UNIVERSITY OF CALGARY

The Role of Cognitive Ability in the Health – Education Nexus

by

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A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF ARTS

DEPARTMENT OF ECONOMICS

CALGARY, ALBERTA

APRIL 2004

UNIVERSITY OF CALGARY

FACULTY OF GRADUATE STUDIES

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies for acceptance, a thesis entitled "The Role of Cognitive Ability in the Health – Education Nexus" submitted by Nirmal S. Sidhu in partial fulfillment of the requirements for the degree of Master of Arts.

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February 27, 2004

ABSTRACT

This thesis, using the National Longitudinal Survey of Youth (NLSY), examines the role of cognitive ability in the health - education nexus and tries to estimate the effect of cognitive ability on health. The results of our study suggest that though schooling is still associated with health, this association is reduced by about half with inclusion of cognitive ability. The effect of cognitive ability on health is more stable and robust to different measures of health. Therefore, the well-documented association between health and schooling is partially attributable to cognitive ability. However, when schooling is treated as endogenous to health, cognitive ability is no longer statistically related to health but schooling appears to cause better health. We also find that studies that do not control for cognitive ability in the schooling equation, or in both the schooling and the health equation, tend to overestimate the association between schooling and health.

ACCNOWLEDGEMENTS

I would like to thank my supervisor, Dr. M.C. Auld, for his supervision and guidance while travelling this less travelled road that studies the role of cognitive ability in the health – education nexus. I thank U.S. Bureau of Labor Statistics whose dataset is the fabric of this research.

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INTRODUCTION

There are striking disparities in health by education throughout the world. For example, in the United States, babies born to women over the age of 20 without a high school diploma are 90 percent more likely to die before their first birthday than babies born to women who graduated from college (National Centre for Health Statistics, 1998). The link between health and education has been observed in many countries, including Canada, UK, the Netherlands, Sweden, France, and others. An extensive review of the literature conducted by Grossman and Kaestner (1997) suggests that the number of years of formal schooling completed are the most important correlate of good health. This finding emerges whether health levels are measured by mortality rates, morbidity rates, self-evaluation of health status, or physiological indicators of health, and whether the units of observation are individuals or groups. The literature also suggests that schooling is a more important correlate of health than occupation or income, the two other components of socio-economic status. This is particularly true when one controls for reverse causality from poor health to low income.

In a broad sense, the observed positive correlation between health and schooling may be explained in one of the three ways. First, there is a causal relationship that runs from increases in schooling to increases in health. Second, the direction of causality runs from better health to more schooling. Third, no causal relationship is implied by the correlation; instead, differences in one or more “third variables,” such as physical and mental ability and parental characteristics, affect both health and schooling in the same direction. It should be noted that these three explanations are not mutually exclusive and can be used to rationalize any observed correlation between any two variables. However, from a public policy perspective, it is important to distinguish among them and to obtain quantitative estimates of the relative magnitudes.

Individuals who choose higher levels of schooling are observed to be healthier than those choosing lower levels of schooling. One possible explanation for this empirical regularity is that those with more schooling are more efficient producers of health. Education may lead to a greater degree of productive efficiency, i.e. able to produce a larger health output from a given health input. Alternatively, education may enhance allocative efficiency, i.e. more efficient choice of inputs, with which to produce health (Grossman and Joyce, 1987). In this case, raising education levels would increase the overall health of the population. But schooling and health are jointly influenced by unobserved genetic, personality, and taste variables, such as time preference. If this is the case, then if individuals who selected greater levels of education are healthier, it does not mean that more education would improve the heath of people. The "third variables" hypothesis is well known and it is widely thought that these "third variables" do explain variation in health. Our interest in this study is to find out whether cognitive ability (or sometimes called "ability") could be one of the third variables responsible in explaining the variation in health.

Inequalities in health and mortality exist among different socio-economic groups. People living in deprived conditions generally suffer more illness and die younger, and socio-economic circumstances in childhood are related to mortality from several illnesses. Educational level also contributes to differences in mortality among socio-economic groups. Higher mental ability, as assessed by psychometric tests, is associated with favourable educational and occupational outcomes (Neusser et al., 1996). Socio-economic status, educational level, and mental ability are closely related. However, there is little information about the link between mental ability and morbidity and health.

Individuals differ in their ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, and to overcome obstacles by thought. These differences could lead to differences in the ability to tackle health problems. Therefore, if the positive correlation between health and education is due to cognitive ability, then education may not be as important a policy variable as it is thought to be at present. This thesis presents evidence on the effect of schooling and cognitive ability on health. We include indicators of cognitive ability and social background into our empirical analysis. Besides purging the estimated schooling effect of biases, this research would provide us with the information about the relative contributions of schooling, general intelligence, and social background.

Mental ability could be a reliable and valid indicator for several disparate antecedents and outcomes. However, the effect of IQ is difficult to separate from the effects of social class and education. These variables are moderately highly correlated, and one can act as a surrogate for one or more of the others in causing associations. For example, personality traits partly explain the association between childhood social class and poor health in adulthood (Bosma et al., 1999). The US National Longitudinal Study of Youth showed that, within the white American population, both parental social class and cognitive ability in the late teens were associated with multiple indices of social, educational, and occupational outcomes many years later, although the effects were small. Social class and mental ability would often retain their influence on outcomes after co-variation was statistically controlled for. This indicated that mental ability is not entirely a surrogate for social class and vice versa. These types of studies attracted renewed attention following the publication of *The Bell Curve* by Herrnstein and Murray (1994), who claim that intelligence is the dominant factor in explaining a large number of different outcomes (among others are earning, employment, poverty, welfare dependency, and crime). An empirical model that captures all possible relations between schooling, cognitive ability, and health is very involved. Interest in schooling has also received renewed attention for the endogeneity of schooling (Card, 1994). Different variables are potentially endogenous (health, education, occupation) and causality may operate in different directions. Empirical studies, therefore, tend to focus on a limited number of relations.

The "Flynn effect" is now a well-documented fact (Neusser et al., 1996). Mean IQs have increased more than 15 points - a full standard deviation – in the past

50 years and the rate is increasing. These gains may be from improved nutrition, cultural changes, schooling, child-rearing practices, and some other unknown factors. One hypothesis to explain these gains is modern improvements in nutrition. Therefore, an important indirect issue is that if IQ affects health and childhood nutrition affects IQ, then childhood nutrition becomes extremely important. If these high rates of malnutrition in the first years of life imply negative effects on IQ, then to find the effect of IQ on health becomes an important issue.

The correct explanation for the observed schooling-health correlation is important from a policy standpoint. In the vast majority of studies conducted by economists considering the determinants of an individual's health, the number of years of schooling has stood out as having a large and significant estimated effect. Grossman (1975) and Auster, Levenson, and Sarachek (1969) have suggested that expenditure on education is a cost effective way for increasing aggregate levels of health. But if this observed correlation is due to cognitive ability, then the results of these studies could be spurious. The contribution of this research is to investigate the role of cognitive ability in the health-education nexus and to investigate the direct effect of cognitive ability on health. To investigate these effects, a series of regressions are done. These include a single equation, two-stage least square regression, and semi-parametric estimation. Each regression controls for a number of observable characteristics of the respondent.

The results of our study suggest that though schooling is still associated with health, this association is reduced by about half with inclusion of cognitive ability. The effect of cognitive ability on health is more stable and robust to different measures of health. Therefore, the well-documented association between health and schooling is partially attributable to cognitive ability. However, when we account for the endogeneity of schooling and use two-stage model, the results above are not very strong and not robust to different measures of health. When schooling is treated as endogenous to health, cognitive ability is no longer statistically related to health but schooling appears to cause better health. We also find that studies that do not control for cognitive ability in the schooling equation, or in both the schooling and the health equation, tend to overestimate the association between schooling and health.

The remainder of this thesis is as follows: Chapter 2 discusses the literature around schooling, socio-economic status (SES), cognitive ability, and nutrition. Chapter 3 discusses the data used in this study. Chapter 4 discusses the analytical framework and empirical model, and Chapter 5 reports the results, empirical analysis, and conclusions of this research. Chapter 6 discusses policy implications.

2

REVIEW OF LITERATURE

This chapter is organised into four different sections. Each section discusses the literature around a particular topic. These are as follows: Section 2.1, schooling and health; Section 2.2, health and socio-economic status (SES); Section 2.3, health and nutrition; and Section 2.4, health and cognitive ability or intelligence. Finally, Section 2.5 concludes the literature reviewed in different sections and points out the contribution of this research to literature.

2.1. HEALTH AND SCHOOLING

In the vast majority of studies conducted by economists considering the determinants of an individual's health, the number of years of schooling has stood out as having a large and significant estimated effect. This is true regardless of the health measure. As it is widely perceived that there is public interest in improving health (including health habits) and education throughout the world, to some extent, improvements in health might be brought about by increasing education. Yet, there is little agreement concerning the mechanisms through which schooling enhances health. Some have argued for a direct effect, whereby schooling enhances the production of health (Ausster, Levenson, and Sarachek 1969, Grossman and Joyce 1987, Rosen and Taubman 1982, and Taubman and Rosen 1982). Others assert that one or more unobserved variables such as genetic or personality factors affect both health and schooling in the same direction (Fuchs 1982, Farrell and Fuchs 1982). Finally, others point to reverse causality, arguing that better health results in more schooling (Edwards and Grossman 1979, Perri 1984, Shakotko, Edwards and Grossman 1981, Wolfe 1985).

The issue of the interrelationship between education and health has produced controversy. In his address to the American Economic Association, Fuchs (1996) argued that the positive correlation between health and years of schooling is not a result of schooling increasing an individual's ability to produce health. He argued that schooling is correlated with time preference, and it is time preference that affects health behaviour rather than schooling.

A study by Fuchs (1982) on time preferences and a study by Farrell and Fuchs (1982) on smoking provide empirical support for this view. Similar evidence was found by Sander (1998) who studied the effects of schooling, cognitive ability, and time preference on the probability that young adults smoke or use marijuana. Schooling, cognitive ability, and time preference all affect likelihood of smoking. Evidence is presented that some of the negative correlations between attending college and smoking can be attributed to a difference in cognitive ability and time preference.

Arendt (2001) investigated whether unobserved variables explain the correlation between health and education. The two hypothesis about unobserved variables being investigated were endowment hypothesis and time preference hypothesis. The results were inconsistent with the above two commonly postulated hypothesis about the effects of unobservables and supported a hypothesis of causal educational effects on health.

In contrast, Grossman (1972, 1975), and Becker and Mulligan (1994) argue that schooling has a positive effect on the production of health through improving health behaviour. Grossman and Kaestner (1997) surveyed a number of studies that show favourable effects of schooling on health behaviour. One of the ways that schooling might improve health habits is through lowering the rate of time preference, thus making individuals more future oriented (Becker and Mulligan, 1994). Berger and Leigh (1989) estimated a model using the Health and Nutrition Examination Survey (HANES) and the National Longitudinal Survey of Young Men (NLS) in which both schooling and health are endogenous and allowed to affect each other. Instrumenting schooling in the health equation, they find that the direct effect of schooling on health is more important than the effect of unobservable factors such as rate of time discount.

Arkes (2001) reported that the schooling effects are greater in the two-stage probit models than in the corresponding standard probit models for two of three health measures. This analysis used intra-state differences in unemployment rates during a person's teenage years as an instrumental variable to address potential selection bias problems in estimating the effects of schooling on adult health outcomes. The two-stage probit models indicated that a year of schooling reduces the probability of having a work-limiting health condition by 2.6 percent points and reduced the probability of requiring personal care by 0.5 percent points. Both these estimates we reported to be statistically significant.

Lleras-Muney (2002) studied the relationship between education and adult mortality for US. The results provided evidence in support of perhaps bigger causal effects of education on mortality than the previous literature suggested. AGLS estimates suggested that an additional year of education lowers the probability of dying in the next 10 years by approximately 1.3 percentage points and IV estimates showed that the effects is 3.6 percentage points. However, the results also suggested that the OLS and the IV estimates are not statistically different.

The effect of education on health investment was also reported by Khan (1998). This empirical work focused on how education affects health investment proxies such as smoking, blood sugar control, and diet. Increased education was reported to have positive impact on diabetic health investment even after controlling for IQ and available information.

2.2. HEALTH AND SOCIO-ECONOMIC STATUS (SES)

In this section, we discuss the literature on the role of Socio-Economic Status (SES) in the health – education nexus.

The bulk of the literature on health and SES discusses the pathways from SES to health. Meara (2001) investigated the possible mechanisms linking Socio-economic status (SES) to health. In a case study of pregnancy and health at birth, she concluded that a limited set of health habits during pregnancy, particularly smoking habits, can explain about half (one third) of the correlation between SES and low birth weight among white (black) mothers. Second, women respond to common knowledge differently by SES, so the knowledge and its use combined explain up to one third of differential smoking by education. Third, the most important determinants of differential health behaviour are "third variables," or the variables that can simultaneously determine health habits and SES. Ettner (1996) provides no evidence of how income affects health, but the most commonly mentioned mechanisms that might lead from SES to health include access to medical care (Townsend et al. 1998, and Adler et al. 1993), and the ability to collect and use health information to make wise investments (Grossman 1975, Townsend et al. 1988, Kenkel 1991, and Chomita et al. 1995), unhealthy life style choices of the poor (Adler et al. 1993, Marmot et al. 1984, Lantz et al. 1998), or that low status relative to others has direct and independent health effects (Wilkinson 1996, Marmot et al. 1992, Sapolsky 1993, Deaton and Paxson 1999). Grossman and Kaestner (1997), while addressing the effects of education on health, point out some striking correlations between increased education and decreased infant mortality. They also indicate that despite the narrowing gap between years of schooling attained by blacks and whites, there has been no narrowing between black and white infant mortality rates. This suggests a new line of research: the education and health correlation might differ across race (Leigh and Dhir, 1997).

There is now increasing evidence that differences in adult health are partly caused by socio-economic factors during early life and upbringing. The contributions of psychological attributes, such as personality factors and coping styles, have received little attention. Psychological attributes are partially rooted in environmental conditions in childhood, (learning) experiences, and rearing styles. There is now increasing evidence that psychological attributes influence health through behavioural mechanisms (for example, smoking). Unhealthy personality factors and coping strategies may, therefore, be the mechanism through which adverse socio-economic conditions in childhood contribute to poor health in adulthood. Bosma et al. (1999) studied the contributions of psychological attributes (personality characteristics and coping styles) to the association between social class in childhood and adult health. Independent of adult social class, low childhood social class was related to self-rated poor health. A higher prevalence of negative personality profiles and adverse coping styles in subjects who grew up in lower social classes explains part of the association between social class in childhood and adult health. Unhealthy psychological attributes (personality factors and coping styles) are more common in people who reported low childhood social class.

2.3. HEALTH AND NUTRITION

Studies that link child nutrition and school performance typically show that malnutrition is correlated with poor school performance. However, most of these studies do not test for causality, that is, whether poor nutrition causes poor school performance (Grantham-McGregor 1995, Behrman 1996). Because disadvantaged children are more likely to be both undernourished and weak students, it is not clear whether their poor performance in school is primarily because of poor nutrition or to other aspects of their disadvantaged circumstances. Behrman and Wolfe (1989) estimated the impact of schooling on women's health and nutrition outcomes in Nicaragua with and without control for unobserved childhood background related ability and motivation. For this, they estimated both random-effects and fixed-effects representations of such background-related characteristics. It was found that women's schooling does positively affect women's health and nutrition even with control for unobserved random and fixed childhood background related characteristics.

A few experimental and quasi-experimental studies generally support the hypothesis that causality runs from poor nutrition to poor school performance (Gorman 1995, Pollitt et al. 1995). Yet, little is known about the mechanisms and process that govern this causality, which in turn hampers efforts to design more effective nutrition policies. The most likely pathways involve the effects of inadequate intake of calories, protein, and specific micronutrients on cognitive development, which in turn affect school performance and hence may be, in turn, affecting health. A study, by Glewwe and King (2001), estimated the effect of the *timing* of early childhood malnutrition on cognitive development, using data from the CLHNS, a joint undertaking of the Office of Population Studies at the University of San Carlos, the Philippines, and the Carolina Population Centre of the University of North Carolina. The tentative conclusions they drew from this study include the following: First, neither the reduced-form nor the conditional demand estimates support Dobbing's claim that the most critical period is the first six months of life, nor do they support the hypothesis that prenatal nutrition is more critical than the post-natal nutrition. Second, both sets of estimates suggest that the period from 18 to 24 months may be critical. Third, the reduced form estimates indicate that price subsidies for food could improve children's nutritional status, but programmes that directly provide medical or education services for young children may be more cost effective. In sum, the results suggest that malnutrition during early childhood can reduce cognitive performance later in life, but do not support the claim by certain observers that certain time periods are critical.

2.4. HEALTH AND INTELLIGENCE

An important indirect issue is that if IQ affects health and childhood nutrition affects IQ, then childhood nutrition becomes extremely important. However, there are only a few studies that estimate the effect of IQ on health. Whalley and Deary (2001) found that childhood mental ability is a significant factor among variables that predict age at death. A 15 point disadvantage in mental ability at age 11 (when IQ test was conducted) conferred a relative risk of 0.79 of being alive at age 65 years later (95% confidence interval 0.75 to 0.84); a 30 point disadvantage reduced this to 0.63 (0.56 to 0.71). Hartog et al. (1998) explored the effect of schooling on health, wealth, and happiness for a cohort of Dutch individuals born around 1940. Schooling affected health but not monotonically, and the highest health status was for secondary education. IQ was reported to have an independent affect on health status, even after controlling for schooling. This points either to an innate correlation between ability and health or to higher IQ, stimulating more prudent health care. On the reverse causality, Behrman and Lavy (1994) explored the influence of a child's health on achievement in school using the Ghanaian Living Standards Measurement Study (LSMS) and found no evidence of an impact of the observed range of child health on child cognitive achievement. The prolonged malnutrition during childhood could have long-term intellectual effects, but these are not easy to establish, in part because many other unfavourable socio-economic conditions are often associated with chronic malnutrition (Ricciuti, 1993; Sigman, 1995).

2.5. CONCLUSION

This chapter summarised the literature dealing with the issues of health and education, socio-economic status (SES), and cognitive ability. The indirect issue of the importance of nutrition is also reviewed in Section 2.3. In general, a wide range of issues to do with health has been studied, but the effect of cognitive ability is investigated in only two studies. These are reviewed in Section 2.4, using a single equation and ignoring the issue of endogenity of schooling.

This study extends these results in two ways. First, the effect of cognitive ability on health is measured using an instrument variable approach, hence taking care of the issue of endogneity of schooling. Second, any misspecification in the functional form leads to inconsistent estimates of the true derivatives and may affect the size and power of any test performed on them. Consequently, the semi-parametic mode of analysis is applied to estimate the effect of cognitive ability.

3

DATA SET AND DATA ISSUES

This chapter introduces the data set and measures of cognitive ability used in this research. Section 3.1 discusses the data set used. Section 3.2 outlines the issues around cognitive ability and its measurement. Section 3.3 discusses the use of the Armed Forces Qualification Test (AFQT) as a measure of intelligence in the semi-parametric estimation. Section 3.4 lists the health variables used in the estimation. Section 3.5 discusses measurement issues and their limitations. In Section 3.6, descriptive statistics are discussed. Finally, Section 3.7 concludes these issues.

