income for 40-year-old men) and INR 120,000

[3] Heckman et al. (2003) provides a good overview of Mincer equations

(4 times the average income for 40-year-old women) for women. The propensity score matching technique suggests a similar figure for women and a slightly higher figure for men – INR 370,000. The IV technique suggests a much higher loss– approximately INR 2,200,000 for men, however, one must be cautious about the validity of this estimate. The first two estimates (from OLS & PSM) seem to be in agreement and should be approached with less skepticism. Further analyses of the OLS results reveal that losses in productivity due to poor health account for 51% of foregone earnings. The remaining proportion of lost earnings is attributable to reduced work intensity (i.e. days worked per year).

The paper is structured as follows: in section 2, an analytic approach will be taken in order to understand health's role as human capital. Empirical literature will be reviewed in section 3. The data will be described in section 4; modelling strategies and results will be discussed in section 5. The conclusion is presented in section 6.

2. THEORY

To help us understand how variations in health can affect people's choices we can first refer to a theoretical framework. Built upon the foundational ideas of Grossman (1972), a theory of health as human capital has formed over the years and is described in Becker (2007). In Becker's descriptions, one version of the framework assumes that individual utility takes the following form:

$$U = \sum B^i S_i u_i(x_i, l_i) \tag{1}$$

where i is the time subscript, B is the discount rate, S_i is the probability of surviving up until age i, u_i is the utility in period i, x_i and l_i represent period i consumption and leisure respectively. If we consider a two-period formulation, then, as Becker demonstrates, (1) simplifies to:

$$U = u_0(x_0, l_0) + BS_1(h)u_1(x_1, l_1) \; with \; S_{1'} > 0 \; and \; S_{1''} \leq 0 \tag{2}$$

where h is the number of units of health purchased to raise S_1. If we now introduce a budget constraint with the assumptions of perfect capital markets, a fixed interest rate, r, and full insurance, we have:

$$x_0 + \frac{S_1 x_1}{1+r} + g(h) = w_0(1 - l_0) + \frac{S_1 w_1(1 - l_1)}{1+r} = W \tag{3}$$

where g(h) is one's expenditure on health. As explained by Becker, (3) essentially states that consumption in both periods, weighted by the discounting factor and the probability of survival, plus spending on healthcare should equal the sum of the similarly discounted wages of both periods. If we maximize (2) subject to (3), we get the following first-order conditions:

$$u_{0x} = B(1+r)u_{1x}, \qquad \frac{u_{0l}}{u_{0x}} = w_0, \qquad and \qquad \frac{u_{1l}}{u_{1x}} = w_1 \tag{4}$$

Equation (4) suggests numerous ways through which individual health may impact labour-market outcomes. It may be reasonably conjectured that poor health lowers worker productivity, particularly among labour-intensive jobs. If wages reflect marginal products of labour, then it can be surmised that poor health should lower individual wages. This would have a negative impact on labour-force participation because the cost of leisure has decreased. However, the total impact of poor health on labour-market outcomes is further complicated by its effects on individual preferences. Declining health may cause individuals to, implicitly or explicitly, place a greater value on leisure due to the necessity of increased self-care. This may raise their reservation wages. However, an increase in requisite healthcare costs may increase the value associated with consumption (of certain goods), potentially incentivizing people to participate in the labour-force. This effect may be particularly acute if one's stock of financial resources are low, as is the case for many individuals in developing nations.

Now we can examine the specific effects of healthcare expenditure. The FOC for h is as follows:

$$\left(\frac{dlogS_1}{dh}\right) BS_1 u_1 = u_{0x}\left\{g'(h) + \left(\frac{1}{1+r}\right)\frac{dS_1}{dh}(x_1 - w_1(1-l_1))\right\} \tag{5}$$

Equation (5) has some interesting insights. As Becker points out, the left-hand side of the equation represents the marginal benefit of spending on healthcare and the right-hand side represents the marginal cost. It can be seen that the marginal benefits of health spending increase as wealth increases since the left-hand side depends on the *level* of utility, as opposed to marginal utility. This is an important result because it implies that individuals with low levels of wealth, whom are prevalent in India, will experience a lower benefit from marginal spending on healthcare. In other words, poor health may paradoxically cause individuals to decrease their healthcare spending if their ailments sufficiently reduce their wages. This decreased healthcare spending may reduce future health and this, in turn, would have implications. If true, this process may shed some light on how poor health can serve as a poverty trap.

Using (4) one can rewrite (5) as:

$$(1+r)\left(\frac{dlogS_1}{dh}\right)\frac{S_1u_1}{u_{1x}} = g'(h) + \left(\frac{1}{1+r}\right)\frac{dS_1}{dh}(x_1 - w_1(1-l_1)) \tag{6}$$

Another key point Becker puts forth is that individuals spend on healthcare because raising the probability of survival (adding additional years to one's life) adds average utility whereas increasing consumption only adds marginal utility. This feature of the model makes healthcare spending attractive.

The numerous forces at play make it difficult to predict the exact behaviour individuals will exhibit if they suffer from poor health. The above mentioned issues carry greater importance in nations where poor health is more prevalent, wages are low and labour-intensive jobs are more common. Certainly, an increased reliance on labour, as is the case in developing countries, elevates health's potential to be a constraining force on economic output. In the next section, we will take a look at literature that investigates these issues empirically.

3. EMPIRICAL LITERATURE

To corroborate both theory and intuition, there is evidence suggesting that poor health has a negative impact on educational attainment and employment outcomes. Studies show that poor health in childhood leads to lower levels of education later on in life.[4] This is troublesome for developing countries where levels of schooling are already low and is reflective of the pernicious process through which health interacts with other forms of

[4] Haas (2006) for example

human capital to keep poverty rates from declining. Strauss and Thomas (1998) extensively discuss the correlation between indicators of health, such as BMI and height, and labour market characteristics, such as income and education. They noted that productivity, earnings and years of schooling were positively correlated with measures of health.