3.1 DATA SET

The primary purpose of the NLSY79 was to collect data on labour market experiences and investments in education and training by each respondent. The content of the survey is much broader because of interest by other governmental agencies besides the Department of Labour, which sponsored this survey.

The National Longitudinal Survey of Youth (NLSY) is designed to represent the entire population of American youth. This survey consists of a randomly chosen sample of 6,111 US civilian youths, a supplementary sample of 5,295 over sampling minority and economically disadvantaged civilian youth, and a sample of 1,280 youth on active duty in the military. All youths were between thirteen and twenty years of age in 1978 and were interviewed annually, starting in 1979 until 1994 and thereafter on biennial basis. The data includes an equal number of males and females. Roughly 16 percent of the respondents are Hispanic and 25 percent are black.

In 1980, NLSY respondents were administered a battery of ten intelligence tests referred to as the Armed Services Vocational Aptitude Battery (ASVAB). The Armed Services Vocational Aptitude Battery (ASVAB)[6] is available for 11,914

NLSY respondents, i.e. 94% of sample size. This data includes the individual respondent raw score, the standard score, and two constructed AFQT (Armed Forces Qualifications Test)[7] scores. The ASVAB is a state-of-the-art aptitude battery (Jensen, 1985; Murphy, 1985) and an excellent source of data for investigating the effect of intelligence (or cognitive ability) on the outcome of interest: health in our case.

There are various reasons for using the NLSY79 to measure the effect of cognitive ability on health. First, it is the only survey that provides information on the Armed Services Vocational Battery (ASVAB) that was administered to the whole sample in 1980. This information makes it possible to measure "g," which is the measure of cognitive ability used in this study. In addition, this survey provides information on the Armed Forces Qualification Test (AFQT) that is used as a measure of intelligence for semi-parametric estimation. Second, this survey provides detailed background characteristics about the respondents, such as education, past health and family background. Third, it provides information on a large number of control variables.

3.2 MEASUREMENT OF COGNITIVE ABILITY

In their controversial book *The Bell Curve*, Herrnstein and Murray (1994) summarize an impressive body of research on the correlations between social outcomes and scores on tests of cognitive ability. A remarkable finding of their research is that one linear combination of tests – called "g" – predicts performance almost as well as the full battery of tests. "g" is formed by taking principal components of the correlation matrix of test scores. The components associated with the largest eigen value is multiplied by the test score to form "g." Spearman first proposed that general intelligence, or "g," is a common ability that explains performance on all tests of intelligence. Both assumptions have been questioned in the literature. Theories of multiple abilities go back to Thurstone (1947). Carroll (1993) provides a comprehensive discussion of the evidence[2]. Here we examine the role of "g" in explaining any variation in health using NLSY data.

The critical issue is the appropriate measure of intelligence to use for measuring the effect on health. Herrnstein and Murray (1994) argue that there is only one significant intelligence factor called general intelligence or "g." They fail to mention that many psychometricians who endorse the theory of general intelligence also maintain that there exist other factors of intelligence, which have less explanatory power than "g" but are nonetheless both statistically and numerically significant in describing outcomes. For example, Spearman (1927) incorporates specific factors "s" which complements general indigence "g." Cattell (1987) describes two forms of general intelligence: "fluid," which is applied to all tasks, and "crystallized," which is a combination of fluid intelligence and practice or study of a specific task. Carrol (1993) posit a three-stratum theory of intelligence in which cognitive abilities range from the narrow to the highly general.

The "g" is measured by the product of the test score vector and the eigenvector associated with the largest eigen value of the matrix of correlations among standardised ASVAB scores. It is well known that the score of "ability" tests rises with the age and education of the test taker. This by itself indicates that the tests measure knowledge and not some abstract ability that is independent of specific knowledge. Because our models do include schooling and age variables, we do account for this finding. We use principal component analysis to construct "g." It should be stressed that the principal components are a mathematical construct, and it can be misleading to describe principal components in terms of observed human skills[3] (for details see Cawley, 1996).

We use principal components to estimate "g," but principal factor analysis and hierarchical factor analysis produce essentially the same results (Heckman, 1996). The principal components method is least affected by sampling errors (Jensen, 1987), and Ree and Earles (1991) find that the correlation between each pair of the three estimates of "g' is 0.996. The mathematically simple principal components (Hotelling, 1933a, 1933b) were chosen to represent "g." These principal components have the additional benefit of being orthogonal, which circumvents the problem of collinearity and enhances their usefulness in regression (Kendall, Stuart, & Ord, 1983). However, no matter which method is used, "g" is only as good a measure of cognitive ability as its constituent tests. Many features of personality, the ability to use knowledge, and motivation are not captured by the ASVAB (Cawley et al., 1996).

Ironically, while Herrnstein and Murray embrace the theory of "g," they use a different measure of intelligence: the Armed Forces Qualification Test (AFQT) score which is the sum of the ASVAB subsets; Work Knowledge, Paragraph Comprehensive, Arithmetic Reasoning, and Mathematics Knowledge are their measures of general intelligence. If AFQT is the best measure of general intelligence, then the first principal components should weight each of the four subsets that constitute AFQT by an equal amount and assign zero weights to all other subsets. Cowley et al. (1996) do not find such a pattern and report that AFQT is highly correlated with "g" (ρ=0.829); it is a sub optimal measure of general intelligence. Moreover, the first principal component is strikingly similar across race and gender (Heckman, 1996)). This has generally been found to be true for different racial populations that share the same language and culture (Jensen, 1987). The key test for a theory of single intelligence is not how well "g" explains performance on the intelligence test from which it is derived, but how well it predicts social outcomes and, in our case, health.

3.3 USE OF AFQT FOR SEMI-PARAMETRIC ESTIMATION

The major complication in a purely nonparametric (NP) approach to estimation is the "curse of dimensionality" and it needs a very large sample if an accurate measurement of the function is to be made. Moreover, the size of sample required increases rapidly with the number of variables involved in any relation. Such a feature leads to the proposition that we restrict all the variables to have a linear impact while allowing measure of intelligence, which is of fundamental concern to us, to be nonlinear one. This combination of parametric and non-parametric methods is described as semi-parametric (SP), henceforth.

The advantage of using AFQT against "g" is that we can group our sample into different percentile groups. For our analysis, we group our sample into

(1) Ten deciles;
(2) Respondents with percentiles score less than 10, in between 10 and 20, 20 and 35, 35 and 55, 55 and 75 and greater than 75.
(3) Four quarters each having 25% of respondents, from lowest to highest;
(4) Five groups each having about 20% of respondents, from lowest of highest;

This grouping of AFQT score helps to analyse how an increase in intelligence level affects health and to see whether a different grouping makes any difference in our results.

We find that there are few observations in the outlier categories: the group with lowest Schooling and highest AFQT score and another group with lowest AFQT with highest Schooling. These two categories could bias our estimates most. By forming a grid as mentioned above, we are able to circumvent this problem.

3.4 HEALTH VARIABLES

The health variables available from NLSY are those traditionally used by economists. The ones used here are binary variables representing the presence of work preventing or limiting disabilities (ICD-9 codes) and the presence of functional limitations. We recognise the possible limitations of these variables (e.g. see Parsons, 1982, Lambrinos, 1981, Gustman and Steinmyer, 1986, Mitchell and Pincus, 1987). Because they are self-reported, they may be subject to measurement error; however, measures of functional limitation are less likely to suffer from incentives to misreport. While these measures provide a picture of a respondent's current health restrictions, they offer little insight into chronic health problems that will affect their labour force activity in future.

Other health measures we use is a respondent's self-assessment of general health on a scale of one to five, and Does health limit moderate activities and ability to climb stairs? and Did pain interfered with normal work? (SF-12). Two other health variables are a respondent's physical health component summary and a mental component summary (SF-12).

To measure mental health, the Centre for Epidemiological Studies Depression Scale (CES-D) is used. This scale measures symptoms of depression and is highly correlated with other depression-rating scales (see Radloff, 1977; Ross and Mirowsky, 1989).

3.5 DESCRIPTIVE STATISTICS

This section describes the covariates used in the study. The summary statistics are listed in Tables 1a and 1b. Section 3.5.1 describes data on the respondent's education. Section 3.5.2 describes the data on socio-economic status and Section 3.5.3 describes the data on demographic characteristics and other control variables.

3.5.1 EDUCATION COVARIATES

The number of years of schooling is constructed in every wave of the survey by administrators. This variable is chosen because it indicates the amount of time a respondent is willing to invest in human capital accumulation. In an effort to maximize the probability that any particular respondent had reached his or her academic goals, the number of completed years of schooling as of May 1 is taken from the 2000 wave of the survey.

3.5.2 SOCIO-ECONOMIC STATUS (SES)

This section describes variables indicating the socio-economic status (SES). It includes the highest level of schooling completed and occupation of parents in 1979. The binary variables are created for different categories of professions and the missing category for both father and mother is professional respondents. These variables, including the number of siblings, were used to instrument education as was done in the Berger and Leigh (1989) study.

3.5.3 DEMOGRAPHIC CHARACTERISTICS AND OTHER CONTROL VARIABLES

This section describes a respondent's ethnicity, gender, age, residence, family size, marital status, and whether the respondent lived with both biological parents until the age of 14. Three binary variables were constructed to represent whether the respondent is Hispanic, Black or White. The omitted category is white, non-Black, non-Hispanic respondents. Three binary variables were constructed of the marital status of the respondent, namely, married, never married, or others. The omitted category is never married respondents.

The information on the residence of the respondent has many covariates. These included whether the respondent lived in the south at the age of 14, the urban/rural status of resident at the age of 14, his or her SMSA (Standard Metropolitan Statistical Area) status, and the urban/rural status of residence in 1979 and 2000.

The empirical model is constructed using two time periods: a schooling period (period 1) and a post-schooling period (period 2). In period 1, the information on demographic and other characteristics is used for the year 1979, and in period 2, the information used is for the year 2000.

3.6 MEASUREMENT ISSUES AND LIMITATIONS

In this section, the limitations of using years of schooling as a measure of education are discussed. Some forms of intelligence which may not come out in intelligence tests are also pointed out in Section 3.6.2. The limitations of using work-limiting health measures are discussed in Section 3.6.3.

3.6.1 LIMITATION OF USING YEARS OF SCHOOLING AND "g"

To treat the years of schooling as a conceptually right and error-free measure of educational attainment is hardly tenable in the light of the extreme diversity of education in US (NLSY is on the US population). The data we use on education is measured by the number of years of schooling. This measure is far from ideal. For the education variable, what we would like to have is a measure of education achieved E. Instead, what we have is years of schooling S completed without reference to the conditions under which individuals obtained their formal schooling and the kinds of schooling pursued. Let us call this discrepancy between the variables "quality" Q (where $E=S+Q$) and assume that it is uncorrelated with the quantity of schooling (S). At the same time, the quality of schooling is likely to be correlated with ability because (1) there is some correlation between socio-economic status and ability, and (2) more able students are more likely to get into better schools.

Allowing for these differences in the quality of education, the assessment of the bias in the estimated education coefficient is somewhat more complicated because the true equation becomes

$$H = \alpha + \beta S + \beta Q + \delta g + u$$

and we do not have a measure of quality.

In this framework, ignoring not only "g" but also Q leads to the same result as before, because b_{QS} (the regression coefficient of quality on quantity of schooling) is zero by assumption. However, when a measure of ability is included in the estimation equation, the estimated education coefficient becomes $b_{HS.g}=\beta+\beta b_{QS.g}$, where $b_{QS.g}$ is the partial regression coefficient of quality on quantity of schooling, holding ability constant. Given our assumptions, it can be shown that $b_{QS.g}= b_{Qg}* b_{gS}/(1-r^2_{gS})$, where r^2_{gS} is the square of the correlation coefficient between the quantity of schooling and ability (Zvi and Mason, 1972). Since we expect both b_{Qg} (the regression coefficient of educational quality on individual ability) and b_{gS} (the regression coefficient of individuals' ability on quantity of schooling) to be positive, $b_{QS.g}$ will be negative. Substituting this expression for $b_{QS.g}$ back into the expression for $b_{HS.g}$ gives $b_{HS.g}=\beta-\beta b_{Qg}* b_{gS}/(1-r^2_{gS})$. Because $b_{HS}=\beta-\delta b_{gS}$, it is clear that by going from b_{HS} to $b_{HS.g}$, we reduce the coefficient of schooling for two reasons (Zvi, and Mason, 1972). First, we eliminate the upward bias due to the earlier omission of ability. Second, however, we introduce another bias owing to the correlation of ability with the left-out quality variable. This new bias is partially a function of the magnitude of the correlation between quantity of schooling and ability. We control for the second type by concentrating on "g," which we get after regressing the test scores on age and education.

3.6.2 LIMITATION OF INTELLIGENCE TESTS

The objection to intelligence testing is that to base a concept of intelligence on test scores alone is to ignore many important aspects of mental ability. It is widely agreed that standardized tests do not sample all forms of intelligence. Obvious examples include creativity, wisdom, motivation, ability to use knowledge, practical sense, and social sensitivity; there are surely others.

3.6.3 LIMITATION OF WORK-LIMITING HEALTH MEASURE

The first health indicator—whether the person has a work-limiting health condition—has a few shortcomings. One may argue that certain illnesses could affect people with different jobs in different ways. For example, a construction worker who breaks a leg would be limited in his work, but a lawyer would not. While this highlights another benefit of schooling—having a better chance of acquiring a job that can be performed mostly independently of physical health—it also demonstrates that, with this variable, there could be a measured health difference between two people even though their physical conditions are the same. Another shortcoming of this health indicator is that some may report having a work-limiting health condition as an ex-post justification for not working. Fortunately, the other two health measures used in this research should not be subject to the shortcomings of the first one.

3.7 CONCLUSION

This chapter introduced the data used for the research. It also discussed the issues involved and advantages of using '"g" as a measure of cognitive ability and use of Armed Forces Qualification Test (AFQT) in semi-parametric estimation. Wide ranges of health measures used in this research are also discussed. We also provided the reasons for using this survey for the present study. A description of the covariates is outlined in Section 3.5. Finally, we discussed the possible limitations of using years of schooling and cognitive ability or intelligence measures.

4

ANALYTICAL FRAMEWORK AND EMPIRICAL MODEL

The analytical framework of the research is outlined in Section 4.1. Section 4.2 lays out the empirical models being estimated in this research. Section 4.3 discusses the estimation techniques employed in this study. Section 4.4 concludes.

4.1 ANALYTICAL FRAMEWORK

In Sections 4.1.1 and 4.1.2, we discuss the conceptual and econometric issues involved in this research. Section 4.1.3 reasons out that non-inclusion of income as one of the regressors. Section 4.1.4 lays out the hypothesis being tested in this study.

4.1.1 CONCEPTUAL ISSUES

The Grossman model of education and health draws an important distinction between allocative efficiency and productive efficiency. In simple terms, allocative efficiency addresses effects due to information. Presumably, better-educated people have more health knowledge than poorly educated people do. However, a second factor is that they not only have more knowledge/information, but they also believe that information/knowledge. Better-educated people are more likely to believe scientific reports or information than poorly educated people are. Productive efficiency refers to the greater ability of the better educated to produce health than the poorly educated people, assuming both have the same information (and believe it). Better-educated people might more frequently follow the doctor's advice than the poorly educated people might.

According to Grossman (1999), schooling increases the production of health because more educated individuals are better producers of health. For example, more educated individuals better understand how their behaviour might affect their health. However, schooling might affect health through other means such as lifestyles, culture, work, and tastes and by making individuals future oriented. According to Fuchs (1982, 1996), Farrell and Fuchs (1982), it is time preference that explains the schooling-health behaviour relationship: individuals with higher (lower) rates of time preference are more (less) likely to smoke and less (more) likely to invest in education. However, another possibility that Farrell and Fuchs did not consider is that schooling might affect the rate of time preference. According to Becker and Mulligan (1994), "educated people should be more productive at reducing the remoteness of future pleasures." They imply that schooling should reduce the rate of time preference and increase the probability that individuals live healthy lifestyles. Recently, Becker (1996) presented a model to describe how schooling might lower time preference. Earlier, Leigh (1986) demonstrated a strong correlation between more years of schooling and lower time preferences in the Panel Study of Income Dynamics.

Moreover, an entire field of Psychology (Cognitive Psychology) has developed around understanding time preferences. One line of research in this field has specifically addressed time preference or what psychologists refer to as the "ability to delay gratification." Maital and Maital (1977), an economist and a psychologist, point out that psychologists have noted strong correlations between education and measures of time preferences or "ability to delay gratification." Psychologists have also found that black children are more likely to have a high time preference than white children are. In part, this may be the result of a black child's disbelief that a promised future reward will indeed be forthcoming.

One view is that time preferences are similar to IQ. It is largely genetically determined. This view is in contrast to that of psychologists who suggest a large role of parents and schooling in determining time preference (Maital and Maital, 1977). Moreover, it could be that high educational attainment among parents helps them inculcate the ability to delay gratification in children. If so, then the benefits of education may be even greater than is commonly believed.

One study by Sander (1998) indicates that attending college has a modest effect on smoking. If adjustments are not made for either cognitive ability or future education (possibly a correlate of time preference), the effect of attending college on smoking is modestly inflated. Further results for cognitive ability reducing smoking also provide support for the hypothesis that schooling matters because test scores are partly result of the quality of schooling. That is, ability in cognitive ability score (or IQ score) is partly acquired through schooling. Test scores are undoubtedly related to other factors such as family background and innate ability. Thus,. Sander's study on smoking behaviour indicates that schooling, mental ability, and time preference all seem to affect smoking behaviour. Thus, he finds support for the argument that both schooling and time preference (future schooling) matter. In other words, he found support for the Grossman model that schooling improves health habits and for Fuchs' view that time preference (using future schooling as a proxy) improves health habits. One implication of this result, however, was that the relationship between education and health habits might be specific to the habit in question, as there are large differences in the determinants of decisions to smoke, use illegal drugs, exercise, and abuse alcohol.

4.1.2 ECONOMETRIC ISSUES

There are certain econometric problems in studying this schooling – IQ - health nexus. For example, poor health in childhood may influence educational attainment. It is generally assumed that poor health would reduce attainment. However, this may not be the case. Youths with rheumatoid arthritis generally attain more education: in part, because they cannot fully participate in children's recreational activities, but they can fully participate in academics (Ansell, 1978). In any case, we have a simultaneous equation bias since ultimately we would like to measure the effect of schooling on health, not the effect of health on schooling.

There is another point that is overlooked by non-economists attempting to assess the implications of education. Non-economists tend to rely on statistical models that place great importance on the percent of variation explained.

Measures of education frequently come up short by this standard. The "addition to R^2" by adding years of schooling to regression may be modest. However, as a practical matter, it is not the "addition to R^2" that should matter, but rather the size and statistical significance of the coefficient on years of schooling (Leigh, 1988).

One issue surrounds the frequent use of years of schooling as the only measure of educational attainment. There is a wide variation in the quality of education that is completely ignored with years of schooling measure (discussed further under limitations). Another issue surrounds the so-called "third variable" or "unobserved heterogeneity" bias. In the context of schooling-health correlation, time preference is frequently singled-out as an important "third variable." Generally, time preference is unobserved. It is likely to influence an individual's investment in health and schooling. Persons with low time preference presumably undertake investment in schooling and preventive medicine. Time preference would enter the error term of a health equation and schooling equation. Then, this error term would be correlated with health and schooling so that single equation estimates of the effects of schooling on health (and vice versa) would be biased.

4.1.3 ISSUE OF NON-INCLUSION OF INCOME AS EXPLANATORY VARIABLE

The question of whether current household income should be included as a variable in the health equation is a difficult choice. It is clear that health and labour earnings are simultaneously determined, especially in the case of the disability measure of health. Therefore, choice is to include an endogenous variable or leave an important variable out of the estimation. Income is a function of variables, such as education and occupation of parents. Therefore, we do not include income as an explanatory variable, but include variables, which determine income, thereby mitigating the problem of the endogenous regressor.

4.1.4 HYPOTHESIS OF THIS THESIS

In the vast majority of studies conducted by economists considering the effect of schooling on health, schooling has stood out as having a large and significant estimated effect. Yet, there is little agreement among economists concerning the mechanism through which schooling enhances the production of health. Some have argued for a direct effect, whereby schooling enhances health (Auster et al. 1969; Grossman 1975; Grossman and Joyce 1987; Rosen and Taubman 1982 and Taubman and Rosen 1982). Others assert that one or more unobserved variables such as genetic or personality factors affect both schooling and health in the same direction (Fuchs 1982; Farrell and Fuchs 1982). The correct explanation of health-schooling nexus is important from a policy standpoint.

Grossman (1975) and Auster, Levenson and Sarachek (1969) have suggested that expenditures on education are a cost effective technique for increasing aggregate levels of health. For instance, policymakers may seek to increase expenditure on health education program as a way to improve overall health. However, if cognitive ability partially explains the observed correlation between schooling and health, estimates of the effect of additional schooling on health promotion are overstated.

This discussion suggests two important hypotheses to be considered empirically:

First, there is wide agreement that education is correlated with health. Cognitive ability and schooling are positively correlated, however, and so it is possible that the health effects, which are thought to be due to education, could be partially due to cognitive ability. A model which ignores cognitive ability could therefore be mis-specified. This research uses the Grossman model to investigate the direct effect of cognitive ability on health.

Second, there is widespread literature on "third variables." In the schooling-health correlation, time preference is frequently singled out as an important "third variable." Therefore, we would test Fuchs' view on time preference and our hypothesis is the following: Could cognitive ability be one of these third variables?

4.2 EMPIRICAL MODELS

This section will outline the different models being estimated. Section 4.2.1 outlines the basic model to start with. Section 4.2.2 outlines our two-stage model, and in Section 4.2.3, we lay out the model estimated by Berger and Leigh (1989). Section 4.2.4 lays out the semi-parametric model. Finally, Section 4.2.5 lays out the model for testing "third variable" hypothesis.

4.2.1 BASIC MODEL

We start with a simple model, for the time being ignoring the problem of endogeneity. The explanatory variables we would include in our analysis can be divided into three categories: schooling, "g" ; and *X* – a vector of control variables, such as Socio-Economic Status (SES), gender, marital status, race, and age.

First, we estimate health equation by including education and control variables as independent variables; therefore, our model would be

$$(1) \qquad H_t = u\ (S_t, X_t)$$

where *S* is years of schooling completed by the respondent; *X* is a vector of control variables.

The vector of control variables *X* includes father's education, mother's education, occupation of both parents, number of siblings, gender, marital status, age, race, SMSA, rural/urban residence, availability of newspaper/magazine at home, and whether the respondent lives with both parents at the age of 14.

Then our model includes "g" and *X* – a vector of control variables.

$$(2) \qquad H_t = v\ (g_t, X_t)$$

To investigate how the inclusion of schooling affects the estimate of "g," the following model is estimated.

$$(3) \qquad H_t = q\ (S_t,\ g_t,\ X_t)$$

Since our basic interest is in estimating the effect of cognitive ability on health, the difference in estimates of equation (2) and (3) would show how the inclusion of schooling affected the estimate of cognitive ability. Hence, we would be able to differentiate between the effects of schooling and cognitive ability.

4.2.2 TWO-STAGE MODELS

Self-selection bias arises because it is only possible to observe individuals making optimal choices. This process truncates the underlying disturbances of the equations so the sample of individuals who make each choice is non-random. Heckman (1976) developed and applied the econometric theory, which follows from self-selection to choices that allow for two outcomes. Garen (1984) developed and applied the theory to continuous choice variables. We follow Berger and Leigh (1989) and use the Garen model here. This model allows us to estimate whether the observed education-health correlation is simply a case of self-selection bias or whether there is also a direct effect of education on health. It can also be determined whether the direct effect of education on health is influenced by unobservables. More education may have a greater effect on the health of those with a low time preference.

The empirical model is constructed using two time periods: a schooling period (period 1) and a post-schooling period (period 2). Equations explaining the amount of education (years of schooling) obtained S_1 and health status in post-schooling period H_2 can be written as

$$(4) \qquad S_{1t} = a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}$$

$$(5) \qquad H_{2t} = b_1Z_t + b_2\hat{S}_{1t} + b_3g_t + b_4CH_{1t} + b_5\hat{S}_{1t}{}^*g_t + u_{2t}$$

where S is the years of schooling, X is a vector of variables which affects education, Z is a vector of variables which affects health status, and CH_1 is exogenous childhood health. Residuals are normally distributed random terms reflecting the effect of unobservable on education and health.

I_{1t} is instrument variable: the set of variables that is used to instrument education (for detailed Review of Literature on Instrumental Variable used for schooling in various studies, see Appendix 1). For our equation (5) to be identified, the necessary condition is that we should have at least as many excluded exogenous variables as many included endogenous variables on the right hand side of the equation. Ours is an over-identified case, and our exclusion restrictions are education and occupation of parents and number of siblings. The over-identifying restrictions are tested using the LM test[4].

Both equations express the measures of health and education as functions of observed and unobserved factors. Variables affecting investment in education, such as family background, parents' education, occupation and Socio-economics status (SES), are included in X in the first equation. Some variables affecting health, such as age, gender, marital status, race, geographic location of residence and household size, are included in vector Z of the second equation. We also included childhood health in the second equation (health equation) that would give an estimate of the relationship between adult health and childhood health or past health.

If there is any health problem (e.g., functional limitations) which the individual is aware of prior to the completion of schooling, the "health causing schooling" explanation cannot be ruled out. Following the Berger and Leigh (1989) study, we control for "health causes schooling" by including childhood health (CH_1) in the first equation (schooling equation).

All youths were between thirteen and twenty years of age in 1978 and were interviewed in 1979 for the first time. Their health in 1979 is what we call past health (CH_1). Because most of the respondents were in the 13 to 20 year age group in 1979 when past health was measured, it makes sense to treat past health as exogenous in schooling equation. Therefore, following Berger and

Leigh (1989), we treat this past health as exogenous.

Our interest in the schooling equation is not in measuring the coefficient of past health; therefore, an inconsistent estimation of this coefficient does not cause any serious concern to our interest in the estimation of the effect of cognitive ability on health in the health equation.

The interaction term allows schooling and cognitive ability to act synergistically to affect health. For example, suppose that b_3 and b_5 are both positive and significant. Then, the effect of cognitive ability varies with schooling. In this case, the cognitive ability will be more effective at improving the health of those with more years of schooling.

Suppose that health could be expressed as a sum of a function of cognitive ability and a function of the schooling: $H = u(g) + v(S)$. (We assume dH/dg and dH/dS are both positive). In this form, the marginal product of schooling, dv/dS, is independent of cognitive ability. This result does not seem plausible, since it implies that people of low cognitive ability have a greater incentive to invest in schooling. This argument implies that health function is mis-specified unless cognitive ability increases the marginal product of schooling.

The expected positive interaction of schooling and cognitive ability on health can also be rationalized in a slightly different way. Suppose we consider cognitive ability as an index of the quality of a person and assume that people of differing cognitive abilities apply the same amount of time to schooling. The possibility of better health of the person with the higher cognitive ability may be considered better output, corresponding to a higher-quality input applied to the educational process.

In terms of equations (4) and (5) (or equations (7) and (8)), the universal finding in various studies is that b_2 is positive and significant. The questions are whether these findings represent the direct effect of education on health or whether the relationship is spurious for some reason. Second, how does "g" affect this relationship?

The simplest way to see the problem of endogeneity is to substitute the first equation in the second equation

$$(6) \qquad H_{2t} = b_1Z_t + b_2\,(a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}) + b_3g_t + b_4CH_{1t} + u_{2t}$$

and we see unobservables those affect schooling also affect health, meaning S_1 and u_2 are correlated and least square estimates of b_2 are biased.

In order to get consistent estimates of b_2, one approach is to estimate equation (4) and find predicted schooling, which is then substituted into the second equation in place of S_1. The effect of schooling on health is $\partial H/\partial S = b_2+b_5g$ and that of "g" on health is $\partial H/\partial g = b_3+b_5S$.

4.2.3 BERGER AND LEIGH MODEL

In this section, we lay out the model estimated by Berger and Leigh (1989) and discuss the purpose for estimating this model in our study.

The model estimated by Berger and Leigh (1989) is as follows:

$$(7) \qquad S_{1t} = a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}$$

$$(8) \qquad H_{2t} = b_1Z_t + b_2\hat{S}_{1t} + b_3CH_{1t} + u_{2t}$$

where all the variables have the same meaning as in our model.

The objectives of the Berger and Leigh (1989) model was to study the effect of schooling on health and to find out whether "third variables" are important in explaining any variation in health. The basic objective of our research, however, is to estimate the direct role of cognitive ability on health while studying the health – education nexus.

As pointed out earlier, education and health are positively correlated, and schooling and cognitive ability are also positively correlated. Therefore, it is possible that the health effects which Berger and Leigh (1989) thought to be due to education, could be partially due to cognitive ability. Their model by ignoring cognitive ability from the health equation could, therefore, have been mis-specified.

Berger and Leigh (1989) used Socio-Economic Status and intelligence measured by AFQT to instrument schooling. In our study, we use cognitive ability measured by "g" instead of intelligence score AFQT. This cognitive ability is not used as an instrument. This way, we would also be able to find out whether the exclusion restriction was valid in the case of the Berger and Leigh model.

4.2.4 SEMI-PARAMETRIC MODEL

In parametric econometrics, the estimation and testing of associated hypothesis are carried out by assuming some functional form for the relationship: in our case, a linear one. Any misspecification in the functional form leads to inconsistent estimates of the true derivatives and may affect the size and power of any test performed on them. Consequently, it is of some interest to investigate whether the semi-parametric mode of analysis outlined earlier in Section 3.3 might be gainfully applied.

$$\text{(9)} \qquad H_{2t} = b_1 Z_t + b_2 S_{1t} + \sum_{j=1}^{j=J} b_{3j} AFQT_{jt} + b_4 CH_{1t} + \sum_{j=1}^{j=J} b_{5j} S_{1t} {*} AFQT_{jt} + u_{2t}$$

where *S* is vector of schooling variables and *AFQT* is vector of different categories of *AFQT* as outlined in section 3.3.

4.2.5 MODEL TO TEST FOR 'THIRD VARIABLE HYPOTHESIS'

The instrumental approach outlined in Section 4.2.2 neither incorporates the effect of both education and unobservables on health nor do they allow for interactions between education and unobservable. To allow for these effects, Garen's self-selection model (1984) would be used for the education-health relationship, and the full mode becomes

$$(10) \quad S_{1t} = a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}$$

$$(11) \quad H_{2t} = c_1Z_t + c_2S_{1t} + c_4CH_{1t} + c_5\hat{u}_{1t} + c_6S_{1t}{*}\hat{u}_{1t} + u_{2t}$$

Estimates of the parameters of equation (11) are obtained by estimating equation (10), getting the residuals and then substituting them into equation (11) in place of u_1.

To allow for the effects of "g," we would add a "g" variable in the equation (11) and see whether the magnitude of unobservable variables changes in any significant way.

$$(12) \quad S_{1t} = a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}$$

$$(13) \quad H_{2t} = c_1Z_t + c_2S_{1t} + c_3g_t + c_4CH_{1t} + c_5\hat{u}_{1t} + c_6S_{1t}{*}\hat{u}_{1t} + c_7S_{1t}{*}g_t + u$$

Here, our interest is to find out how the magnitude of c5 changes with the addition of "g" to equation (13) (i.e. as compared to magnitude of c5 in equation (11)).

4.3 ESTIMATION TECHNIQUES

This section outlines the three different techniques used in estimation. Section 4.3.1 outlines the single equation technique, Section 4.3.2 outlines the instrumental variable technique, and Section 4.3.3 outlines the semi-parametric techniques used for the single equation model. Section 4.3.4 discusses the theoretical issue of instrumental variables, over-identification test, the test for weak instruments, and test for endogeneity. Section 4.3.5 discusses the basic idea of bootstrapping.

4.3.1 SINGLE EQUATION TECHNIQUE

We start with a single equation estimation technique, for the time being ignoring the problem of endogeneity. The explanatory variables we would include in our analysis can be divided into three categories: schooling; "g"; and other control variables, such as Socio-Economic Status (SES), gender, marital status, race and age.

If unobservables, which affect education and "g," also affect health, then probit estimates of education and "g" would be biased. To take care of this problem, we instrument education using the instrumental variable approach. This is discussed in the next section.

4.3.2 INSTRUMENTAL VARIABLE TECHNIQUE

The ideal setup to control for the issue of endogeneity would be a randomized experiment with a treatment group that receives education and a control group that is refused access to education. In reality, however, such randomization is impossible and one has to resort to observational studies where individuals may decide themselves whether to participate or not and thus are self-selected. There are three methods used to account for this issue. First, one tries to control for all variables that rule the selection process and the outcome variable under study; in particular, "g" score may reduce ability bias (see Blackburn and Neumark, 1995; Kane & Rouse, 1995; Murnane, Willett & Levy, 1995). Another promising approach is identical twins, who share a common family background and common genetic heritage (see Ashenfelter & Krueger, 1994; Ashenfelter & Rouse, 1998a; Miller, Mulvey & Martin, 1995). Finally, exogenous determinants of schooling are exploited in an instrumental variable framework (see Angrist & Krueger, 1991; Card, 1993; Kane & Rouse, 1993) to identify the effect of education, something that is sometimes referred to as "natural experiments." We adopt the third approach.

To estimate the Berger and Leigh (1989) model, the same data would be used as is used in our model, so that we could compare the results.

4.3.3 SEMI-PARAMETRIC ESTIMATION TECHNIQUE

The first derivative indicates the response coefficient (regression coefficient if relation is linear) of health with respect to cognitive ability, and hence it describes the effect on dependent variable due to changes in the regressor. In parametric econometrics, the estimation of these derivatives and testing of associated hypothesis are carried out by assuming some functional form for the relationship - in our case a linear one. Any misspecification in the functional form leads to inconsistent estimates of the true derivatives and may affect the size and power of any test performed on them. Consequently, it is of some interest to investigate whether the semi-parametric mode of analysis outlined earlier in Section 3.3 might be gainfully applied.

4.3.4 INSTRUMENTAL VARIABLES, UNOBSERVED HETEROGENEITY, TEST FOR OVER-IDENTIFYING RESTRICTIONS, TEST FOR WEAK INSTRUMENTS, AND TEST FOR ENDOGENEITY

A number of studies reviewed in preparation for the empirical work examine the impact of education on health. Many of them assumed that schooling is exogenously determined in the statistical model. This assumption is tenuous because health and schooling are jointly determined in the health production context. In the most general case, schooling determines health and health determines schooling. This endogeneity of schooling would result in a non-zero correlation between the error term and the measure of schooling. Therefore, the assumption of the classical linear regression model is violated.

Continuing with our model, schooling is endogenous, so if we use the single equation method, we would get biased and inconsistent estimates.

(4) $$S_{1t} = a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}$$

(5) $$H_{2t} = b_1Z_t + b_2\hat{S}_{1t} + b_3g_t + b_4CH_{1t} + b_5\hat{S}_{1t}{}^*g + u_{2t}$$

The simplest way to see it is to substitute the first equation into the second equation.

$$(6) \qquad H_{2t} = b_1Z_t + b_2(a_1X_t + a_2g_t + a_3CH_{1t} + a_4I_{1t} + u_{1t}) + b_3g_t + b_4CH_{1t} + u_{2t}$$

and we see unobservables; those which affect schooling also affect Health; meaning S_1 and u_2 are correlated i.e. $E(S_1u_2) \neq 0$. This violates one of the assumptions of the Classical Linear Regression Model (CLRM), and our estimates of b_2 are biased and inconsistent.

Here we use the method of instrumental variables (IV). A variable is a valid instrument if it is not significant in predicting the outcome variable but is significant in predicting the conditioning variable. In this case, an instrument is valid if it strongly correlates with schooling but not Health. We use the same instruments as used by Berger and Leigh (1989). Using these variables as instruments, we get consistent estimates of the schooling coefficient.

We proceed by regressing schooling S_1 on W and get the predicted values P_wS_1.

$$S_1=W\phi+\text{residuals} \qquad \text{where } W=(X\ g\ CH_1\ I)$$

We then regress Health (H_2) on P_wS_1 (i.e. predicted schooling) and Z, g, CH_1 to get consistent estimates of the schooling coefficient.

UNOBSERVED HETEROGENEITY AND OMITTED VARIABLE BIAS

Both unobserved heterogeneity and omitted variables bias also prevent the ordinary least square estimation technique from producing accurate estimates. Unobserved heterogeneity occurs when a characteristic is present for some individuals and not for others. This information is not captured in the data, but it does impact the outcome. For example, there may be something about an individual, maybe his or her attitude or upbringing that will cause him or her to fare better on his or her health or schooling. In our case, unobserved heterogeneity may take the form of a discount rate. Because this comparative advantage is not observable, statistical methods that do not correct for unobserved heterogeneity will produce estimated impacts of education that are less positive or more positive. The instrumental variable technique will also correct for unobserved heterogeneity across respondents.

Omitted variable bias would also prevent OLS from accurately estimating the impact of cognitive ability on health. The obvious way to remedy this problem is to include a rich set of regressors in the determination of health. However, fortunately, our data set has a wide range of variables which would mitigate this problem.

OVER-IDENTIFICATION TEST/TEST FOR VALIDITY OF INSTRUMENTS

The problem with the method of Instrumental Variables (IV) is that there is not much choice in finding valid instruments. We say an instrument is valid if $E(Wu_2) = 0$ or W does not belong in S_1.

The correct specification of a simultaneous equation is as important as the modeling itself. The LM test is the easiest test for over-identifying restrictions (i.e. the restrictions leading to the exclusion of some variables from some equations). We can see if these restrictions are correct against the alternative hypothesis that they are improper. For this test, obtain the residuals from an efficient single-equation estimator and regress them on all the predetermined variables in the model. The sample size times, the R^2 from this regression, will be distributed asymptotically as a chi-square, with degrees of freedom equal to the number of over identifying restrictions (i.e., with number of predetermined variables outside that equation less than the number of endogenous variables serving as regressors).

Let u_2 be residuals from the second equation, W is all exogenous variable (not just the excluded one), and S_{1nxk} and W_{nxl} and l>k.

$$\hat{u}_2 = W\phi + \text{residuals}$$

$nR^2 \sim x^2$ distribution with l-k degrees of freedom. High R^2 or rejecting means either $E(Wu_2) \neq 0$ or excluded Ws belong in S_1.