Additionally, poor health has been shown to reduce labour-force participation and wages. In Cai & Kalb (2006), the authors investigated how poor self-assessed health (SAH) affected labour force participation in Australia. They found that poor SAH reduced labour force participation rates in both men and women. This effect was stronger for older groups (ages 50-64) and for women. The authors also hypothesized that a feedback effect may exist between labour force participation and SAH. They suggested that people not in the labour force may tend to report poor health to "rationalize" their non-participation. This would render SAH endogenous and overestimate the negative effects of poor health. They tested this hypothesis and found that labour force participation has a significant positive effect on older females' health and a significant negative impact on younger (ages 15-49) males' health. The effects were not significant for the other groups. In order to avoid this potential endogeneity problem, this paper will focus on medical symptoms rather than self-assessments.

Pelkowski and Berger (2004) used data from the Health and Retirement Study to estimate the effects of temporary and permanent illness on wages, annual hours worked and labour force participation. They used three techniques to compute estimates: OLS, fixed effects and the Heckman procedure. With a few exceptions, they found that permanent illness significantly reduced wages and hours worked for both men and women. The effect on wages was larger for women whereas the effect on hours worked was larger for men. They found that temporary illness doesn't have a significant effect on the above mentioned labour market outcomes. More interestingly, the authors tried to assess the loss in lifetime earnings associated with health problems. They did this by taking into account the reduced earnings, hours worked and likelihood of labour force participation, as suggested by the Heckman parameter estimates. They found that permanent health conditions reduced the log of earnings by approximately -0.734 for men and -0.741 for women. This reduction was largely mediated through the reduced likelihood of labour force participation (-0.603 for men and -0.627 for women), with the reduction in wages and hours worked playing much smaller roles.

Contoyannis and Rice (2001) conducted an investigation using British Household Panel data and found that lower self-assessed general and psychological health reduced hourly wages for males, while excellent self-assessed health increased the hourly wage for females. They estimated this via a modified Mincer equation and by using instrumental variable (IV) techniques.

The above mentioned studies seem to indicate that poor health generally pushes people away from labour-market activities and investments in schooling. This suggests that the substitution effect dominates in the theoretical framework presented in section 2 - people would rather increase their leisure time (due to its lower opportunity cost as a result of lower wages) than devote additional time in the labour-force and try to increase spending on healthcare and consumption.

4. DATA

4.1 Variables Selection

Data is taken from the second round of the Indian Human Development Survey (IHDS) dataset. The Indian Human Development Survey (IHDS), jointly organized by the University of Maryland and the National Council of Applied Economic Research, is a multi-topic panel survey of approximately 42,000 households in India. The first round was conducted in 2005. For this paper, individual-level (cross-sectional) data from the second round (2012) will be used. The survey includes data on health, education, employment, economic status, marriage, fertility, gender relations, and social capital. Key variables of interest include indicators from the "short-term morbidity" classification such as the number of days disabled in the past month, number of days ill in the past month and the incidence of diarrhea. These short-term health variables are used jointly and serve as a dummy indicator reflecting poor health. More specifically, if an individual experienced a positive number of days where they were ill, disabled or had diarrhea, then they would be classified as having poor health. In other words, an indication of sickness from *any* of those 3 variables would render the poor health binary indicator to equal 1. In this paper, the aim is not to capture the effects of disabling, terminal illnesses, but rather to capture the effects of generalized poor health that is treatable and resolvable through standard healthcare.

There are multiple reasons why a focus on medical symptoms and explicit manifestations of poor health (rather than self-assessed health) is proposed. Firstly, self-assessed health (SAH) suffers from biases such as those outlined by Cai & Kalb (described in section 3). Second, given the high levels of illiteracy (>30%) in India, the ability of individuals to provide accurate, meaningful and comparable assessments of their health is questionable. As a result, self-assessed health may not be a good choice as a health indicator. This is why there is an emphasis on health symptoms in this paper.

The set of independent variables used as controls include age, age-squared, years of schooling, marital status and several socioeconomic indicators. In India, average levels of education are very low; therefore, using years of schooling, as opposed to categories of educational attainment, provides a more relevant and finer description of one's education. Years of schooling may also provide information about one's socioeconomic background. It is characteristic of those of a higher socioeconomic status (SES) to pursue above-average levels of education. In an attempt to further incorporate information about one's socioeconomic background variables such as literacy, English ability, computer use and caste are used. In India, one's 'caste' still proves to be informative about one's socioeconomic status.[5] One's literacy (not clearly reflected through years of schooling) and English ability may also shed some light on one's socioeconomic background; these variables tend to have high persistence from one generation to the next. Similarly, one's ability to use a computer (at any location including home, work, internet cafes et cetera) may provide additional information on SES. More traditional indicators of SES such as parental education and parental income were not recorded in the dataset. A list of variables that will be used in modelling can be found in Table 3 in the Appendix section.

For IV estimation (detailed in the next section), two variables are used: smoking activity and alcohol consumption. The smoking activity variable pertains to the use of "beedis," a low-cost cigarette (more commonly used than regular cigarettes in India), and

[5] The caste system in India historically classified people into social groups primarily based on ancestral occupations, but also incorporated other factors. One's caste is still very informative and is the principal basis for affirmative action measures in India

"hukkahs," a type of utensil used to smoke tobacco. Both smoking activity and alcohol consumption are divided into 4 categories: never, rarely, sometimes and daily.

4.2 Descriptive Statistics

Table 1C in the Appendix provides some general information about the sample in the dataset. Information about specific topics are provided in this section. Table 1A summarizes labour force participation rates among working age men and women, subject to their health status. Among married and unmarried males, it seems that poor health only decreases labour force participation by a small amount – by 0.5% and 2.2% respectively. Among married females, poor health seems to paradoxically be associated with a higher participation rate. Poor health has a large negative impact on the participation rates of unmarried females, however they are the smallest group among labour force participants. Initial results suggest that poor health does not have a significant negative impact on labour force participation. However, this may be misleading. Firstly, labour force participation does not take into account the type of work that people engage in, rather it merely considers whether or not they are engaged in *some* work. In this dataset, more than 47% of healthy, working age males are engaged in agriculture, cultivation, small business or independent work. This proportion goes up to 55% if they are characterized with poor health. This may indicate that poor health limits the types of work individuals may undertake and may impel people to pursue certain types of work. Namely, work that has few requirements to take up and is generally not associated with a formal contract. Since this type of work is common in India, it is hard to differentiate between those who are genuinely participating in the labour force and those who are essentially non-participants. This issue is also discussed in Strauss and Thomas (1998).

Table 1A. Labour Force Participation Rates Among Working Age Individuals		
	Baseline	Poor health
Male, married (Ages 15-65)		
% in labour force	94.5%	94.0%
Observations	40087	4791
Female, married (Ages 15-65)		
% in labour force	22.9%	24.3%
Observations	45033	10004
Male, unmarried (Ages 15-65)		
% in labour force	91.3%	89.1%
Observations	11481	1092
Female, unmarried (Ages 15-65)		
% in labour force	37.7%	31.8%
Observations	5445	808

Another reason why the findings above may be misleading is that labour force participation does not take into account the intensity of participation. Perhaps a more useful way to measure health's labour market effects would be in terms of work intensity (i.e. the number of days worked per year and the number of hours worked per day). Table 1B illustrates this information.

Table 1B. Work Intensity Among The Healthy & Unhealthy			
	Baseline	Poor health	Difference
Male (Ages 15-65)			
Number of days worked per year	237	215	-22
Number of hours worked per day	8.1	8.08	-0.02
Female (Ages 15-65)			
Number of days worked per year	201	187	-14
Number of hours worked per day	7.34	7.31	-0.03

These results are more consistent with the findings of other studies. It can be seen that poor health is associated with a material reduction in the number of days worked per year – a decrease of 9.3% for men and 7.0% for women. On the other hand, the data suggests poor health does not greatly affect the number of hours worked per day.

Health's effect on levels of schooling is another important dimension to investigate. Table 2 illustrates the association between health status and years of schooling. Poor health seems to be associated with lower levels of schooling and this pattern seemingly holds for virtually all age groups and for both genders.

Table 2. Years of Schooling

	Male		Female	
	Baseline	Poor Health	Baseline	Poor Health
Ages 15-19				
Years of schooling	6.4	6.0	6.4	6.5
Ages 20-29				
Years of schooling	8.4	8.3	7.7	7.0
Ages 30-39				
Years of schooling	8.1	7.1	5.1	3.9
Ages 40-49				
Years of schooling	6.9	6.2	3.4	2.5
Ages 50-59				
Years of schooling	6.3	5.2	2.5	1.8
Ages 60-65				
Years of schooling	4.6	4.0	1.1	0.6

The data makes clear that India, like numerous developing countries, is burdened by low levels of schooling. Education serves as an important channel through which individuals may rise from poverty; if the attainment of education is jeopardized by poor health, it renders the escape from poverty more difficult. The above data seems to corroborate the view that health complements education and, therefore, should also be a concern for policy makers not explicitly focusing on health.

5. MODELLING STRATEGIES & RESULTS

5.1 Basic OLS Model

Now that we have seen data on how health is associated with certain labour force characteristics, we can go further and try to quantify health's effects on earnings. These figures can help us estimate how poor health impacts one's value of life. In order to do this, a Mincerian-type equation will be used to estimate individual earnings. The specific form of the basic OLS model will be as such:

$$\ln(\text{AnnualEarnings}) = \beta_0 + \beta_1{*}\text{Age} + \beta_2{*}\text{Age}^2 + \beta_3{*}\text{YearsOfSchooling} + \beta_4{*}\text{Married} + \beta_5{*}\text{Literate} + \beta_6{*}\text{EnglishAbility} + \beta_7{*}\text{UrbanDwelling} + \beta_8{*}\text{UsesComputer} + \beta_9{*}\text{DisadvantagedCaste} + \beta_{10}{*}\text{PoorHealth}{*}\text{Age} + \varepsilon \tag{7}$$

This will also be done using the hourly wage so that we can differentiate between the effect of reduced work intensity from the effect of reduced productivity on earnings.

$$\ln(\text{HourlyWage}) = \beta_0 + \beta_1{*}\text{Age} + \beta_2{*}\text{Age}^2 + \beta_3{*}\text{YearsOfSchooling} + \beta_4{*}\text{Married} + \beta_5{*}\text{Literate} + \beta_6{*}\text{EnglishAbility} + \beta_7{*}\text{UrbanDwelling} + \beta_8{*}\text{UsesComputer} + \beta_9{*}\text{DisadvantagedCaste} + \beta_{10}{*}\text{PoorHealth}{*}\text{Age} + \varepsilon \tag{8}$$

These two equations will be regressed separately on males/females. In addition, health status is made to interact with age. This was done in order to reflect the assumption that health's effects are not constant over time. Other types of interactions and specifications did not seem to result in a better model (interactions of health status with other variables were tested but were not significant). The results of the OLS models can be seen in Table 4 below.