WEAK INSTRUMENTS

Our instruments are weak if they explain little variation in S_1.

$$V(\beta)=\sigma_0^2(S_1'P_wS_1)^{-1}$$

$P_wS_1 \approx 0$ if W and S_1 are almost uncorrelated and, in this case, we get a very large variance.

TEST FOR WEAK INSTRUMENTS

Let W=[X g CH_1 I]. Regress columns of S_1 on W=[X g CH_1 I] and calculate F statistics on columns of I and if F stat>10, then our instruments are not weak (Staiger and Stock, 1997).

TEST FOR ENDOGENITY

A test of the specification of the exogeneity of the variables designed as exogenous involves testing the null hypothesis of no correlation between these variables and the structural disturbances. To test this hypothesis, we can use the Hausman test. The idea is that if there is no endogeneity, then plim$\beta_{OLS} = \beta_0$ and plim$\beta_{2SLS} = \beta_0$ and, if there is endogeneity, then plim$\beta_{OLS} \neq \beta_0$ and plim$\beta_{2SLS} = \beta_0$. We test Null Hypothesis: $\beta_{OLS} = \beta_{2SLS}$.

However, we proceed as follow: Our null hypothesis is that there is no endogeneity or the coefficient of "predicted schooling" is zero. We regress schooling on all exogenous variables in the model and get predicted schooling. Then, we regress health on exogenous variables, schooling, and predicted schooling and test the coefficient of predicted schooling. If the "predicted schooling" is unnecessary variable, its coefficient should be zero.

4.3.5 ON BOOTSTRAPPING

An accurate estimate of the uncertainty associated with parameter estimates is important to avoid misleading inferences. This uncertainty is usually summarized by a confidence interval or region, which includes the true parameter value with a specified probability. However, the accuracy of this interval depends upon the asymptotic normality of $\hat{\theta}$, and this assumption is questionable with so few observations. Accordingly, we may want to construct a confidence interval that does not depend on this assumption. Bootstrapping provides a ready, reliable way to do this.

Recent advances in statistical methodology allow the construction of highly accurate approximate confidence intervals, even for very complicated probability models and elaborate data structures. However, most confidence intervals are approximate, with by far the favourite approximation being the standard interval:

$$(14) \qquad \hat{\theta} \pm z^{(\alpha)} \hat{\sigma}$$

Here $\hat{\theta}$ is a point estimate of the parameter of interest θ, $\hat{\sigma}$ is an estimate of $\hat{\theta}$'s standard deviation, and $z^{(\alpha)}$ is the 100αth percentile of normal deviate, $z^{(0.95)}$ = 1.645, and so on.

The trouble with standard intervals is that they are based on an asymptotic approximation that can be inaccurate in practice. Over the years, statisticians have developed tricks for improving (14), involving bias-corrections and parameter transformations. The bootstrap confidence intervals that we will discuss here can be thought of as automatic algorithms for carrying out these improvements without human intervention.

Approximate confidence intervals based on bootstrap computations were introduced by Efron (1981, 1982a). The word "approximate" is important, because in only a few special situations can exact confidence intervals be constructed. They tend to be more accurate than the standard intervals. In those problems where exact confidence limits exist, the endpoints are typically of the form

$$(15) \qquad \hat{\theta} + \hat{\sigma}\,(z^{(\alpha)} + A_n^{(\alpha)}/\sqrt{n} + B_n^{(\alpha)}/n + \ldots)$$

where n is the sample size. The standard intervals (14) are first-order correct in the sense that the term $\hat{\theta} + \hat{\sigma}\ (z^{(\alpha)}$ asymptotically dominates (15). However, the second-order term $\hat{\sigma}\, A_n^{(\alpha)}/\sqrt{n}$ can have a major effect in small-sample situations. The bootstrap methods described in Efron (1985) was shown to be second-order correct in a certain class of problems, automatically producing intervals of correct second-order asymptotic form

$$\hat{\theta} + \hat{\sigma}\,(z^{(\alpha)} + A_n^{(\alpha)}/\sqrt{n} + .\quad /\quad /).$$

The standard interval (14) is based on taking literally the asymptotic normal approximation

$$(16)\qquad (\hat{\theta} - \theta)/\hat{\sigma} \sim N(0,1)$$

with the estimated standard error considered being a fixed constant. In certain cases, it is well known that both convergence to normality and consistency of σ can be dramatically improved by considering instead of $\hat{\theta}$ and θ a monotone transformation $\hat{\phi} = g(\hat{\theta})$ and $\phi = g(\theta)$. The bias corrected bootstrap intervals previously introduced by Efron (1981, 1982a) assumes that normality and constant standard error can be achieved by some transformation $\hat{\phi} = g(\hat{\theta})$ and $\phi = g(\theta)$, say

$$(17)\qquad (\hat{\phi} - \phi)/\tau \sim N(-z0,1)$$

τ being the constant standard error of $\hat{\phi}$. Allowing the bias constant z0 in (17) considerably improves the approximation in many cases. The advantage of the BC method is that all of this is done automatically from bootstrap calculations, without requiring the statistician to know the correct transformation g.

ACCURACY AND CORRECTNESS

It is less clear what the authors mean by "correctness.'" They appear to be talking about the closeness of the bootstrap interval endpoints to certain ideal confidence interval endpoints, for example, those corresponding to the most accurate or smallest expected length confidence intervals for the given problem.

ON NUMBER OF BOOTSTRAP SIMULATIONS

The bootstrap's reduction of error of coverage probability, from $O(n^{-1/2})$ to $O(n^{-1})$, is available uniformly in B, provided nominal coverage probability is a multiple of $(B+1)^{-1}$. In fact, this improvement is available even if the number of simulations is held fixed as n increases. However, smaller values of B can result in longer confidence intervals. In addition, B does not have to be particularly large before exact coverage probability agrees with the theoretical limit as $B \to \infty$. For example, if B equals sample size, then the probabilities only disagree at the level $O(n^{-2})$ (Hall P, 1986).

For 90-95 percent confidence intervals, most practitioners (Efron and Tibshirani, 1993, page162, Davison and Kinkley, 1997, page 194) suggest that B should be between 1000 and 2000.

4.4 CONCLUSIONS

There are many theoretical and econometric issues involved in the modeling and estimation of the models in our research. We discussed those issues in addition to issues involved in instrumental variable approach of estimation. Because we used bootstrapped standard errors, we discussed the basic idea of bootstrapping.

5

RESULTS AND ANALYSIS

The results and analysis are presented in the following sections and the results are probit estimates. Throughout this chapter, a bigger sample refers to a sample size of 6551 observations, and a smaller sample refers to 2697 observations. In Section 4.1, we discuss basic single equation model results and in Section 4.2, we discuss two period least square models. In both these sections, "g" is used as the measure of cognitive ability. Section 4.3 discusses the semi-parametric results using AFQT as of the cognitive ability measure. In Section 4.4, we test the hypothesis of whether cognitive ability could be one of the "third variables." In Section 4.5, the robustness of the results is discussed, and Section 4.6 discusses the weakness of instruments and over-identification restrictions. Section 4.7 discusses the possible mechanism for association of cognitive ability and health. Finally, conclusions are laid out in Section 4.8.

5.1 BASIC SINGLE EQUATION MODELS

In this section, we discuss the single equation ordinary least square results. All the estimates are probit estimates.

The dependent variable in our analysis is health status. Health measures used are listed in Section 3.4. These are subjective measures of health, and the health literature reveals that an individual's subjective perception of his or her own health is a good indicator of overall health (see Kemna, 1987, page. 194-95). We expect the subjective evaluation to be correlated with a medical assessment, but we also believe that the self-assessment has a virtue in its own right, as a variable that is related to personal evaluation of well-being. We assume that across individuals, the term "good," "fair," etc. have the same meaning.

Table 2 presents the results for different specifications of the basic single equation model. Model Ia reports schooling and control variables, Model Ib reports with "g" and control variables, and Model Ic reports both schooling and "g" along with control variables.

The results indicate that if cognitive ability is not included, then the effect of schooling is quite large, but the inclusion of "g" reduces the effect of schooling by almost half. If schooling and "g" are positively associated, then a measure of the contribution of schooling to health that ignores "g" will be biased upwards by the amount δb_{gS}, where δ is coefficient of "g" and b_{gS} is the regression coefficient of "g" on schooling in the sample. The effects with the inclusion of schooling on the effect of cognitive ability are similar. To investigate the magnitude of bias and to take care of this problem, we estimated the model (Model 1c) by including both schooling and cognitive ability. Results presented in the last column indicate that schooling and cognitive ability have a complementary effect on health. Therefore, models, which ignores the cognitive ability as regressor, overestimates the effect of schooling.

The effect of cognitive ability is always positive and significant and remarkably similar across different measurements of health used in this basic model except in two cases. These two exceptional cases are when health variables are "Does health limit the kind of work and other activities?" and CESD-depressed (Table 2a). Those with a higher cognitive ability have better health, irrespective of how we measure health. An interesting feature of the results is that both estimates and standard errors remain roughly the same in both the bigger sample (6551 observations) and the smaller sample (2697 observations); for both the health variables those could be logically compared. This indicates that we get the same magnitude of coefficients and same precision in our estimates in both the samples.

We find that cognitive ability measured by "g" is a significant factor among variables that affect health, and this effect is independent of education level. A 10-point advantage in cognitive ability confers a relative advantage of 1.3 percent to 2.2 percent of reporting "better health," depending upon how we measure health. Because we have taken care of other unfavourable socio-economic conditions and demographic variables that could confound our results, our results do establish the positive effect of cognitive ability on health.

These results are similar to those reported by Whalley and Deary (2001) and to those reported by Hartog et al. (1998). Both these studies reported a positive significant effect of cognitive ability on health using different data sets and different health measures.

The results indicate that significant differences in health exist by gender, race, marital status, location of residence, previous health status, and whether the respondent lived with both the parents or not until the age of 14, apart from schooling. Those who reported that health limits work or other activities in 1979 are significantly more likely to report work disability or a functional limitation in 2000. Surprisingly, the family background measured by the schooling of parents does not have any effect on health, but the occupation of the father does have an effect on the health of the children. Another significant finding is that blacks and Hispanics have better health as compared to others.

5.2 TWO STAGE MODELS

In this section, we discuss and analyse the results of both our two-stage model and the model used by Berger and Leigh (1989) that we reproduced using our data set.

The results in Table 3 indicate that significant differences in health (measured as functional limitation) exist by gender, marital status, whether the respondent lived with both the parents until the age of 14, and location of residence. Again, those who reported that health limits work or other activities in 1979 are significantly more likely to report work disability or a functional limitation in 2000. However, if the health is measured as a general assessment of a respondent's health, then whether the respondent lived with the parents until the age of 14 does not have any effect on health. The effect of family size, whether the respondent lived in the south at age 14, urban/rural residence and availability of reading material did not have any effect on health, irrespective of the way health is measured.

Another finding of this research is that the effect of all the control variables and family background or socio-Economic Status variables was remarkably similar in both the models: the model with an interaction term of cognitive ability and schooling and the model without this interaction term. This indicates that the effect of most of the control variables used is quite stable and robust in different specifications of the model. The significant effect of marital status and gender was remarkably similar whether health was measured as a functional limitation or as an assessment of respondent's general health. This indicates that the effect of gender differences and marital status is quite stable irrespective of the model specification (inclusion or exclusion of interaction of schooling and cognitive ability term) and how we measure health. But the effect of whether the respondent lived with both the parents at the age of 14 varied with the health measure used.

In the single equation model (i.e. ignoring the issue of endogeneity of schooling to health), the effect of cognitive ability is quite similar across different health measures. However, when schooling is replaced by "predicted schooling'" (two-stage model), the effect of cognitive ability and schooling varied across different measurements of health. In a model where the interaction term between schooling and cognitive ability is not included, the effect of cognitive ability goes down by 31% to 86%, depending upon the health measure used. But in the full model, which includes the interaction term, the estimated effect of cognitive ability goes up by 21% to 59%. It is not logical to compare the coefficient of cognitive ability in the two models because in the first one, the marginal effects of cognitive ability are given by the coefficient of "g" (i.e. b_3) and in the second one, it is given by $\partial H/\partial g = b_3+b_5S$. Therefore, we have not done this comparison.

Another finding of our analysis is that the effect of cognitive ability does not vary with schooling, as the interaction term was insignificant in all cases. This brings out the fact that the effect of cognitive ability does not vary with schooling. This result is interesting but has to be seen in the light that we imposed some specific linear relationship on model estimation (for effects of how some relaxation of this linear relationship affects the results, see Section 4.3).

From the results in Table 3a, we can make three observations. First, the model specification, i.e. inclusion or exclusion of interaction of schooling and cognitive ability, makes a significant difference in terms of magnitude of the cognitive ability (see also the last two paragraphs of Section 4.4, for similar observations). Second, in the bigger sample, not only does standard error go down, which is an obvious result, but also the magnitude of cognitive ability in the bigger sample increases by 2 to 4 times as compared to the smaller sample when health is measured as functional limitation. This change in the estimate of cognitive ability for the same health measures, but with different sample sizes could be partially because our health measures are not perfect. Third, the observation above that the magnitude of cognitive ability goes up in the bigger sample is true whether the model included the interaction term or not.

The effect of schooling goes up, whether the interaction term is included or not, from 66% to 309% when schooling is replaced by "predicted schooling." In all the measures of health, schooling was found to have a significant effect on health. This huge variation in effect of schooling indicates that effect of schooling on health depends upon the model specification and on how we measure health. Another explanation for this could be as follows: in the two-stage models, we are using predicted schooling instead of schooling, and this predicted schooling is not measured as accurately as schooling. Therefore, as compared to single equation models, schooling has a huge variation in its effects.

The results taken together across different measures of health (Table 3a) suggest that the effect of cognitive ability on health is significant at 10 percent level when health is measured as functional limitation for bigger sample. In these two cases, the effect of cognitive ability was significant after controlling for schooling. For a small sample size, this effect was insignificant as it was across other measures of health. We fail to reject the null hypothesis that the effect of cognitive ability on health does not vary with schooling except in two cases: when health is measured as a physical component summary score and whether health limits the kind of work (SF-12). In the former case, the effect of cognitive ability was significant at 11 percent after controlling for schooling and in the latter case at 17 percent.

We replicated the results of Berger and Leigh (1989) and other studies which did not use cognitive ability in the schooling equation. Empirical models in Berger and Leigh (1989) were estimated using two data sets: the Health and Nutrition Examination Survey I (HANES) and the National Longitudinal Survey of Young Men. The health variables used were blood pressure from the HANES data set and functional limitation from the National Longitudinal Survey of Young Men data set. The functional limitation measure is one of the health variables used in our study.

The results presented in Table 4 indicate that, in general, the effect of education on health is overestimated in both Berger and Leigh's (1989) and other specifications which did not include cognitive ability in the schooling equation. This bias ranges from anything up to 100%. For the health variables that Berger and Leigh (1989) used, the bias ranges from 70 to 100%. In studies that ignore cognitive ability from both schooling and health equation, this bias ranges from 30 to 46%. In both specifications, the direct effect of schooling on health is significant. Therefore, the conclusion of Berger and Leigh (1989) and other studies that there is a direct effect of schooling on health stands. However, when these results are taken together with our two-stage models, we find that though the direct effect of schooling is still significant, its magnitude could be smaller than that indicated by Berger and Leigh (1989) and other studies. Studies which do not control for cognitive ability tend to overestimate the association between schooling and health.

5.3 SEMI-PARAMETRIC MODEL

In this section, the results of the semi-parametric model are discussed and analysed and the results are reported in Tables 8a to 8f.

As outlined in Section 3.3, we employed four different ways of grouping the AFQT score. Since we have very few observations in categories with the highest intelligence level and lowest schooling, and highest schooling and lowest intelligence level, these were not estimated with precision, giving a high level of standard error. As pointed out earlier in Chapter 3, the major complication in semi-parametric estimation is the "curse of dimensionality." Discussing the results of all the models estimated (sixteen in all) would create more confusion than clarity. Therefore, for the purpose of clarity, we discuss the results of only the model where education categories are these three: schooling<12, schooling=12, and schooling>12 years, and measure of intelligence, AFQT, has four categories: each quarter of respondent's score on AFQT test. These results are available in the lowest section of Table 8c and 8d.

We find that in moving from the lowest schooling (schooling<12) and top AFQT score category (top 25 percent of respondents in terms of AFQT score), the probability of reporting "better health" increases from 5.8 percent to 9.3 percent. This indicates the effect of schooling. In moving from the highest schooling category (schooling>12) in the lowest AFQT score category to the highest AFQT score category in the same schooling range (schooling>12 category), the probability of reporting "better health" goes up from 4.5 percent to 9.3 percent. This finding indicates the effect of cognitive ability.

The effect of cognitive ability in moving from the lowest to the highest quarter in terms of AFQT is 5.8 percent increase in probability of reporting "better health." Moreover, the effect of schooling in moving from schooling of less than 12 years to schooling of more than 12 years is a 4.5 percent increase in probability of reporting better health. All these estimates are statistically significant at a convention significance level of 5 percent. These probabilities are similar, but there is little different in magnitude, depending upon the health measure used.

These and other results (not discussed but available in Tables 8a to 8f) indicate that both the increase of schooling and intelligence level have a positive effect on health. This finding indicates that a higher intelligence level could compensate for a deficiency of lower schooling, and higher schooling could compensate for a deficiency of a lower intelligence level. This result is quite interesting in the sense that since both schooling and cognitive ability act as substitutes for each other, schooling remains as a policy variable.

The second finding of this semi-parametric estimation is that both schooling and intelligence level have a complementary effect on health. Anyone having higher schooling and a higher intelligence level has a better probability of health against someone having higher level of only either one of these. This complementary effect is huge by any standards. The probability of reporting "better health" is 9.3 percent more when a respondent moves from the lowest schooling and lowest AFQT score category to the highest category of both schooling and the AFQT score.

The third finding of semi-parametric estimation is that with both schooling and intelligence level, the probability of better health increases, and it does not saturate at any level. This result is apparent in all the models estimated. This indicates that people with the highest schooling and the highest intelligence level have a higher probability of better health than any other category.

This complementary effect of schooling and cognitive ability is in contrast to what we got in the two-stage model, where the interaction term was invariably insignificant.

5.4 RESULTS OF COGNITIVE ABILITY AS A ""THIRD VARIABLE" HYPOTHESIS

In this section, our hypothesis is to find out whether unobservable variables explain any variations in health or not. Furthermore, we further explore if cognitive ability could be one of those "third variables." At the end of this section, the results are compared with those from Berger and Leigh (1989). The results are presented in Table 5 and Table 6.

In all the models estimated for this purpose, we find that unobservables have a significant effect on health except when mental health (Centre for Epidemiological Studies Depression Scale (CES-D)) is used. In all cases, the unobservables were significant and interaction of schooling and residuals term was found to be insignificant, indicating that unobservables do affect health, and this effect of unobservables does not change with schooling. This finding suggests that there is some variable, which is stable with schooling, that is influencing health. These results are robust and, therefore, we estimate the Model specified by equation 12 and 13, to find out how inclusion of cognitive ability alters our results.

With the inclusion of "g," our estimate of residuals goes down and becomes insignificant, except in the case when health is measured as a respondent's general health status, experiencing pain and physical component score, where it still remains significant. Only in the bigger sample, when health is measured as a functional limitation, is cognitive ability significant. This indicates that cognitive ability could be one of the "third variables," but this evidence is not strong.