Table 4. OLS Estimation Results

	Males	Females
Annual Earnings Equation (t-stats in parentheses)		
Age	0.0601 (18.9)	0.0631 (11.9)
Age squared	-0.000664 (-17.3)	-0.000651 (-10.2)
Years of Schooling	0.0434 (20.3)	0.0670 (15.4)
Married	0.0805 (4.57)	0.0614** (1.68)
Literate	-0.0556 (-2.84)	-0.147 (-4.31)
English Ability		
None	-	-
Little	0.184 (12.3)	0.325 (9.11)
Fluent	0.569 (21.4)	0.815 (14.4)
Urban Dwelling	0.735 (63.5)	0.577 (25.7)
Uses Computer	0.385 (17.5)	0.448 (9.47)
Disadvantaged Caste (SC, ST, OBC)	-0.135 (-10.8)	-0.0564* (-2.21)
Poor Health Dummy*Age	-0.00494 (-11.9)	-0.00235 (-4.20)
Constant	8.70 (155.4)	7.84 (81.6)
F-stat	1367.58	554.35
R^2 (adjusted)	0.300	0.36
N	35110	10824
Hourly Wage Equation (t-stats in parentheses)		
Age	0.0314 (15.7)	0.0276 (7.95)
Age squared	-0.000257 (-10.6)	-0.000243 (-5.79)
Years of Schooling	0.0313 (23.3)	0.0421 (14.8)
Married	0.0366 (3.30)	0.120 (5.04)
Literate	-0.037 (-3.00)	-0.128 (-5.72)
English Ability		
None	-	-
Little	0.116 (12.3)	0.252 (10.8)
Fluent	0.483 (28.8)	0.735 (19.9)
Urban Dwelling	0.228 (31.3)	0.162 (11.0)
Uses Computer	0.308 (22.2)	0.329 (10.6)
Disadvantaged Caste (SC, ST, OBC)	-0.0713 (-9.07)	0.00592** (0.35)
Poor Health Dummy*Age	-0.00235 (-8.96)	-0.00157 (-4.30)
Constant	2.047 (58.0)	1.65 (26.3)
F-stat	1207.86	458.76
R^2 (adjusted)	0.275	0.318
N	35070	10811

All coefficients significant at 1% except those marked with * or **
* indicates a significance level between 1% and 5%
** indicates a significance level greater than 5%

The above estimates indicate that one's earnings are significantly reduced due to poor health. In addition, this effect seems to increase with age. This is reflected through the significant and negative coefficient associated with the PoorHealthDummy*Age variable for both genders and equations. The caste variable, meant to capture some socioeconomic information, also seems to have a coefficient which is negative and significant for both genders for the first equation and for males for the second equation; this suggests that being associated with a historically disadvantaged caste imposes an earnings discount even after controlling for several factors. In general, the other estimated coefficients seem to be consistent with expectations and the model seems to adequately capture the effect of interest.

The results of the estimated equations can be seen visually in Figures 1A, 1B, 2A and 2B below. They are produced using the average levels of education and SES characteristics for 18-21 year olds. This is done in order to capture forward looking characteristics of the newer generation of labour force entrants.

Figure 1A: Projected Lifetime Earnings
(Married Males, 18-65)

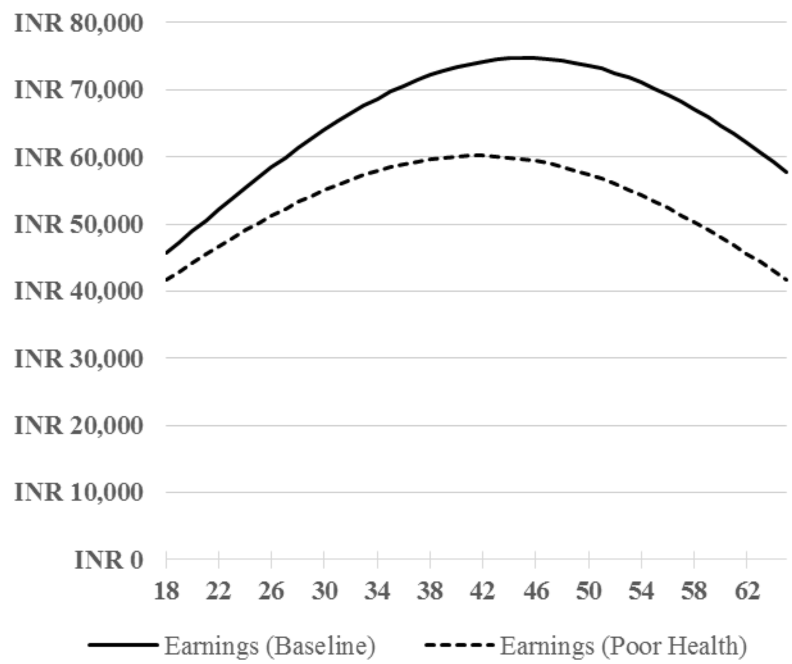
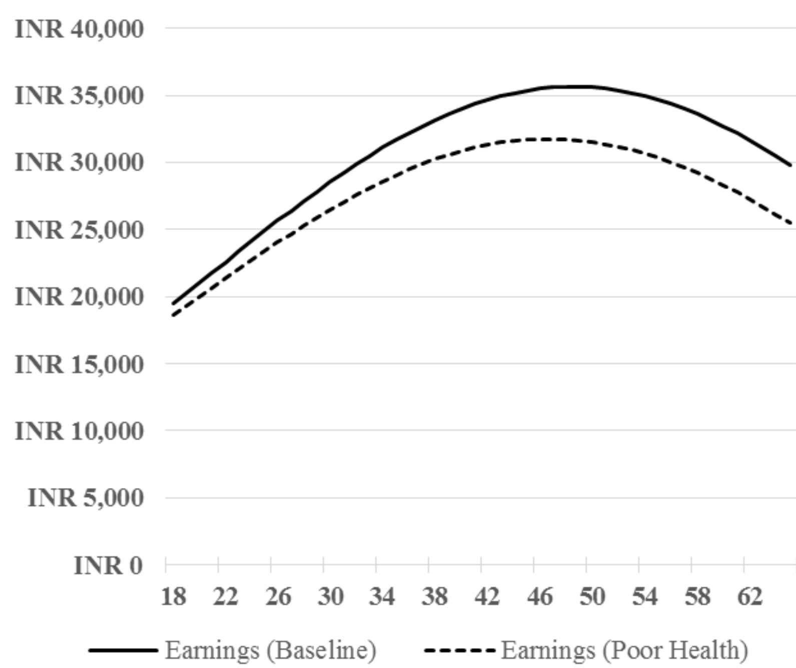
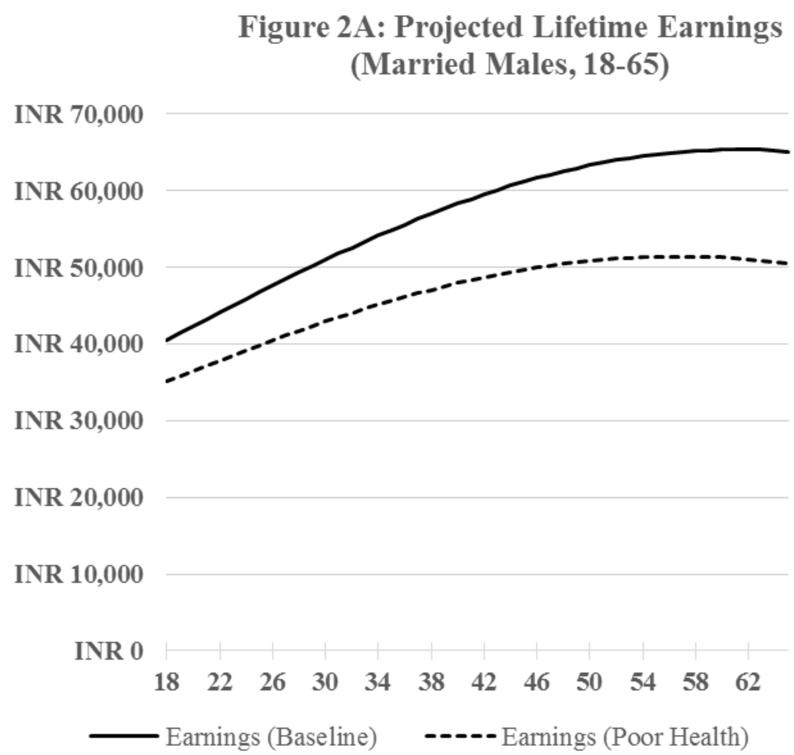
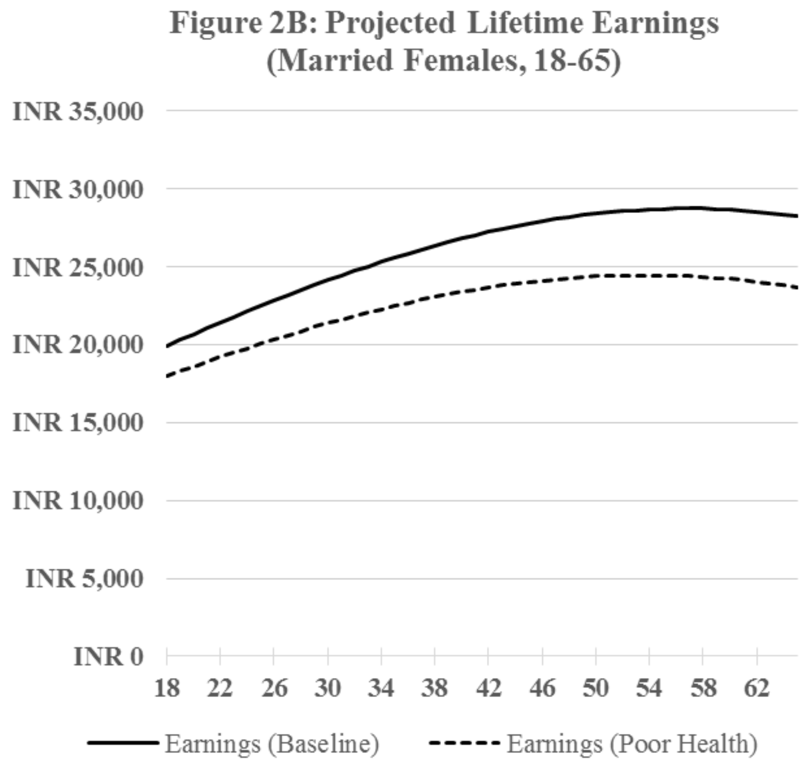


Figure 1B: Projected Lifetime Earnings
(Married Females, 18-65)



Figures 1A and 1B represent the projected lifetime earnings of average 18-21 year olds, estimated using (7) (the annual earnings equation). Figures 2A and 2B represent the same information, estimated using (8) (the hourly wage equation).





The differences between the projections in Figures 1A and 1B and those in 2A and 2B are very interesting. The projections in Figures 1A and 1B implicitly capture the effects of work intensity; most notably the number of days worked per year. The projections in Figures 2A and 2B do not capture this effect and only reflect the differences in the hourly wage (annualized using average statistics and assuming constant work intensity), which is a closer measure of productivity. This suggests that the concavity in one's earnings profile is very much influenced by the reduction in work intensity over time (refer to Figures 1C and 1D in the Appendix).

In order to estimate the economic loss associated with poor health, the methods outlined in Becker (2007) for calculating "value of life" are used – I use average hours worked per year, allocate 68 hours per week for sleep and maintenance, value all other household time at the hourly wage and apply a 5% discount rate. The results of this method are presented in Table 4A below.

Table 4A. Economic Loss Associated With Poor Health (OLS estimates)

	PV of Foregone Earnings	PV of Loss Associated With Household Time	PV of Total Loss
Males	INR 164,416	INR 138,503	INR 302,919
Females	INR 55,372	INR 63,964	INR 119,336

The above estimates suggest that poor health results in material economic losses – a loss of 302,919 rupees for males (5.2 times the average annual earnings of a 40 year old male) and a loss of 119,336 rupees for females (4.4 times the average annual earnings of a 40 year old female). Additional analysis reveals that poor health affects lifetime earnings equally through its effects on productivity and work intensity. If work intensity is assumed to be homogenous (i.e. not affected by health status) then the PV of foregone earnings due to poor health is reduced by 49%. This indicates that 51% of foregone earnings are attributable to lower productivity (as reflected through hourly wages). If one analyzes the PV of total loss, then reduced productivity accounts for 72% of the loss. This is in contrast with the findings of Pelkowski & Berger (2004) which indicate that the variation in annual earnings is primarily mediated through health's effects on labour force participation, with productivity effects having a smaller impact.