In the bigger sample, when health is measured as a functional limitation, cognitive ability is significant after controlling for the effect of schooling. It means that cognitive ability has an independent effect on health and it does not vary with the level of schooling.

In a model that does not include "g" and the interaction term with schooling, the effect of schooling on health varied with unobservables. However, when we include "g" and the interaction term of cognitive ability and schooling, then the unobservables become insignificant, and this result is robust irrespective of how we measure health. This indicates that the effect of schooling on health varies with unobservables and one of these unobservables could be cognitive ability. Hence, the effect of additional years of schooling on health would vary with the level of cognitive ability. This finding leads to the conclusion that additional schooling would have a different effect on health depending upon the cognitive ability.

Here, we compare the results of models laid out by equation (5) and (13). The difference between two models is that the first model contains predicted schooling and the latter model contains predicted residuals and its interaction with schooling. In both the models, the effect of cognitive ability on health is quite different (see results in Tables 3 and 5). The probability of reporting better health is about 2.5 to 5 times higher in the model specified by equation (13) as compared to the model specified by equation (5). Also, the standard errors are significantly lower in the latter model as compared to the first one. This finding indicates that model specification is important in terms of estimating the effect of cognitive ability.

The estimates of interaction of schooling and cognitive ability are quite similar and insignificant in both the models, irrespective of whether we used predicted schooling or schooling. This indicates that the effect of cognitive ability does not vary with schooling, irrespective of model specification.

The comparison of these results with the Berger and Leigh (1989) study is presented in Tables 5 and 6. The conclusions of the Berger and Leigh's study were that

Taken together, the results strongly suggest that the observed schooling-healthy correlation . . . is due primarily to the direct effect of schooling on the production of health rather than due to the effect of unobservables such as differences in the rate of time discount.

This result holds if the interaction term of schooling residual and schooling are dropped out . . . schooling residual coefficients never approach significance.

These conclusions are different from those of ours. When we estimated equation 11 (this is the same as equation (3) of Berger and Leigh's (1989) original paper), we found that the unobservables were significant and, with the inclusion of cognitive ability, these unobservables became insignificant. This indicates that the results could be sensitive to the data set and health variables used.

5.5 ROBUSTNESS OF RESULTS

In the basic model (single equation model), the effect of cognitive ability is remarkably similar across different measurements of health variables (Table 2a). However, in the two-stage model, we do not observe a similar finding (Table 3a). The effect of cognitive ability is quite variable across the different health measures employed.

A potential problem with our model was that initial health (CH_1) might be correlated with the disturbance term in current health and schooling equations. However, when the different models (basic model, two stage model and models for testing "third variable hypothesis") are estimated without past health (CH_1), the main results (Table No. 7) of the study remain unchanged. This indicates that our results are robust to inclusion or exclusion of past health as regressor. Our results are more stable in the large sample size as compared to the smaller size, which is an obvious observation.

While using the AFQT score, we used two different measures of health: Does health limit the amount of work a respondent can do? or Does health limit the kind of work a respondent can do? Both the results gave similar estimates, indicating the robustness of our results. In addition, we employed two different ways of dividing the schooling level. One way was to divide schooling into three categories, namely, those have less than 12 years of schooling, equal to 12 years of schooling and greater than 12 years of schooling. In another division, we further divided greater than 12 years of schooling into two categories, that is, in-between 12 and 16 years of schooling and greater than 16 years of schooling. In both, the analysis of the first two categories, namely, less than 12 and equal to 12 years of schooling, gave almost the same probability level, indicating that how we divide our sample into different schooling categories does not affect our results.

5.6 DIAGNOSTIC TESTS ON WEAKNESS OF INSTRUMENTS, OVER IDENTIFYING RESTRICTIONS AND ENDOGENEITY

As detailed in Section 4.3.4, we tested our instruments for their validity and weakness. In our case, our instruments are weak if they explain little variation in schooling (S_1).

Let W=[X g CH_1 I], where X is a vector of variables that determines schooling, IQ is cognitive ability, CH_1 is past health of respondent and I is the set of instruments used to instrument education. We regress columns of schooling (S_1) on W and calculate F statistics on columns of I, and we reject the null hypothesis that our instruments are weak.

The over-identifying restrictions are tested using LM test. Here we find that our exclusion restrictions are valid.

To test for endogeneity, our null hypothesis is that there is no endogeneity or the coefficient of predicted schooling is zero. We proceed by regressing schooling on all exogenous variables in the model and get predicted schooling. Then we regress health on exogenous variables, schooling, and predicted schooling and test the coefficient of predicted schooling. We fail to reject the null hypothesis of endogeneity.

5.7 POSSIBLE MECHANISM FOR ASSOCIATION

Various, non-exclusive explanations exist for the association between cognitive ability and health. These include genetic factors, environmental factors before and after birth, childhood illness, and nutrition.

The cognitive ability test could reflect the effect of multiple factors on the developing brain. These might include the quality of antenatal care, prenatal and postnatal nutrition, and the disabling effects of chronic childhood physical illness. In this scenario, cognitive ability in part represents a record of a subject's neurological tribulations for the period before it was measured. As such, cognitive ability might be seen partly as a mediator between physical and social disadvantages and health.

Cognitive ability might be related to the acquisition of behaviours conducive to good health. These include adopting healthy diets, sensible alcohol consumption, avoidance of injury, and not smoking.

The environment includes a wide range of influences on intelligence. Some of those variables are social, some biological, and some are still mysterious. The cultural environment - how people live, what they value, what they do - has a significant effect on the intellectual skills development. Cultures typically differ from one another in so many ways that particular differences can rarely be ascribed to single causes. Family environment has many aspects - including intellectual aspects - of the development of a child. Attendance at school is both a dependent and an independent variable in relation to intelligence. Therefore, it is quite possible that cognitive ability works through these mechanisms.

Another aspect is that every individual has a biological as well as a social environment, one that begins in the womb and extends throughout life. Many aspects of that environment can affect intellectual development. We know that a number of biological factors - malnutrition, exposure to toxic substances and alcohol and prenatal stressors - result in lowered psychometric intelligence under at least some condition. These factors in turn affect health.

5.8 CONCLUSIONS

This thesis examines the role of cognitive ability in the health - education nexus and tries to estimate the effect of cognitive ability on health. Models are estimated with data from the National Longitudinal Survey of Youth (NLSY). Twelve different measures of health are employed: binary variables representing the presence of work preventing or limiting disabilities (ICD-9 codes) and the presence of functional limitations, a respondent's self-assessment of general health, Does health limit moderate activities and ability to climb stairs? and Did pain interfere with normal work? (SF-12). Two other health variables are a respondent's physical health component summary and his or her mental component summary (SF-12). To measure mental health, the Centre for Epidemiological Studies Depression Scale (CES-D) is used. Two sample sizes (a bigger sample of 6551 observations, and a smaller sample of 2697 observations) are used for estimation purposes.

The two hypotheses being tested in this thesis are the following:

There is wide agreement that education affects health. Also, we know cognitive ability and schooling are positively correlated. It is quite possible that the effect, which is thought to be due to education, could be partially due to cognitive ability. Hence, the model, which ignores cognitive ability, could be mis-specified. This research uses the Grossman model to investigate the direct effect of cognitive ability on health.

The second hypothesis is that there is widespread literature on "'third variables." Could cognitive ability be one of these third variables?

The results suggest that when endogeneity of schooling to health is ignored, the cognitive ability does affect health, and this effect is similar across different measures of health used and in two different data samples. This is true whether we use the single equation models or the semi-parametric estimation technique. Though schooling still significantly affects health, the inclusion of cognitive ability brings its magnitude to about half. Furthermore, on the average, across different health measures, we find the effect of cognitive ability is more stable than schooling. This result could be quite dramatic in studying the health - education nexus and bringing out the importance of cognitive ability for better health output.

In the two-stage model, when "predicted schooling" is used, the effect of cognitive ability varies in different model specifications and different sample sizes. Since the effect of cognitive ability varies quite significantly depending upon the health measure, better objective measures of health could put more light on the role of cognitive ability in this health - education nexus. We find that although schooling appears to cause better health, studies which do not control for cognitive ability tend to overestimate the association between schooling and health. Our results could be reconciled with earlier literature which ignores cognitive ability either from schooling or both schooling and health equations. We find a smaller effect of education because by including cognitive ability, we block the effect of cognitive ability on health. This effect of cognitive ability is otherwise credited to schooling in the studies that ignore cognitive ability in schooling or both schooling and health equation.

Another finding is that when "predicted schooling" is used (two-stage model), the effect of cognitive ability does not vary with schooling. However, ignoring endogeneity of schooling to health (semi-parametric estimation), the effect of cognitive ability (using the AFQT score) on health does vary with schooling, indicating a complementary effect of schooling and cognitive ability on health. This could be because we relax the linear restrictions imposed in the two-stage model while employing the semi-parametric estimation technique. This brings out the fact that the specification of the model does matter and our two stage model may be mis-specified.

Our study reinforces earlier results that significant health differences exist by gender, marital status, whether the respondent lived with both the parents until the age of 14, and location of residence. The estimates of these factors were quite stable, irrespective of the health measure used and model specification. However, the same was not true about schooling. This indicates that in the analysis of the health - education nexus, the importance of cognitive ability is obvious from this research.

The findings do support the hypothesis that cognitive ability could be one of the "third variables." Hence, the effect of additional years of schooling on health would vary with the level of cognitive ability. This leads to the conclusion that additional schooling would have a different effect on health depending upon the cognitive ability. Perhaps this is an important observation in the light of our knowledge on smoking behaviour, that it is not only education which is important, but also the ability to use this knowledge which is equally important. In addition, it is quite possible that this ability to use knowledge is influenced by this "third variable" which we find could be cognitive ability.

The conclusions of this study remain unchanged, irrespective of the measure of cognitive ability used. Our results are robust to inclusion or exclusion of past health as regressor, and results are more stable in the large sample size as compared to the smaller size, which is an obvious observation.

This study has public policy implications (discussed in detail in the next chapter) suggesting that schooling is still a policy variable affecting health.

6

IMPLICATIONS FOR PUBLIC POLICY

Our interest in this area of research was from both the scientific and social policy angles. In a field of health and cognitive ability, where so many issues are unresolved and so many questions unanswered, it nevertheless remains socially as well as scientifically important. In this chapter, policy issues are discussed in reference to those factors which the research elsewhere have shown to influence IQ. Section 6.1 discusses the alcohol and smoking aspect of public policy, Section 6.2 discusses the education aspect and Section 6.3 discusses the nutrition aspect of public policy. Finally, Section 6.4 sums up the public policy case.

6.1 ON ALCOHOL AND SMOKING

Daniels and Stephen (1997) found evidence to support potent environment effects on IQ, namely, through the maternal (womb) environment and through the shared-family environment. Extensive prenatal exposure to alcohol (which occurs if the mother drinks heavily during pregnancy) can give rise to fetal alcohol syndrome, which includes mental retardation as well as a range of physical symptoms. Smaller "doses" of prenatal alcohol may have negative effects on intelligence even when the full syndrome does not appear. Streissguth et al. (1989) found that mothers who reported consuming more than 1.5 oz. of alcohol daily during pregnancy had children who scored some 5 points below controls at age four. Low birth weight infants typically show a deficit in mental ability when they later begin schooling (Wahlsten, 1997). Meara (2001) investigated the possible mechanisms linking Socio-economic status (SES) to health. In a case study of pregnancy and health at birth, she concluded that a limited set of health habits during pregnancy, particularly smoking habits, can explain about half (one third) of the correlation between SES and low birth weight among white (black) mothers.

As our research suggests, cognitive ability affects health, and if cognitive ability is in turn is affected by consumption of alcohol and smoking (smoking leading to low birth weight and low birth weight showing deficit mental ability) during pregnancy, then the negative effects of alcohol consumption on the future health of a child are more significant than believed otherwise.

6.2 ON EDUCATION

Education is widely regarded as a key mechanism to elevate the less well off and to narrow racial differences in social and economic status. The literature on the effects of educational programs on intelligence is massive; however, there is little consensus as to its findings or their implications. Christopher and Korenman (1997) in their article *Does Staying in School Make you Smarter?* concluded, as did Jencks, that evidence suggests that IQ-along with education and family background-is an important contributor to social and economic success, but not the dominant determinant, as Herrnstein and Murray stress in *The Bell Curve*. Because IQ is one of the important predictors of success, a logical question to ask is, What determines IQ?

Dickens et al. (1997) argue that if IQ is as important a determinant of social and economic success as *The Bell Curve* suggests, then investments that increase IQ even modestly will have substantially payoffs. Fischer et al. as opposed to Herrnstein and Murray have argued that the effect of education on IQ is considerably more important than the effect of early IQ on later IQ. The conclusion of the review of literature and research by Christopher and Korenman (1997) was that although it is impossible to arrive at a single estimate for the effect of education on IQ, a year of education most likely increases IQ by between 2 and 4 points. From their analysis, the estimated effect is 2.7 points of IQ per year of education.

If the effect of education on IQ is within the broad range estimate suggested above, *The Bell Curve*'s demonstration of the importance of IQ for social and economic success (in combination with other evidence of substantial "direct" effects of education) and our conclusion of effect on health provides evidence for the importance of educational investment as a policy instrument.

Of special relevance are the results of recent studies that attempted to improve the lives of infants born with obvious disadvantages, including low birth weight and poverty. The evidence from these studies is especially convincing because all used random assignments of children and families to treatment and control condition. The review of studies by Douglas (1997) demonstrates conclusively that enriched educational experiences early in life can substantially improve performance on IQ tests. They indicate that a substantial elevation in the intelligence of children in an entire country could be achieved by a suitable program of universal day care, and they prove that substandard school performance of children from certain minority groups could be enhanced considerably by better experiences.

Two-generation intervention has now become the latest emphasis in children's programming, not because of scientific support but for political reasons. Today, public sentiments are strong to reform welfare and move recipients from the public dole into jobs. Early childhood programs can provide their children with needed childcare. This could fit well into the needs of a nation that seems to be losing patience with expensive social entitlements. Canada has received some international criticism regarding children living in poverty within our relatively wealthy country. In this light, the recent Federal government's National Child Care program could prove helpful in improving health indirectly through improving cognitive ability.

6.3 ON NUTRITION

There is no argument that children who are healthy and adequately nourished are better learners than those who are hungry and frequently absent from school because of illness. Improved nutrition is, in fact, thought to be responsible for the Flynn effect (Lynn, 1990). Among children at high risk for school failure, substantial increases in IQ have been documented after vitamin supplement regimens (Schoenthaler et al. 1991). Such studies have been questioned, however, and not all studies have shown cognitive gains as a result of better nutrition (Pagliari, 1993). The calculated numerical value of "heritability"' has no valid implication for government policies and that evidence of a non-specific genetic influence on human mental ability places no constraint on the consequences of an improved environment (Schoenthaler et al. 1991). On the contrary, a very small change in environment, such as dietary supplement, can lead to major change in mental development, provided the change is appropriate to the specific kind of deficit that in the past impaired development (Schoenthaler et al. 1991).

Consequently, there is direct role of nutrition in the health of a person. Our study brings out the indirect importance of nutrition in health. Nutrition leads to a better effect on cognitive ability (direct effect) and, according to our study, leads to better health in the future (indirect effect). Therefore, our study reinforces in a stronger way that childhood nutrition remains a policy variable in the development of health.

6.4 SUM UP OF PUBLIC POLICY IMPLICATIONS

There are many ways to improve health through the cognitive development of disadvantaged children. Our study reinforces the already held views from another angle, i.e. development of health via cognitive development. Whether this scientific knowledge should be translated into effective policy is a matter of political will, the social calculus of cost/benefit ratios, and the question of costs to whom and benefits for whom.

END NOTES

1. For historical reasons, the term "IQ" is often used to describe "general intelligence" or "g". IQ originally referred to an "intelligence quotient" that was formed by dividing a so-called mental age by a chronological age, but this procedure is no longer used.
2. The theory of habitability of intelligence is simplified by, but does not require, unidimensional ability. The Bell Curve embraces both "g" and habitability. Moreover, it extends Spearman and attempts to demonstrate that differences in "g" explain discrepancies in social outcomes across race.
3. Not much should be made of the fact that "g" explains a majority of the variance in the test scores. The classical theory of "g" is an artefact of linear correlation analysis. Using a result established by Suppes and Zanotti (1981), a scalar measure of ability can always be constructed to fully explain the variance in a battery of test scores. This is a theorem in mathematics and not a statement about behaviour. Ironically, Spearman and his successors rob "g" of explanatory power by estimating it using linear methods. The best measure of "g" is in general a non-linear function of the constituent test scores.
4. Obtain the residuals from an efficient single-equation estimator and regress them on all of the predetermined variables in the model. The sample size time the R^2 from this regression will be distributed asymptotically as a chi-square with degrees of freedom equal to the number of over identifying restrictions (i.e., with number of predetermined variables outside that equation less the number of edogenous variables serving as regressors).
5. It is well known that the score of "ability" tests rises with age and education of the test taker. This by itself indicates that the tests measure knowledge and not some abstract ability that is independent of specific knowledge. To account for this finding, we present three test results, each associated with different measure of cognitive ability. We construct these measures of "g" by estimating principal component from the matrix of correlations of:

(1) Test scores adjusted for age;

(2) Test scores adjusted for age and education.

By "adjusted" we mean that each of the ten ASVAB tests were regressed on the appropriate combination of age and education and principal components were estimated for the residuals. The residuals were standardized to mean zero and variance one. Principal components were estimated from the standardised residuals. The first principal component or factor is "g". The remaining components are sometimes referred to as specific factors, "s".

6. Armed Services Vocational Aptitude Battery (ASVAB) is a vocational aptitude test that determines areas of competency in the following 10 areas: general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop information, mathematics knowledge, mechanical comprehension, and electronics information.

7. Armed Forces Qualifications Test (AFQT) determines general aptitude for enlistment in the Armed Forces. Two methodologies of calculating AFQT, developed by the U.S. Department of Defense, have been used to produce two AFQT variables in the NLSY79: R06182. (AFQT80) and R06183. (AFQT89). R06182. is the AFQT percentile score created from the procedures in use in 1980 and consists of the sum of the number of correct scores for the following sections of the ASVAB: arithmetic reasoning + word knowledge + paragraph comprehension + 1/2 (numerical operations). R06183. is the AFQT percentile score based on new procedures established in 1989 and is created in the following manner: (1) compute a verbal composite score by summing the word knowledge and paragraph comprehension raw scores; (2) convert subtest raw scores to standard scores for verbal, math knowledge, and arithmetic reasoning; (3) multiply verbal by 2; (4) sum the standard scores for verbal, math knowledge, and arithmetic reasoning; and (5) convert the summed standard score to a percentile.