5.2 Instrumental Variables (IV) Method

The basic OLS model was a good first step but it did not address a serious concern of endogeneity. Namely, that of reverse causation between wages and health. There are reasons to believe that earnings have an effect on health. In order to address this problem, IV techniques (two-stage least squares) can be used. Smoking activity and alcohol consumption may be viable contenders for the IVs – there is a logical pathway suggesting that increased smoking and alcohol use deteriorates health. At the same time, smoking and alcohol use are, on average, not expected to directly cause changes in income. Descriptions of these variables can be found in section 4. The specific form of the two-stage least squares equations are as follows:

$$\text{PoorHealthDummy} = \gamma_0 + \gamma_1\text{*Age} + \gamma_2\text{*Age}^2 + \gamma_3\text{*YearsOfSchooling} + \gamma_4\text{*Married} + \gamma_5\text{*}$$
$$\gamma_6\text{*Literate} + \gamma_7\text{*EnglishAbility} + \gamma_8\text{*UrbanDwelling} + \gamma_9\text{*UsesComputer} +$$
$$\gamma_{10}\text{*DisadvantagedCaste} + \gamma_{11}\text{*SmokingActivity} + \gamma_{12}\text{*AlcoholConsumption} + \nu \quad (9)$$

$$\ln(\text{HourlyWage}) = \beta_0 + \beta_1\text{*Age} + \beta_2\text{*Age}^2 + \beta_3\text{*YearsOfSchooling} + \beta_4\text{*Married} +$$
$$\beta_5\text{*Literate} + \beta_6\text{*EnglishAbility} + \beta_7\text{*UrbanDwelling} + \beta_8\text{*UsesComputer} +$$
$$\beta_9\text{*DisadvantagedCaste} + \beta_{10}\text{*}PoorHe\widehat{alth}Dummy + \varepsilon \quad (10)$$

The results of the IV regressions can be seen in Table 5 in the Appendix. The new estimates indicate that poor health imposes a more deleterious effect on earnings than initially calculated in the previous subsection. However, this model seems to be weaker than the previous one. The significance of many coefficients do not meet the 5% level.

The new projections are presented below in Figure 3A for males.[6] These projections are produced in the same manner as the ones in section 5.1.

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[6] The estimates for females are not analyzed as they were not sensible; this was likely due to the small sample size resulting from a low incidence of women smoking/consuming alcohol; their projections are partially presented in Figure 3B in the Appendix

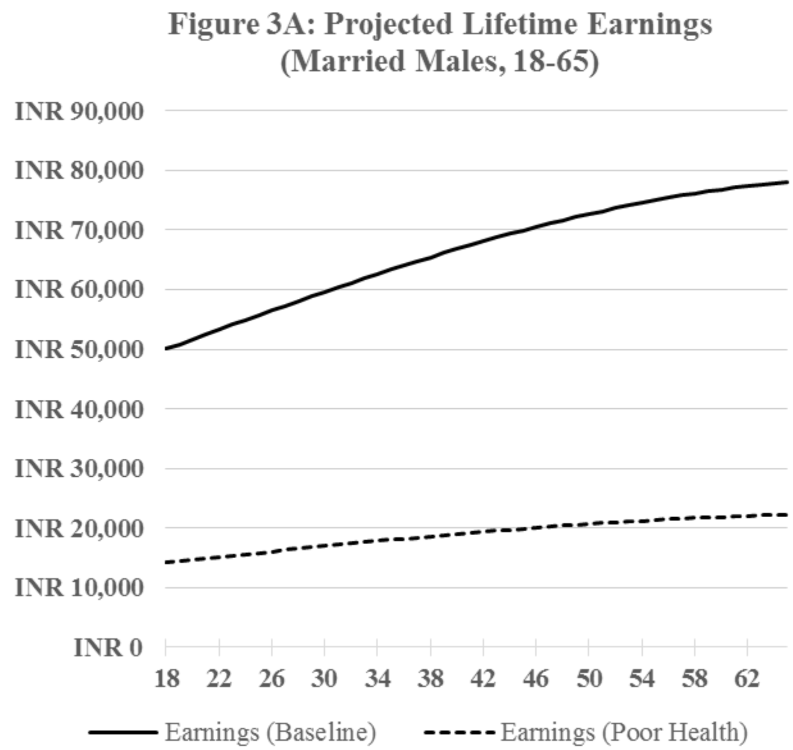


Figure 3A's projections were computed using the estimates of equation (10) and a direct comparison can be made with Figure 2A. These new estimates suggest that poor health has far greater consequences in terms of earnings and value of life. The estimated losses are presented for males in Table 5A.

Table 5A. Economic Loss Associated With Poor Health (IV estimates)

	PV of Foregone Earnings	PV of Loss Associated With Household Time	PV of Total Loss
Males	INR 828,678	INR 1,368,368	INR 2,197,046

The loss of 2,197,046 rupees is around 33 times the average annual earnings of a 40 year old male, as suggested by the new model. This figure is much larger than the estimate earlier presented.

5.3 Propensity Score Matching

Another method that can be used to estimate poor health's effects is propensity score matching. One benefit propensity score matching has over the previous two methods is that there is no parametric assumption in the estimation of the 'treatment effect.' When applying this method, the same set of independent variables as in (7) and (8) were used, with the exception of the PoorHealthDummy which was assigned as the 'treatment variable.' The results of the technique are shown below:

Table 6. Treatment Effect Estimates (Annual Earnings)

	Average Treatment Effect (ATE)	Average Treatment Effect on Treated (ATET)
Males	-INR 15,018	-INR 7,128
Females	-INR 6,157	-INR 2,409

All the above coefficients were significant at the 1% level, except the one for ATET, females (which was significant at the 10% level).

The economic loss associated with the ATET estimates can be seen in Table 6A below.