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Table 1a. Summary Statistics

Sample With Work Preventing Sample With SF-12 Variables Or Limiting Disabilities (Icd-9 Codes) 6551 Observations				
Variable	Mean	Std. Dev.	Min.	Max.
Lived in South at 14	0.3829	0.4861	0	1
Urban/Rural at 14	0.7921	0.4058	0	1
Lived with Parents at 14	7.7410	5.0230	0	11
Received Magazine at 14	0.5756	0.49430	0	1
Received Newspaper at 14	0.7627	0.4255	0	1
Library Membership at 14	0.7179	0.4501	0	1
Highest Grade of Mother 79	10.469	3.9301	-4	20
Occupation of Mother 79	330.56	360.36	-4	984
Highest Grade of Father 79	9.5841	5.5221	-4	20
Occupation of Father 79	377.11	307.77	-4	984
Highest Grade of Mother (Missing)	0.0372	0.1894	0	1
Highest Grade of Father (Missing)	0.1079	0.3103	0	1
Occupation of Father (Missing)	0.2364	0.4249	0	1
Occupation of Mother (Missing)	0.4076	0.4914	0	1
No. of Siblings	3.8055	2.6307	0	19
Does Health Limit Kind of Work 79?	0.0568	0.315	0	1
Does Health Limit Amount of Work 79?	0.0423	0.2011	0	1
Race	2.3517	0.7565	1	3
Sex	0.4834	0.4998	0	1
Urban/Rural 79	0.6960	0.7762	-4	1
Urban/Rural (Missing)	0.0232	0.1508	0	1
SMSA 79	0.6760	0.4681	0	1
Age 79	17.549	2.249	14	22
Highest Grade 79	10.376	1.936	0	16
Highest Grade 79 (Revised)	10.375	1.930	0	16
Marital Status 79	1.1132	0.3649	1	3
Family Size 79	4.7067	2.2270	1	15
ASVAB Tests in Different Areas				
General Science	14.1492	5.1554	0	25
Arithmetic Reasoning	15.6703	7.1614	0	30
Word Knowledge	23.2283	8.3849	0	35
Paragraph Comprehension	9.91327	3.6818	0	15
Numerical Operations	31.7061	11.4441	0	50
Coding Speed	42.0114	16.4926	0	84
Auto Shop Information	12.267	5.4028	0	25
Mathematics Knowledge	12.0435	6.1691	0	25
Mechanical Comprehension	12.4052	5.1718	0	25
Electronic Information	9.91898	4.2609	0	20
AFQT	39.9445	28.5610	1	99
AFQT (Revised)	40.1422	28.6598	1	99
Does Health Limit Kind of Work 00?	0.1011	0.3016	0	1
Does Health Limit Amount of Work 00?	0.09435	0.2923	0	1
Family Size 00	3.267398	1.6218	1	18
Marital Status 00	2.042086	0.6584	1	3
Highest Grade 00	13.21885	2.3906	0	20

Table 1a. Summary Statistics

Sample With Work Preventing Sample With SF-12 Variables Or Limiting Disabilities (Icd-9 Codes) 6551 Observations				
Variable	Mean	Std. Dev.	Min.	Max.
Highest Grade 00 (Revised)	13.27672	2.4082	0	20
Age 00	38.93477	2.2487	35	44
Urban/Rural 00	0.7229821	0.5774	-4	2
Urban/Rural 00(Missing)	0.0195401	0.1384	0	1
SMSA 00	0.0683902	0.2524	0	1
Occupation of Father Professional	0.1908	0.3930	0	1
Occupation of Father Clerk	0.0689	0.2534	0	1
Occupation of Father Farmer	0.0184	0.1347	0	1
Occupation of Father Foreman	0.3368	0.4726	0	1
Occupation of Father Labourer	0.0778	0.2679	0	1
Occupation of Father Service	0.0595	0.2366	0	1
Occupation of Father Other	0.0003	0 .0173	0	1
Occupation of Father Armed Forces	0.0106	0.1027	0	1
Occupation of Mother Professional	0.0958	0.2944	0	1
Occupation of Mother Clerk	0.1746	0.3797	0	1
Occupation of Mother Farmer	0.0007	0 .0274	0	1
Occupation of Mother Foreman	0.1240	0.3296	0	1
Occupation of Mother Labourer	0.0214	0.1450	0	1
Occupation of Mother Service	0.1402	0.3472	0	1
Occupation of Mother Other	0.0353	0.1846	0	1
Hispanics	0.1721	0.3774	0	1
Black	0.3040	0.4600	0	1
White	0.52388	0.4994	0	1
Never Married 79	0.90326	0.2957	0	1
Married 79	0.0804	0.2719	0	1
Married (Others) 79	0.0163	0.1269	0	1
Never Married 00	0.1966	0.3974	0	1
Married 00	0.5647	0.4958	0	1
Married (others) 00	0.2386	0.4263	0	1
AFQT 1st Decile	0.1787	0.3831	0	1
AFQT 2nd Decile	0.1557	0.3626	0	1
AFQT 3rd Decile	0.1247	0.3304	0	1
AFQT 4th Decile	0.1001	0.3001	0	1
AFQT 5th Decile	0.0934	0.2911	0	1
AFQT 6th Decile	0.0817	0.2747	0	1
AFQT 7th Decile	0.0710	0 .257	0	1
AFQT 8th Decile	0.0742	0.2622	0	1
AFQT 9th Decile	0.0620	0.2416	0	1
AFQT 10th Decile	0.0580	0.2337	0	1
g (Not Standardised)	55.9826	18.0803	0	96.37
ASVAB Tests in Different Areas (Residualised on Age)				
General Science	-9.60e-07	1.000	-2.91	2.33
Arithmetic Reasoning	-1.51e-07	1.0000	-2.39	2.16
Word Knowledge	-2.52e-07	1.0000	-2.97	1.67
Paragraph Comprehension	-1.03e-06	1.0000	-2.91	1.59

Table 1a. Summary Statistics

Sample With Work Preventing Sample With SF-12 Variables Or Limiting Disabilities (Icd-9 Codes) 6551 Observations				
Variable	Mean	Std. Dev.	Min.	Max.
Numerical Operations	-1.99e-06	1.0000	-2.7	1.72
Coding Speed	-2.04e-06	1.0000	-2.84	2.78
Auto Shop Information	-4.25e-07	1.0000	-2.49	2.59
Mathematics Knowledge	-1.13e-06	1.0000	-1.99	2.14
Mechanical Comprehension	2.07e-07	1.0000	-2.478	2.52
Electronic Information	-1.16e-07	1.0000	-2.56	2.60
g (Standardized for Age)	55.9148	18.0653	0	96.27
ASVAB Tests in Different Areas (Residualised on Age and Education)				
General Science	0.0000185	1.0000	-2.76	3.62
Arithmetic Reasoning	0.0000259	1.0000	-2.39	3.39
Word Knowledge	0.0000195	1.0000	-3.14	3.05
Paragraph Comprehension	0.0000183	1.0000	-3.32	4.23
Numerical Operations	0.0000153	1.0000	-3.54	3.39
Coding Speed	0.0000142	1.0000	-3.87	3.48
Auto Shop Information	5.17e-06	1.0000	-2.96	2.92
Mathematics Knowledge	0.0000308	1.0000	-2.73	3.28
Mechanical Comprehension	0.0000141	1.0000	-2.78	2.70
Electronic Information	0.0000133	1.0000	-2.68	2.77
g (Standardized for Age and Schooling)	54.9463	17.7903	0	94.81
Age Square 79	313.0114	79.833	196	484
Age Square 00	1520.972	175.9	1225	1936

Note:

1. Highest Grade 79 and Highest Grade 00 refers to years of schooling attained in 1979 and 2000.
2. *79 refers to year 1979 and *00 refers to year 2000.

Table 1b. Summary Statistics

Sample With Work Preventing Sample With SF-12 Variables Or Limiting Disabilities (Icd-9 Codes) 2697 Observations				
Variable	Mean	Std. Dev.	Min.	Max.
Lived in South at 14	0.3759	0.4844	0	1
Urban/Rural at 14	0.7938	0.4046	0	1
Lived with Parents at 14	8.0022	4.8987	0	11
Received Magazine at 14	0.5717	0.4949	0	1
Received Newspaper at 14	0.7923	0.4056	0	1
Library Membership at 14	0.7430	0.4370	0	1
Highest Grade of Mother 79	10.4290	4.0977	-4	20
Occupation of Mother 79	310.8884	355.01	-4	984
Highest Grade of Father 79	9.4846	5.5462	-4	20
Occupation of Father 79	364.7208	307.3497	-4	965
Highest Grade of Mother (Missing)	0.0448	0.2070	0	1
Highest Grade of Father (Missing)	0.1082	0.3107	0	1
Occupation of Father (Missing)	0.2536	0.4351	0	1
Occupation of Mother (Missing)	0.4282	0.4949	0	1
No. of Siblings	3.9907	2.7028	0	17
Does Health Limit Kind of Work 79?	0.0752	0.2638	0	1
Does Health Limit Amount of Work 79?	0.0571	0.2320	0	1
Race	2.3767	0.7432	1	3
Sex	0.4679	0.4990	0	1
Urban/Rural 79	0.5821	1.0750	-4	1
Urban/Rural (Missing)	0.0237	0.1522	0	1
SMSA 79	0.6711	0.4698	0	1
Age 79	19.8316	1.1347	18	22
Highest Grade 79	11.9087	1.5399	1	16
Highest Grade 79 (Revised	11.9061	1.5375	1	16
Marital Status 79	1.2450	0.5062	1	3
Family Size 79	4.0500	2.3466	1	15
ASVAB Tests in Different Areas				
General Science	14.7456	5.2295	0	25
Arithmetic Reasoning	16.3122	7.4380	0	30
Word Knowledge	24.4456	8.5885	0	35
Paragraph Comprehension	10.3359	3.6306	0	15
Numerical Operations	32.3704	11.844	0	50
Coding Speed	44.1549	17.1919	0	84
Auto Shop Information	13.2035	5.7154	0	25
Mathematics Knowledge	12.0986	6.1850	0	25
Mechanical Comprehension	12.8572	5.3763	0	25
Electronic Information	10.6681	4.3539	0	20
AFQT	43.9829	30.0603	1	99
AFQT (Revised)	43.4019	29.4282	1	99
Does Health Limit Kind of Work 00?	0.118279	0.3229	0	1
Does Health Limit Amount of Work 00?	0.113459	0.3172	0	1

Family Size 00	3.24175	1.6125	1	18
Marital Status 00	2.0723	0.6488	1	3
Highest Grade 00	13.2009	2.3931	1	20

Table 1b. Summary Statistics

Sample With Work Preventing Sample With SF-12 Variables Or Limiting Disabilities (Icd-9 Codes) 2697 Observations

Variable	Mean	Std. Dev.	Min.	Max.
Highest Grade 00 (Revised)	13.2625	2.4181	1	20
Age 00	41.2576	1.0726	40	44
Urban/Rural 00	0.7230	0.5898	-4	2
Urban/Rural 00(Missing)	0.0456	0.2086	0	1
SMSA 00	0.0704	0.2559	0	1
SF-12 Variables				
Respondent's General Health	0.1279	0.3340	0	1
Does Health Limits Moderate Activities?	0.1093808	0.3121	0	1
Does Health Limits Climbing Stairs?	0.1375603	0.3445	0	1
Does Health Limit the Kind of Work?	0.1053022	0.3069	0	1
Did Pain Interfere with Work?	0.1186504	0.3234	0	1
SF-12 Physical Component Score	5208.7	804.6613	1342	6837
SF-12 Mental Component Score	5288.127	848.8165	760	7094
Centre for Epidemiological Studies Depression Scale (CES-D) variables				
Depressed	0.1015944	0.3021	0	1
Occupation of Father Professional	0.19429	0.3957	0	1
Occupation of Father Clerk	0.0697	0.2546	0	1
Occupation of Father Farmer	0.0207	0.1426	0	1
Occupation of Father Foreman	0.3266	0.4690	0	1
Occupation of Father Labourer	0.0671	0.2502	0	1
Occupation of Father Service	0.0585	0.2348	0	1
Occupation of Father Armed Forces	0.0092	0.0958	0	1
Occupation of Mother Professional	0.1004	0.3006	0	1
Occupation of Mother Clerk	0.1742	0.3794	0	1
Occupation of Mother Farmer	0.0003	0.0192	0	1
Occupation of Mother Foreman	0.1153	0.3194	0	1
Occupation of Mother Labourer	0.0181	0.1335	0	1
Occupation of Mother Service	0.1253	0.3311	0	1
Occupation of Mother Other	0.0378	0.1907	0	1
Hispanics	0.1586	0.3654	0	1
Black	0.3058	0.4608	0	1
White	0.5354	0.4988	0	1
Never Married 79	0.7905	0.4070	0	1
Married 79	0.1738	0.3790	0	1
Married (Others) 79	0.0355	0.1853	0	1
Never Married 00	0.1768	0.3816	0	1
Married 00	0.57397	0.4945	0	1
Married (others) 00	0.24916	0.4326	0	1
AFQT 1st Decile	0.16794	0.3739	0	1
AFQT 2nd Decile	0.1349	0.3417	0	1
AFQT 3rd Decile	0.1067	0.3088	0	1
AFQT 4th Decile	0.0897	0.2858	0	1

AFQT 5th Decile	0.0860	0.2804	0	1
AFQT 6th Decile	0.0889	0 .2847	0	1
AFQT 7th Decile	0.0782	0.2685	0	1

Table 1b. Summary Statistics

Sample With Work Preventing Sample With SF-12 Variables Or Limiting Disabilities (Icd-9 Codes) 2697 Observations

Variable	Mean	Std. Dev.	Min.	Max.
AFQT 8th Decile	0.0849	0.2787	0	1
AFQT 9th Decile	0.0756	0.2644	0	1
AFQT 10th Decile	0.0867	0.2815	0	1
g (Not Standardised)	58.66934	18.9261	0	6.49
ASVAB Tests in Different Areas (Residualised on Age)				
General Science	2.08e-07	1.0001	-2.84	2.10
Arithmetic Reasoning	-2.88e-06	1.0001	-2.33	1.95
Word Knowledge	-1.99e-06	1.0001	-2.87	1.39
Paragraph Comprehension	-1.78e-06	1.0001	-2.93	1.41
Numerical Operations	-3.20e-06	1.0001	-2.66	1.56
Coding Speed	-1.17e-06	1.0001	-2.67	2.34
Auto Shop Information	2.72e-06	1.0001	-2.33	2.20
Mathematics Knowledge	-9.60e-07	1.0001	-1.98	2.12
Mechanical Comprehension	1.95e-06	1.0001	-2.34	2.39
Electronic Information	2.51e-06	1.0001	-2.47	2.22
g (Standardized for Age)	58.6646	18.9259	0	96.4
ASVAB Tests in Different Areas (Residualised on Age and Education)				
General Science	0.0000	1.0002	-2.79	3.03
Arithmetic Reasoning	0.0000	1.0001	-2.59	2.76
Word Knowledge	0.0000	1.0001	-3.38	2.85
Paragraph Comprehension	0.0000	1.0001	-3.38	2.65
Numerical Operations	0.0000	1.0001	-3.47	2.83
Coding Speed	0.0000	1.0001	-3.87	3.35
Auto Shop Information	5.41e-06	1.0001	-2.80	2.69
Mathematics Knowledge	0.0000	1.0002	-2.55	3.91
Mechanical Comprehension	0.0000	1.0001	-2.65	2.52
Electronic Information	0.0000	1.0001	-2.46	2.58
g (Standardized for Age and Schooling)	57.32663	18.5252	0	94.3
Age Square 79	394.5821	45.1156	324	484
Age Square 00	1703.347	88.7999	1600	1936

Note:

1. Highest Grade 79 and Highest Grade 00 refers to years of schooling attained in 1979 and 2000.
2. *79 refers to year 1979 and *00 refers to year 2000.

Table 2. Probit Estimates - Basic Single Equation Models

	Does health limits the amount of work respondent can do?			Assessment of respondent's general health		
Explanatory Variables	Model Ia	Model Ib	Model Ic	Model Ia	Model Ib	Model Ic
School	-0.1069(0.0120)		-0.0659(0.0134)	-0.1205(0.0175)		-0.0785(0.0198)
"g"		-0.0177(0.0017)	-0.0134(0.0019)		-0.0175(0.0024)	-0.0123(0.0027)
Age00	0.1749(0.3648)	0.2751(0.3652)	0.2397(0.3667)	-0.2667(2.7983)	-0.6535(2.7985)	-0.2206(2.8144)
$Age^2 00$	-0.0017(0.0046)	-0.0027(0.0047)	-0.0023(0.0046)	0.0028(0.0338)	0.0076(0.0338)	0.0024(0.0340)
Sex	-0.2563(0.0466)	-0.2143(0.0467)	-0.2415(0.0472)	-0.2084(0.0675)	-0.1337(0.0672)	-0.1718(0.0683)
Hispanic	0.1172(0.0737)	-0.2327(0.0745)	-0.1866(0.0750)	0.0020(0.1072)	-0.1547(0.1079)	-0.0812(0.1096)
Black	0.0505(0.0632)	-0.3050(0.0663)	-0.2236(0.0685)	-0.0759(0.0903)	-0.3670(0.0956)	-0.2583(0.0996)
Married00	0.3726(0.0648)	-0.3369(0.0651)	-0.3278(0.0654)	-0.2986(0.0985)	-0.2437(0.0990)	-0.2492(0.0995)
Married (Others)00	0.1764(0.0630)	-0.1269(0.0631)	-0.1482(0.0635)	0.0366(0.0945)	0.1128(0.0949)	0.0756(0.0956)
Family Size00	-0.0106(0.0153)	-0.0086(0.0154)	-0.0130(0.0155)	0.0167(0.0218)	0.0239(0.0216)	0.0185(0.0218)
SMSA 2000	0.2231(0.0917)	0.2377(0.0920)	0.2178(0.0923)	-0.0129(0.1394)	0.0233(0.1391)	-0.0036(0.1401)
Health 79 (H1)	0.5782(0.0874)	0.5460(0.0883)	0.5470(0.0883)			
School (Father)79	-0.0127(0.0087)	-0.0121(0.0086)	-0.0094(0.0087)	0.0016(0.0122)	0.0028(0.0122)	0.0045(0.0122)
School (Mother)97	0.0012(0.0101)	0.0038(0.0101)	0.0078(0.0102)	-0.0177(0.0142)	-0.0171(0.0143)	-0.0122(0.0144)
Xschool (Mother)79	0.0071(0.1607)	0.0284(0.1602)	0.0402(0.1614)	-0.1882(0.2171)	-0.1763(0.2167)	-0.1669(0.2182)
Xschool (Father)79	-0.0779(0.1210)	-0.0802(0.1207)	-0.0504(0.1216)	0.1252(0.1700)	0.1367(0.1696)	0.1455(0.1709)
Father Clerk79	0.0313(0.1093)	0.0257(0.1096)	0.0113(0.1101)	0.0820(0.1637)	0.0897(0.1633)	0.0637(0.1646)
Father Farmer79	-0.4488(0.2479)	-0.3968(0.2444)	-0.4355(0.2469)	-0.7152(0.4324)	-0.7090(0.4312)	-0.7426(0.4370)
Father Foreman79	-0.0012(0.0776)	0.0103(0.0777)	-0.0261(0.0783)	0.1058(0.1178)	0.1377(0.1172)	0.0876(0.1184)
Father Laborer79	0.0082(0.1077)	0.0182(0.1079)	-0.0138(0.1083)	0.2825(0.1586)	0.3195(0.1581)	0.2689(0.1591)
Father Service79	-0.0680(0.1161)	-0.0609(0.1163)	-0.0890(0.1168)	0.1752(0.1665)	0.2008(0.1667)	0.1593(0.1672)
Father AForces79	-0.2978(0.2921)	-0.2238(0.2878)	-0.2723(0.2924)	0.6600(0.3112)	0.7223(0.3116)	0.6866(0.3127)
XOccupation Father 79	-0.0284(0.0885)	-0.0432(0.0889)	-0.0620(0.0893)	0.2201(0.1294)	0.2313(0.1289)	0.2011(0.1298)
No. Sibling79	0.0137(0.0088)	0.0105(0.0089)	0.0087(0.0089)	0.0194(0.0125)	0.0167(0.0126)	0.0147(0.0126)
Lived in South14	-0.0413(0.0510)	-0.0689(0.0513)	0.0652(0.0515)	0.1134(0.0726)	0.0940(0.0726)	0.0999(0.0730)
Urban/Rural14	0.0573(0.0607)	0.0316(0.0609)	0.0340(0.0612)	-0.0200(0.0863)	-0.0582(0.0862)	- 0.0475(0.0869)
Lived Parent 14	-0.0173(0.0047)	-0.0183(0.0047)	-0.0171(0.0049)	0.0085(0.0073)	0.0070(0.0074)	0.0084(0.0073)
Magazine Available14	-0.0333(0.0521)	-0.0064(0.0527)	0.0050(0.0528)	-0.0311(0.0763)	-0.0112(0.0771)	0.0054(0.0773)
Newspaper Available 14	-0.0876(0.0570)	-0.0623(0.0573)	-0.0603(0.0574)	-0.1747(0.0850)	-0.1513(0.0852)	-0.1483(0.0855)
Library Membership14	0.0501(0.0548)	0.0557(0.0551)	0.0676(0.0553)	0.0115(0.0816)	0.0075(0.0816)	0.0315(0.0822)
Urban/Rural00	-0.0121(0.0444)	-0.0117(0.0442)	-0.0126(0.0448)	-0.0098(0.0621)	-0.0059(0.0614)	-0.0060(0.0623)
Xurban/Rural00	-0.0273(0.1479)	-0.0464(0.1472)	-0.0318(0.1484)	0.1122(0.2088)	0.0556(0.2071)	0.0851(0.2087)
Log likelihood	-1889.40	-1877.89	-1865.40	-923.30	-921.15	-913.10

Note: 1. Number of observations is 6651 when 'Does health limits the amount of work respondent can do?' is used as health variable and 2697 when 'Assessment of respondent's general health' is used as health variable.
2. Past health was not available for second model and X appearing before any variable means missing observations.
3. Standard errors are reported in parenthesis.