Table 6A. Economic Loss Associated With Poor Health (Propensity score matching estimates)

	PV of Foregone Earnings	PV of Loss Associated With Household Time	PV of Total Loss
Males	INR 135,297	INR 232,880	INR 368,177
Females	INR 45,725	INR 78,705	INR 124,430

These estimates are very close to the ones calculated from the OLS model in section 5.1.

6. DISCUSSION & CONCLUSION

Loss estimates in this paper (provided in Tables 4A, 5A & 6A) are varied, but it is clear is that the economic costs associated with poor health in India are substantial. A significant proportion of these losses are attributable to the decreased value of household time. This is a result of household time being valued at a lower wage rate. The losses associated with forgone earnings are attributable to a combination of fewer working days and lower productivity. These two factors seem to play a roughly equal role in reducing earnings. These costs belong in the evaluation of healthcare programs. In addition, this paper has provided evidence that decreasing levels of poor health should be an important consideration not only for health-related policy-makers, but also for those parties interested in increasing average levels of education, work intensity, productivity and earnings.

7. APPENDIX

Table 1C

Key statistics about population in dataset:

Table 1C. Descriptive Statistics

Age (mean)	29.8
% Female	50.1%
% Married	54.8%
Years of schooling (mean)	
if male	6.1
if female	4.7
% in labour force	35.3%
% Studying	27.2%
% Literate	68.4%
Annual household expenditure per capita (mean)	INR 24,323 (USD 518 in 2011)
% who smoke daily	30.1%
Total number of observations in dataset	204,569

Table 3

List of variables used in equations (7) – (10):

Table 3. Variable Definitions

Variable	Description
Poor Health Dummy	1 if individual was ill, disabled or had diarrhea in past 30 days
Age	Age in dataset
Age squared	Age squared
Years of Schooling	Number of years of formal education
Married	1 if married, 0 otherwise
Poor Health Dummy*Age	Poor Health Dummy x Age
Smoking Activity	1 if never, 2 if rarely, 3 if sometimes, 4 if daily
Alcohol Consumption	2 if never, 2 if rarely, 3 if sometimes, 4 if daily
Literate	1 if literate, 0 otherwise
English Ability	1 if none, 2 if little, 3 if fluent
Urban Dewlling	1 if urban, 0 otherwise
Uses Computer	1 if uses computer (any location), 0 otherwise
Lower Caste	1 if individual belongs to Scheduled Tribe (ST), Scheduled Caste (SC), Other Backward Classes (OBC) or Others group, 0 otherwise

<u>Figures 1C and 1D</u>

The below figures (1C and 1D) illustrate work intensity over time, subject to one's health status. These were estimated by regressing days worked on age and age^2.

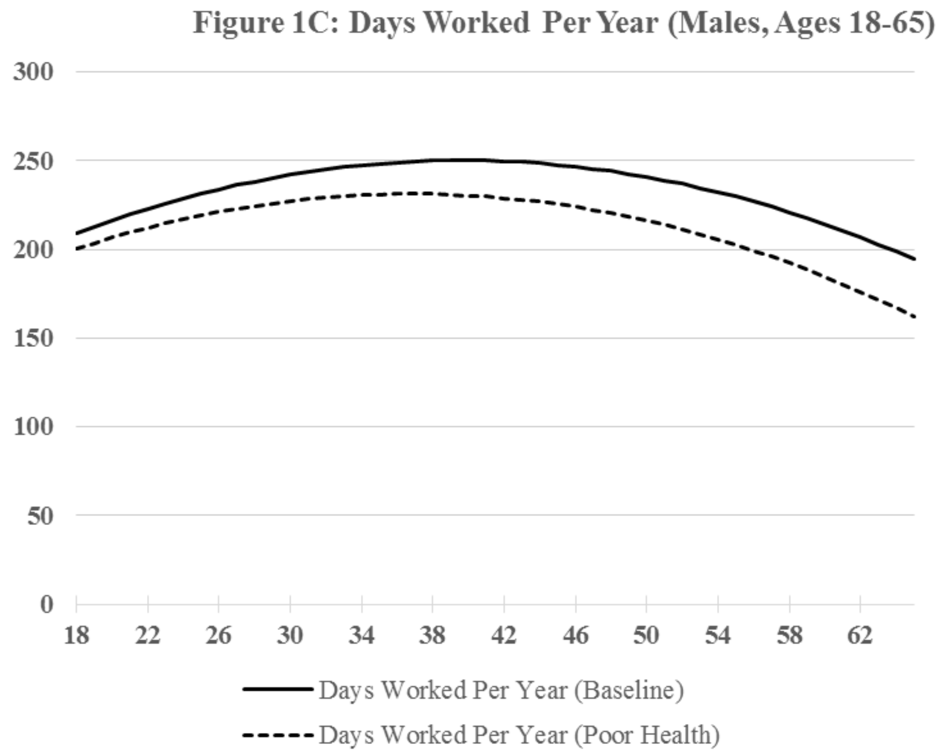


Figure 1D: Days Worked Per Year (Females, Ages 18-65)