Table 2a. Probit Estimates Schooling and "g" Using Different Health Variables
(Basic Single Equation Models, S*g not included in Models)

Different Explanatory Variables	↓School or g	Model Ia	Model Ib	Model Ic
Work Preventing Or Limiting Disabilities (ICD-9 Codes) – 6551 observations				
Does health limit the kind of work respondent can do?	School	-0.0974(0.0117)		-0.0642(0.0130)
	g		-0.0151(0.0017)	-0.0108(0.0019)
Does health limit the amount of work respondent can do?	School	-0.1069(0.0120)		-0.0660(0.0134)
	g		-0.0178(0.0017)	-0.0134(0.0020)
For The Sample Used For SF-12 Variables – 2697 Observations				
Does health limit the kind of work respondent can do?	School	-0.1123(0.0179)		-0.0824(0.0200)
	g		-0.0144(0.0024)	-0.0090(0.0028)
Does health limit the amount of work respondent can do?	School	-0.1180(0.0183)		-0.0837(0.0205)
	g		-0.0157(0.0024)	-0.0103(0.0028)
SF-12 Variables – 2697 Observations				
Assessment of respondent's general health	School	-0.1205(0.0176)		-0.0784(0.0198)
	g		-0.0175(0.0024)	-0.0123(0.0027)
Does respondent's health limit moderate activities?	School	-0.0786(0.0172)		-0.0426(0.0194)
	g		-0.0140(0.0025)	-0.0110(0.0028)
Does respondent's health limit climbing stairs?	School	-0.0835(0.0163)		-0.0615(0.0185)
	g		-0.0109(0.0023)	-0.0067(0.0026)
Health limit kind of work or other activities?	School	-0.0516(0.0167)		-0.0400(0.0192)
	g		-0.0064(0.0024)	-0.0036(0.0028)
Did pain interfered with normal work in the past 4 weeks?	School	-0.0498(0.0164)		-0.0327(0.0186)
	g		-0.0075(0.0024)	-0.0052(0.0027)
CESD Variable – 2697 Observations				
CESD-depressed	School	-0.0560(0.0173)		-0.0448(0.0197)
	g		-0.0059(0.0025)	-0.0024(0.0029)
SF-12 Variables – 2697 Observations				
SF-12 score, Physical component summary	School	44.659(7.4576)		32.784(8.4904)
	g		6.1537(1.1352)	3.7598(1.2909)
SF-12 score, Mental component summary	School	15.508(7.8775)		7.7315(8.9777)
	g		3.0268(1.1972)	2.4623(1.3650)

Table 3. Health Status Equation Probit Estimates - Basic Single Equation Models & Two Stage Models

	Does health limits the amount of work respondent can do?			Assessment of respondent's general health		
	Single Equation Model	Two Stage Models		Single Equation Model	Two Stage Models	
Schooling	-0.0659(0.0134)			-0.0785(0.0198)		
predicted Schooling		-0.1079(0.0476)	-0.1147(0.1981)		-0.2156(0.0639)	-0.4599(0.2242)
"g"	-0.0134(0.0019)	-0.0095(0.0044)	-0.0108(0.0352)	-0.0123(0.0027)	-0.0015(0.0058)	-0.0447(0.0379)
School*g			0.0001(0.0029)			0.0036(0.0031)
Age00	0.1749(0.3648)	0.2026(0.3618)	0.2008(0.3650)	-0.2667(2.7983)	-0.6535(2.7985)	-0.0642(2.8306)
Age²00	-0.0017(0.0046)	-0.0019(0.0047)	-0.0019(0.0046)	0.0028(0.0338)	0.0076(0.0338)	0.0005(0.0342)
Sex	-0.2563(0.0466)	-0.2570(0.0490)	-0.2580(0.0564)	-0.2084(0.0675)	-0.1337(0.0672)	-0.2597(0.0808)
Hispanic	0.1172(0.0737)	-0.1659(0.0731)	-0.1653(0.0750)	0.0020(0.1072)	-0.1547(0.1079)	-0.0811(0.1096)
Black	0.0505(0.0632)	-0.1619 (0.0868)	-0.1600(0.1026)	-0.0759(0.0903)	-0.3670(0.0956)	0.0328(0.1430)
Married00	0.3726(0.0648)	-0.3527(0.0651)	-0.3527(0.0652)	-0.2986(0.0985)	-0.2437(0.0990)	-0.2860(0.1025)
Married (Others)00	0.1764(0.0630)	-0.1407(0.0641)	-0.1406(0.0641)	0.0366(0.0945)	0.1128(0.0949)	0.0713(0.0977)
Family Size00	-0.0106(0.0153)	-0.0073(0.0156)	-0.0073(0.0156)	0.0167(0.0218)	- 0.0239(0.0216)	- 0.0274(0.0232)
SMSA 2000	0.2231(0.0917)	- 0.2553(0.0938)	- 0.2351(0.0941)	-0.0129(0.1394)	-0.0233(0.1391)	-0.0054(0.1407)
Health 79 (H1)	0.5782(0.0874)	- 0.5319(0.0921)	- 0.5319(0.0459)			
School (Father)79	-0.0127(0.0087)			0.0016(0.0122)		
School (Mother)97	0.0012(0.0101)			-0.0177(0.0142)		
Xschool (Mother)79	0.0071(0.1607)			-0.1882(0.2171)		
Xschool (Father)79	-0.0779(0.1210)			0.1252(0.1700)		
Father Clerk79	0.0313(0.1093)			0.0820(0.1637)		
Father Farmer79	-0.4488(0.2479)			-0.7152(0.4324)		
Father Foreman79	-0.0012(0.0776)			0.1058(0.1178)		
Father Laborer79	0.0082(0.1077)			0.2825(0.1586)		
Father Service79	-0.0680(0.1161)			0.1752(0.1665)		
Father AForces79	-0.2978(0.2921)			0.6600(0.3112)		
XOccupation Father 79	-0.0284(0.0885)			0.2201(0.1294)		
No. Sibling79	0.0137(0.0088)			0.0194(0.0125)		
Lived in South14	-0.0413(0.0510)	-0.0505(0.0525)	-0.0508(0.0533)	0.1134(0.0726)	0.0940(0.0726)	0.1128 (0.0825)
Urban/Rural14	0.0573(0.0607)	0.0536(0.0610)	0.0534(0.0616)	-0.0200(0.0863)	-0.0582(0.0862)	- 0.0124(0.0910)
Lived Parent 14	-0.0173(0.0047)	-0.0159(0.0047)	-0.0159(0.0046)	0.0085(0.0073)	0.0070(0.0074)	0.0065(0.0070)
Magazine Available14	-0.0333(0.0521)	-0.0181(0.0557)	0.0182(0.0560)	-0.0311(0.0763)	-0.0112(0.0771)	0.0262(0.0822)
Newspaper Available 14	-0.0876(0.0570)	-0.0738(0.0573)	-0.0731(0.0602)	-0.1747(0.0850)	-0.1513(0.0852)	-0.1575(0.0939)
Library Membership14	0.0501(0.0548)	0.0808(0.0575)	0.0813(0.0602)	0.0115(0.0816)	0.0075(0.0816)	0.1127(0.0919)
Urban/Rural00	-0.0121(0.0444)	-0.0093(0.0427)	-0.0093(0.0428)	-0.0098(0.0621)	-0.0059(0.0614)	-0.0040(0.0732)
Xurban/Rural00	-0.0273(0.1479)	-0.0459(0.1531)	-0.0459(0.1533)	0.1122(0.2088)	0.0556(0.2071)	0.0685(0.2318)
Log likelihood	-1889.40	-1877.89	-1880.09	-923.30	-921.15	-925.85

Note: (1) Standard errors for Two Stage Models are bootstrap standard errors. (2) Number of observations is 6651 when 'Does health limits the amount of work respondent can do?' is used as health variable and 2697 when 'Assessment of respondent's general health' is used as health variable. (3) Past health was not available for second model and X appearing before any variable means missing observations. (4) Standard errors are reported in parenthesis.

Table 3a. Health Status Equation Probit Estimates Using Different Health Variables - Two Stage Models

Health Variable	"g" estimate		
	S*g not included	S*g included	
	g	g	S*g
Work Preventing Or Limiting Disabilities (ICD-9 Codes) – 6551 observations			
Does health limit the kind of work respondent can do?	-0.0074(0.0042)	-0.0166(0.0341)	0.0008(0.0028)
Does health limit the amount of work respondent can do?	-0.0095(0.0044)	-0.0107(0.0352)	0.0001(0.0029)
For The Sample Used For SF-12 Variables – 2697 Observations			
Does health limit the kind of work respondent can do?	-0.0034(0.0058)	0.0058(0.0369)	0.0008(0.0030)
Does health limit the amount of work respondent can do?	-0.0020(0.0060)	0.0226(0.0380)	-0.0020(0.0031)
SF-12 Variables – 2697 Observations			
Assessment of respondent's general health	-0.0015(0.0058)	-0.0447(0.0379)	0.0036(0.0031)
Does respondent's health limit moderate activities?	-0.0061(0.0060)	0.0219(0.0384)	-0.0023(0.0031)
Does respondent's health limit climbing stairs?	-0.0047(0.0058)	0.0385(0.0366)	-0.0036(0.0030)
Health limit kind of work or other activities?	0.0044(0.0062)	0.0079(0.0374)	-0.0003(0.0031)
Did pain interfered with normal work?	0.0067(0.0058)	-0.0057(0.0400)	0.0010(0.0032)
CESD Variable – 2697 Observations			
CESD-depressed	0.0020(0.0062)	-0.0217(0.0365)	0.0019(0.0030)
SF-12 Variables – 2697 Observations			
SF-12 score, Physical component summary	-1.1273(2.7520)	2.8682(18.934)	-0.3354(1.5895)
SF-12 score, Mental component summary	-1.8969(3.0310)	30.881(20.461)	-2.7516(1.6940)

Note: 1. Standard errors are reported in parenthesis.
2. Standard errors for Two Stage Models are bootstrap standard errors.

Table 4. Comparison With Berger and Leigh Model: Probit Estimates of Schooling and "g" Using Different Health Variables (Two-Stage Models, S*g not included in Models)

Different Explanatory Variables	↓School or g	Model IIa	Model IIb	Model IIc
Work Preventing Or Limiting Disabilities (ICD-9 Codes) – 6551 observations				
Does health limit the kind of work respondent can do?	School	-0.1336(0.0257)	-0.1755(0.0181)	-0.1003(0.0462)
	g			-0.0074(0.0042)
Does health limit the amount of work respondent can do?	School	-0.1466(0.0259)	-0.2042(0.0181)	-0.1079(0.0476)
	g			-0.0095(0.0044)
For The Sample Used For SF-12 Variables – 2697 Observations				
Does health limit the kind of work respondent can do?	School	-0.1692(0.0388)	-0.1864(0.0272)	-0.1519(0.0656)
	g			-0.0034(0.0058)
Does health limit the amount of work respondent can do?	School	-0.1940(0.0392)	-0.2110(0.0263)	-0.1907(0.0676)
	g			-0.0020(0.0059)
SF-12 Variables – 2697 Observations				
Assessment of respondent's general health	School	-0.2219(0.0364)	-0.2308(0.0263)	-0.2156(0.0645)
	g			-0.0015(0.0058)
Does respondent's health limit moderate activities?	School	-0.1305(0.0393)	-0.1644(0.0259)	-0.1022(0.0682)
	g			-0.0061(0.0062)
Does respondent's health limit climbing stairs?	School	-0.1109(0.0365)	-0.1362(0.0243)	-0.0885(0.0643)
	g			-0.0047(0.0056)
Health limit kind of work or other activities?	S chool	-0.1305(0.0375)	-0.1055(0.0272)	-0.1505(0.0680)
	g			-0.0044(0.0062)
Did pain interfered with normal work in the past 4 weeks?	School	-0.1407(0.0392)	-0.1202(0.0251)	-0.1878(0.0651)
	g			-0.0067(0.0058)
CESD Variable – 2697 Observations				
CESD-depressed	School	-0.0686(0.0397)	-0.0742(0.0267)	-0.0947(0.0690)
	g			0.0022(0.0062)
SF-12 Variables – 2697 Observations				
SF-12 score, Physical component summary	School	92.744(17.254)	88.259(11.797)	99.520(29.914)
	g			-1.1276(2.7521)
SF-12 score, Mental component summary	School	50.541(18.823)	45.996(12.696)	64.945(32.154)
	g			-1.8969(2.9617)

Note: 1. Model IIa is the same as our model represented by equation 7 and 8, but there is no "g" in schooling equation.
2. Model IIb is the same as our model represented by equation 7 and 8 (Berger and Leigh (1989) Model)
3. Model IIc is the same as our model represented by equation 4 and 5, but excluding interaction of schooling and g.
4. School in this table means predicted schooling.
5. Standard errors are reported in parenthesis.

Table 5. Probit Estimates – The Effect Of Residuals On Health With And Without Including "g"

	Dependent variables			
	Does health limits the amount of work respondent can do?		Assessment of respondent's general health	
Explanatory Variables	Model without "g"	Model with "g"	Model without "g"	Model with "g"
Schooling	-0.2127(0.0185)	-0.1300(0.0603)	-0.2401(0.0273)	-0.2706(0.0860)
Predicted Residuals	0.1150(0.0515)	0.0298(0.0752)	0.1202(0.0878)	0.1473(0.1212)
S*Predicted Residuals	0.0027(0.0037)	0.0021(0.0043)	0.0036(0.0064)	0.0009(0.0075)
"g"		-0.0117(0.0082)		-0.0093(0.0119)
g*Schooling		0.0002(0.0006)		0.0007(0.0009)
Age2000	0.1270(0.3598)	0.2128(0.3632)	-0.1145(2.8281)	-0.0457(2.8366)
Age^{2}2000	-0.0011(0.0046)	-0.0020(0.0046)	0.0011(0.0342)	0.0002(0.0343)
Sex	-0.2988(0.0476)	-0.2648(0.0497)	-0.2407(0.0716)	-0.2390(0.0760)
Hispanic	-0.1153(0.0706)	-0.1595(0.0738)	-0.0876(0.1023)	0.0818(0.1097)
Black	-0.0171(0.0608)	-0.1458(0.0882)	-0.0063(0.0923)	-0.0013(0.1316)
Married2000	-0.3568(0.0679)	-0.3374(0.0657)	-0.2832(0.1019)	-0.2781(0.1035)
Othermarried2000	-0.1722(0.0638)	-0.1535(0.0645)	0.0446(0.0968)	0.0491(0.0981)
Famsize2000	-0.0113(0.0157)	-0.0122(0.0157)	0.0219(0.0232)	0.0211(0.0233)
SMSA2000	0.2077(0.0946)	0.2137(0.0950)	-0.0285(0	-0.0293(0.1417)
Health1979	0.5331(0.0945)	0.5386(0.0922)		
Lived in South14	-0.0387(0.0527)	-0.0568(0.0529)	0.1279(0.0798)	0.1232(0.0810)
Urban/Ruralat14	0.0680(0.0611)	0.0493(0.0615)	-0.0136(0.0891)	0.0112(0.0915)
Lived with Parents14	-0.0144(0.0046)	-0.0159(0.0046)	0.0065(0.0070)	0.0063(0.0071)
Magazine Available14	0.0418(0.0545)	0.0166(0.0569)	0.0307(0.0798)	0.0261(0.0815)
Newspaper Available 14	-0.0707(0.0578)	-0.0645(0.0578)	-0.1764(0.0893)	0.1744(0.0897)
Library Membership14	0.1075(0.0570)	0.0835(0.0578)	0.0853(0.0853)	0.0866(0.0874)
Urban/Rural2000	-0.0087(0.0439)	-0.0110(0.0438)	-0.0017(0.0773)	-0.0030(0.0774)
XUrban/Rural2000	-0.0308(0.1544)	-0.0321(0.1543)	0.0962(0.2426)	0.0888(0.2449)
Log likelihood	-1870.90	-1868.52	-919.33	-918.97

Note:
1. Standard errors for Two Stage Models are bootstrap standard errors.
2. Number of observations is 6651 when 'Does health limits the amount of work respondent can do?' is used as health variable and 2697 when 'Assessment of respondent's general health' is used as health variable.
3. Past health was not available for second model.
4. Standard errors are reported in parenthesis.