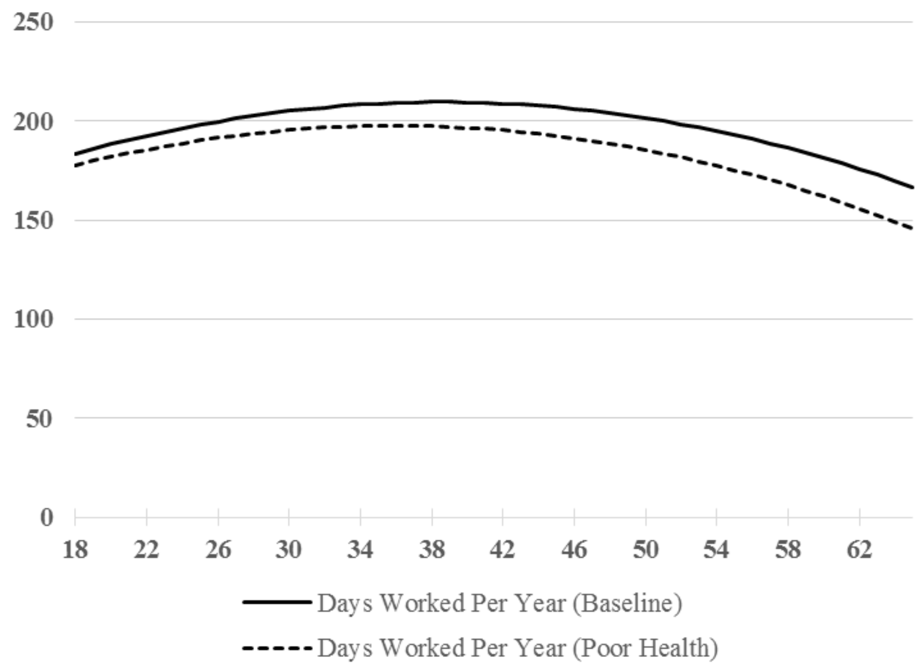


Table 5 - Results of IV regression (equations (9) and (10)):

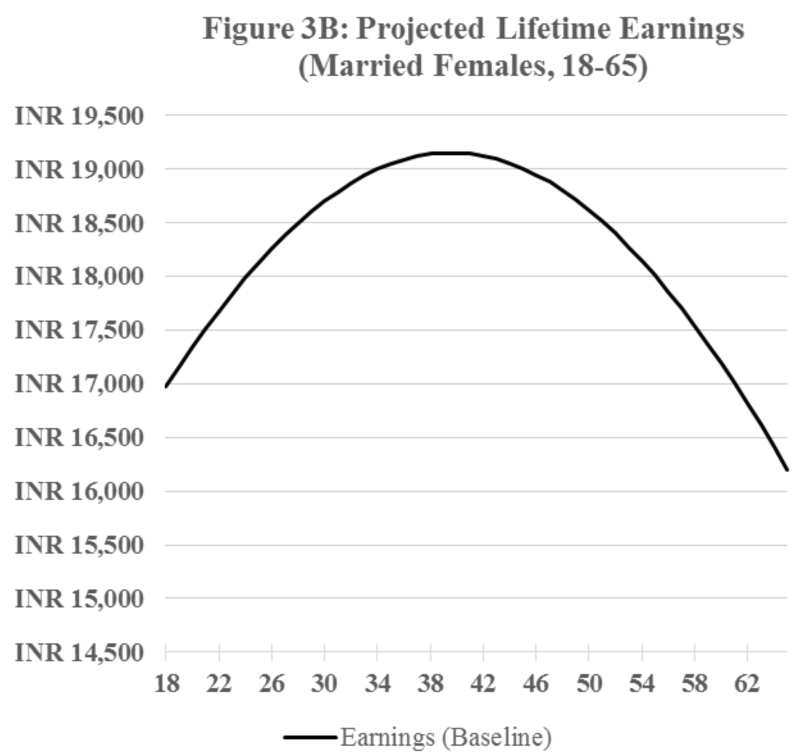
Table 5. Two-Stage IV Estimation Results		
	Males	Females
1st Stage Health Equation (t-stats in parentheses)		
Age	-0.00612* (-3.61)	0.00181 (0.22)
Age squared	0.0000927* (4.66)	0.0000118 (0.13)
Years of Schooling	-0.00138 (-1.24)	0.00219 (0.27)
Married	0.0129 (1.10)	0.0392 (0.43)
Literate	-0.00686 (-0.74)	-0.0558 (-1.10)
English Ability		
None	-	-
Little	0.00432 (0.53)	-0.0261 (-0.41)
Fluent	-0.0270 (-1.56)	0.0602 (0.36)
Urban Dwelling	-0.0151** (-2.47)	0.0174 (0.52)
Uses Computer	-0.000188 (-0.01)	-0.308 (-1.74)
Disadvantaged Caste (SC, ST, OBC)	0.00722 (1.08)	-0.0354 (-0.88)
Smoking Activity		
Never	-	-
Rarely	-0.00461 (-0.27)	-0.149 (-1.05)
Sometimes	0.0134(1.30)	0.0389 (0.41)
Daily	0.0270* (4.52)	0.0570 (1.23)
Alcohol Consumption		
Never	-	-
Rarely	0.00486 (0.48)	-0.0531 (-0.65)
Sometimes	-0.00190 (-0.31)	0.0235 (0.44)
Daily	-0.0269* (-2.88)	0.0677 (1.06)
Constant	0.207* (6.50)	0.146 (0.87)
F-stat	10.34	1.63
2nd Stage Hourly Wage Equation (z-stats in parentheses)		
Poor Health Dummy	-1.16* (-3.02)	1.032 (1.33)
Age	0.0216* (5.23)	0.0205 (1.53)
Age squared	-0.000146* (-2.72)	-0.000259 (-1.74)
Years of Schooling	0.0282* (11.8)	0.0274** (2.07)
Married	0.076* (3.07)	-0.111 (-0.74)
Literate	-0.0550* (-2.86)	0.0503 (0.53)
English Ability		
None	-	-
Little	0.125* (7.35)	0.323* (3.03)
Fluent	0.476* (12.7)	1.13* (4.11)
Urban Dwelling	0.284* (19.6)	0.195* (3.51)
Uses Computer	0.370* (11.4)	0.484 (1.31)
Disadvantaged Caste (SC, ST, OBC)	-0.0960* (-6.92)	0.104 (1.49)
Constant	2.35* (22.69)	1.78* (5.94)
Wald Chi-squared (11)	3658.3	184.39
N	16595	1349

Significant at 1% marked with *

Significant at 5% marked with **

Figure 3B

Figure 3B below illustrates projected earnings for the average female labour market entrant using estimates from equation (10). The results were unusual for those in poor health, likely due to the small sample size, and are not presented here.



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