Table 6. 'Third Variable' Hypothesis Estimation: Probit Estimates Using Different Health Variables

	'Third Variable' Hypothesis Estimation			
	g not included		g included	
Health Variable	uhat	S*uhat	uhat	S*uhat
Work Preventing Or Limiting Disabilities (ICD-9 Codes) – 6551 observations				
Health limit the kind of work respdt. can do?	0.1208(0.0501)	0.0001(0.0036)	0.0890(0.0740)	-0.0028(0.0043)
Health limit the amount of work respdt. can do?	0.1150(0.0513)	0.0027(0.0037)	0.0298(0.0752)	0.0021(0.0043)
For The Sample Used For SF-12 Variables – 2697 Observations				
Health limit the kind of work respdt. can do?	0.0402(0.0777)	0.0061(0.0055)	0.0246(0.1140)	0.0048(0.0066)
Health limit the amount of work respdt. can do?	0.0653(0.0774)	0.0061(0.0056)	0.0261(0.1175)	0.0075(0.0069)
SF-12 Variables – 2697 Observations				
Assessment of respondent's general health	0.1202(0.0878)	0.0036(0.0064)	0.1472(0.1212)	0.0009(0.0075)
Respondent's health limit moderate activities?	0.0380(0.0802)	0.0073(0.0057)	0.0247(0.1208)	0.0040(0.0069)
Does respondent's health limit climbing stairs?	0.0141(0.0791)	0.0052(0.0055)	0.0466(0.1115)	0.0061(0.0064)
Health limit kind of work or other activities?	-0.0516(0.0806)	0.0097(0.0056)	0.0881(0.1199)	0.0033(0.0069)
Did pain interfered with normal work?	0.0778(0.0735)	0.0014(0.0052)	0.1855(0.1097)	-0.0012(0.0062)
CESD Variable – 2697 Observations				
CESD-depressed	-0.0863(0.0776)	0.0091(0.0053)	-0.0000(0.1186)	0.0047(0.0067)
SF-12 Variables – 2697 Observations				
SF-12 score, Physical component summary	-5.4519(45.2421)	-3.9534(2.9923)	-60.0634(59.34)	-1.1146(3.3276)
SF-12 score, Mental component summary	24.7770(43.2198)	-4.8007(2.9633)	45.9696(56.41)	-1.4012(3.2237)

Note:

1. Standard errors for Two Stage Models are bootstrap standard errors.
2. Standard errors are reported in parenthesi

Table 7. Probit Estimates: With and Without Past Health (CH_1) In the Model

	With CH_1 in Model		Without CH_1 in Model	
	g	g*Schooling	g	g*Schooling
Sample Size – 6651 observations				
Basic Single Equation Models				
Health limits amount of work respondent can do?	-0.0134(0.0020)		-0.0140(0.0019)	
Health limit kind of work respondent can de?	-0.0108(0.0019)		-0.0116(0.0019)	
Two Stage Models - Interaction term of Schooling and "g" not included				
Health limits amount of work respondent can do?	-0.0095(0.0044)		-0.0088(0.0046)	
Health limit kind of work respondent can de?	-0.0074(0.0042)		-0.0063(0.0045)	
Two Stage Models – Interaction term of Schooling and "g" included				
Health limits amount of work respondent can do?	-0.0107(0.0352)	0.0001(0.0029)	-0.0110(0.0336)	0.0002(0.0027)
Health limit kind of work respondent can de?	-0.0166(0.0341)	0.0008(0.0028)	-0.0280(0.0326)	0.0018(0.0026)
'Third Variable' Hypothesis Estimation: g not included				
Health limits amount of work respondent can do?	0.1150(0.0513)	0.0027(0.0037)	0.1256(0.0513)	0.0026(0.0037)
Health limit kind of work respondent can de?	0.1208(0.0501)	0.0000(0.0036)	0.1330(0.0498)	0.0001(0.0036)
'Third Variable' Hypothesis Estimation: g included				
Health limits amount of work respondent can do?	-0.0117(0.0082)	0.0002(0.0006)	-0.0108(0.0083)	0.0002(0.0006)
Health limit kind of work respondent can de?	-0.0168(0.0083)	0.0008(0.0006)	-0.0152(0.0084)	0.0008(0.0006)
Sample Size – 2697 observations				
Basic Single Equation Models				
Health limits amount of work respondent can do?	-0.0103(0.0028)		-0.0112(0.0028)	
Health limit kind of work respondent can de?	-0.0090(0.0028)		-0.0102(0.0027)	
Two Stage Models - Interaction term of Schooling and "g" not included				
Health limits amount of work respondent can do?	-0.0020(0.0060)		-0.0029(0.0064)	
Health limit kind of work respondent can de?	-0.0034(0.0058)		-0.0049(0.0066)	
Two Stage Models – Interaction term of Schooling and "g" included				
Health limits amount of work respondent can do?	0.0226(0.0380)	-0.0020(0.0031)	0.0355(0.0362)	-0.0031(0.0029)
Health limit kind of work respondent can de?	0.0059(0.0369)	-0.0008(0.0030)	0.0183(0.0353)	-0.0019(0.0028)
'Third Variable' Hypothesis Estimation: g not included				
Health limits amount of work respondent can do?	0.0653(0.0774)	0.0061(0.0056)	0.0875(0.0778)	0.0051(0.0057)
Health limit kind of work respondent can de?	0.0402(0.0777)	0.0061(0.0055)	0.0623(0.0773)	0.0053(0.0055)
Third Variable' Hypothesis Estimation: g included				
Health limits amount of work respondent can do?	0.0027(0.0123)	-0.0004(0.0009)	0.0022(0.0125)	-0.0004(0.0009)
Health limit kind of work respondent can de?	-0.0072(0.0121)	0.0003(0.0009)	-0.0072(0.0125)	0.0002(0.0009)

Note: 1. In case of Model III, it is estimates of uhat and Schooling*uhat in the column where g and g*Schooling is reported.
2. Standard errors are reported in parenthesis.

Table 8a. Semi-Parametric Estimation

Dependent Health Variable:
Does the health limit the amount of work the respondent can do?

AFQT categories (Percentiles) →	AFQT<11	10<AFQT<21	20<AFQT<36	35<AFQT<56	55<AFQT<76	AFQT>75
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0220	-0.0606	-0.0569	-0.0291	0.0416
		(0.0151)	(0.0091)	(0.0127)	(0.0564)	(0.1742)
Schooling=12	-0.0284	-0.0570	-0.0522	-0.0622	-0.0674	-0.0658
	(0.0097)	(0.0069)	(0.0075)	(0.0066)	(0.0057)	(0.0062)
Schooling>12 & <16	-0.0282	-0.0661	-0.0581	-0.0697	-0.0690	-0.0799
	(0.0155)	(0.0058)	(0.0069)	(0.0058)	(0.0059)	(0.0051)
Schooling>16	----------	-0.0537	-0.0689	-0.0591	-0.0689	-0.0799
		(0.0256)	(0.0077)	(0.0104)	(0.0056)	(0.0042)
AFQT (% of total respondents) →	**Lowest 20%**	**Next 20%**	**Next 20%**	**Next 20%**	**Top 20%**	
Schooling categories (No. of Years)↓						
Schooling<12	----------	-0.0292	-0.0603	-0.0512	-0.0143	
		(0.0133)	(0.0103)	(0.0190)	(0.0911)	
Schooling=12	-0.0287	-0.0564	-0.0552	-0.0684	-0.0697	
	(0.0096)	(0.0071)	(0.0074)	(0.0060)	(0.0054)	
Schooling>12 & <16	-0.0364	-0.0561	-0.0688	-0.0732	-0.0798	
	(0.0131)	(0.0072)	(0.0058)	(0.0058)	(0.0059)	
Schooling>16	---------	-0.0644	-0.0620	-0.0651	-0.0814	
		(0.0129)	(0.0105)	(0.0067)	(0.0043)	
AFQT (% of total respondents) →	**Lowest 25%**	**Next 25%**	**Next 25%**	**Top 25%**		
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0365	-0.0570	0.0567		
		(0.0131)	(0.0129)	(0.1218)		
Schooling=12	-0.0323	-0.0546	-0.0613	-0.0699		
	(0.0088)	(0.0074)	(0.0069)	(0.0056)		
Schooling>12 & <16	-0.0458	-0.0599	-0.0711	-0.0800		
	(0.0098)	(0.0067)	(0.0061)	(0.0062)		
Schooling>16	-0.0103	-0.0706	-0.0604	-0.0809		
	(0.0800)	(0.0068)	(0.0085)	(0.0046)		

Table 8b. Semi-Parametric Estimation

Dependent Health Variable:
Does the health limit the kind of work the respondent can do?

AFQT categories (Percentiles) →	AFQT<11	10<AFQT<21	20<AFQT<36	35<AFQT<56	55<AFQT<76	AFQT>75
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0324	-0.0636	-0.0570	-0.0417	---------
		(0.0151)	(0.0113)	(0.0166)	(0.1084)	
Schooling=12	-0.0286	-0.0596	-0.0554	-0.0669	-0.0598	-0.0705
	(0.0109)	(0.0079)	(0.0085)	(0.0075)	(0.0087)	(0.0073)
Schooling>12 & <16	-0.0366	-0.0747	-0.0634	-0.0726	-0.0762	-0.0847
	(0.0159)	(0.0062)	(0.0078)	(0.0068)	(0.0065)	(0.0059)
Schooling>16	---------	-0.0584	-0.0767	-0.0664	-0.0770	-0.0836
		(0.0297)	(0.0087)	(0.0112)	(0.0061)	(0.0052)
AFQT (% of total respondents) →	Lowest 20%	Next 20%	Next 20%	Next 20%	Top 20%	
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0327	-0.0611	-0.0267	----------	
		(0.0146)	(0.0138)	(0.0340)		
Schooling=12	-0.0272	-0.0562	-0.0589	-0.0644	-0.0721	
	(0.0109)	(0.0084)	(0.0083)	(0.0079)	(0.0069)	
Schooling>12 & <16	-0.0433	-0.0657	-0.0675	-0.0810	-0.0830	
	(0.0139)	(0.0075)	(0.0074)	(0.0064)	(0.0067)	
Schooling>16	---------	-0.0704	-0.0690	-0.0724	-0.0853	
		(0.0161)	(0.0118)	(0.0075)	(0.0052)	
AFQT (% of total respondents) →	Lowest 25%	Next 25%	Next 25%	Top 25%		
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0397	-0.0478	0.0330		
		(0.0145)	(0.0200)	(0.0633)		
Schooling=12	-0.0301	-0.0564	-0.0609	-0.0672		
	(0.0101)	(0.0084)	(0.0082)	(0.0075)		
Schooling>12 & <16	-0.0546	-0.0644	-0.0742	-0.0844		
	(0.0101)	(0.0075)	(0.0070)	(0.0070)		
Schooling>16	-0.0052	-0.0782	-0.0642	-0.0858		
	(0.0918)	(0.0079)	(0.0101)	(0.0053)		

Table 8c. Semi-Parametric Estimation

Dependent Health Variable:
Does the health limit the amount of work the respondent can do?

AFQT categories (Percentiles) →	AFQT<11	10<AFQT<21	20<AFQT<36	35<AFQT<56	55<AFQT<76	AFQT>75
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0221	-0.0610	-0.0573	-0.0293	0.0416
		(0.0151)	(0.0091)	(0.0127)	(0.0567)	(0.1747)
Schooling=12	-0.0285	-0.0573	-0.0526	-0.0626	-0.0679	-0.0662
	(0.0097)	(0.0069)	(0.0076)	(0.0066)	(0.0058)	(0.0061)
Schooling>12	-0.0292	-0.0662	-0.0601	-0.0705	-0.0733	-0.0911
	(0.0153)	(0.0058)	(0.0068)	(0.0060)	(0.0060)	(0.0056)

AFQT (% of total respondents) →	Lowest 20%	Next 20%	Next 20%	Next 20%	Top 20%
Schooling categories (No. of Years)↓					
Schooling<12	---------	-0.0294	-0.0608	-0.0515	-0.0141
		(0.0134)	(0.0103)	(0.0191)	(0.0920)
Schooling=12	-0.0290	-0.0567	-0.0556	-0.0689	-0.0703
	(0.0096)	(0.0071)	(0.0074)	(0.0060)	(0.0054)
Schooling>12	-0.0376	-0.0574	-0.0700	-0.0760	-0.0928
	(0.0129)	(0.0071)	(0.0058)	(0.0061)	(0.0064)

AFQT (% of total respondents) →	Lowest 25%	Next 25%	Next 25%	Top 25%
Schooling categories (No. of Years)↓				
Schooling<12	---------	-0.0368	-0.0576	0.0578
		(0.0133)	(0.01319)	(0.1230)
Schooling=12	-0.0324	-0.0549	-0.0617	-0.0705
	(0.0089)	(0.0074)	(0.0069)	(0.0056)
Schooling>12	-0.0452	-0.0621	-0.0728	-0.0934
	(0.0100)	(0.0067)	(0.0064)	(0.0071)

Table 8d. Semi-Parametric Estimation

Dependent Health Variable:
Does the health limit the kind of work the respondent can do?

AFQT categories (Percentiles) →	AFQT<11	10<AFQT<21	20<AFQT<36	35<AFQT<56	55<AFQT<76	AFQT>75
Schooling categories (No. of Years)↓						
Schooling<12	---------	-0.0324	-0.0638	-0.0572	-0.0418	---------
		(0.0151)	(0.0113)	(0.0166)	(0.1086)	
Schooling=12	-0.0285	-0.0598	-0.0556	-0.0671	-0.0600	-0.0707
	(0.0109)	(0.0079)	(0.0086)	(0.0075)	(0.0087)	(0.0074)
Schooling>12 & <16	-0.0376	-0.0745	-0.0656	-0.0737	-0.0808	-0.0939
	(0.0157)	(0.0062)	(0.0075)	(0.0069)	(0.0065)	(0.0064)

AFQT (% of total respondents) →	Lowest 20%	Next 20%	Next 20%	Next 20%	Top 20%
Schooling categories (No. of Years)↓					
Schooling<12	---------	-0.0327	-0.0613	-0.0266	---------
		(0.0147)	(0.0139)	(0.0342)	
Schooling=12	-0.0272	-0.0564	-0.0590	-0.0645	-0.0723
	(0.0110)	(0.0084)	(0.0084)	(0.0080)	(0.0069)
Schooling>12 & <16	-0.0444	-0.0666	-0.0689	-0.0835	-0.0942
	(0.0137)	(0.0074)	(0.0074)	(0.0067)	(0.0073)

AFQT (% of total respondents) →	Lowest 25%	Next 25%	Next 25%	Top 25%
Schooling categories (No. of Years)↓				
Schooling<12	---------	-0.0399	-0.0480	0.0326
		(0.0146)	(0.0201)	(0.0643)
Schooling=12	-0.0301	-0.0566	-0.0610	-0.0675
	(0.0101)	(0.0084)	(0.0083)	(0.0076)
Schooling>12 & <16	-0.0538	-0.0667	-0.0754	-0.0968
	(0.0103)	(0.0075)	(0.0073)	(0.0078)

Table 8e Semi-Parametric Estimation

Dependent Health Variable:
Does the health limit the amount of work the respondent can do?

Schooling categories (No. of Years) → AFQT categories (Deciles)↓	Schooling<12	Schooling=12	12<Schooling<16	Schooling>16
1st	----------	-0.0279	-0.0276	----------
		(0.0096)	(0.0152)	
2nd	-0.0221	-0.0561	-0.0649	-0.0529
	(0.0147)	(0.0068)	(0.0057)	(0.0249)
3rd	-0.0639	-0.0493	-0.0487	-0.0631
	(0.0077)	(0.0077)	(0.0083)	(0.0124)
4th	-0.0535	-0.0526	-0.0652	-0.0682
	(0.0156)	(0.0074)	(0.0057)	(0.0074)
5th	-0.0396	-0.0584	-0.0664	-0.0579
	(0.0271)	(0.0068)	(0.0056)	(0.0141)
6th	----------	-0.0616	-0.0673	-0.0596
		(0.0064)	(0.0054)	(0.0096)
7th	0.1639	-0.0643	-0.0662	-0.0667
	(0.2691)	(0.0062)	(0.0057)	(0.0063)
8th	0.0652	-0.0667	-0.0666	-0.0705
	(0.2025)	(0.0056)	(0.0057)	(0.0048)
9th	--------	-0.0733	-0.0707	-0.0698
		(0.0039)	(0.0050)	(0.0051)
10th	--------	-0.0436	-0.0701	-0.0766
		(0.0205)	(0.0050)	(0.0038)

Schooling categories (No. of Years) → AFQT categories (Deciles)↓	Schooling<12	Schooling=12	Schooling>12
1st	--------	-0.0281	-0.0288
		(0.0096)	(0.0151)
2nd	-0.0224	-0.0568	-0.0654
	(0.0148)	(0.0068)	(0.0058)
3rd	-0.0647	-0.0500	-0.0506
	(0.0078)	(0.0078)	(0.0081)
4th	-0.0543	-0.0533	-0.0672
	(0.0157)	(0.0075)	(0.0056)
5th	-0.0402	-0.0592	-0.0673
	(0.0274)	(0.0068)	(0.0057)
6th	---------	-0.0624	-0.0681
		(0.0065)	(0.0056)
7th	0.1645	-0.0652	-0.0690
	(0.2699)	(0.0062)	(0.0054)
8th	0.0667	-0.0676	-0.0709
	(0.2048)	(0.0056)	(0.0053)
9th	--------	-0.0743	-0.0745
		(0.0038)	(0.0049)
10th	--------	-0.0443	-0.0784
		(0.0207)	(0.0045)

Table 8f Semi-Parametric Estimation

Dependent Health Variable: Does the health limit the kind of work the respondent can do?				
Schooling categories (No. of Years) →	Schooling<12	Schooling=12	12<Schooling<16	Schooling>16
AFQT categories (Deciles)↓				
1st	----------	-0.0282	-0.0361	---------
		(0.0107)	(0.0156)	
2nd	-0.0322	-0.0590	-0.0734	-0.0576
	(0.0147)	(0.0077)	(0.0060)	(0.0289)
3rd	-0.0717	-0.0524	-0.0539	-0.0703
	(0.0084)	(0.0087)	(0.0093)	(0.0142)
4th	-0.0492	-0.0570	-0.0673	-0.0766
	(0.0221)	(0.0084)	(0.0072)	(0.0080)
5th	-0.0239	-0.0632	-0.0720	-0.0656
	(0.0394)	(0.0078)	(0.0064)	(0.0149)
6th	-0.0570	-0.0606	-0.0740	-0.0613
	(0.0311)	(0.0086)	(0.0061)	(0.0127)
7th	0.1749	-0.0570	-0.0737	-0.0787
	(0.2800)	(0.0101)	(0.0062)	(0.0052)
8th	--------	-0.0662	-0.0715	-0.0788
		(0.0082)	(0.0067)	(0.0052)
9th	--------	-0.0822	-0.0775	-0.0782
		(0.0040)	(0.0056)	(0.0055)
10th	--------	-0.0504	-0.0740	-0.0771
		(0.0219)	(0.0063)	(0.0058)

Schooling categories (No. of Years) →	Schooling<12	Schooling=12	Schooling>12
AFQT categories (Deciles)↓			
1st	--------	-0.0282	-0.0372
		(0.0108)	(0.0155)
2nd	-0.0325	-0.0593	-0.0735
	(0.0148)	(0.0078)	(0.0062)
3rd	-0.0723	-0.0528	-0.0557
	(0.0084)	(0.0088)	(0.0090)
4th	-0.0496	-0.0574	-0.0696
	(0.0222)	(0.0084)	(0.0069)
5th	-0.0243	-0.0638	-0.0728
	(0.0395)	(0.0078)	(0.0065)
6th	-0.0576	-0.0611	-0.0735
	(0.0312)	(0.0087)	(0.0064)
7th	0.1743	-0.0575	-0.0776
	(0.2798)	(0.0102)	(0.0057)
8th	--------	-0.0668	-0.0767
		(0.0082)	(0.0061)
9th	--------	-0.0828	-0.0816
		(0.0040)	(0.0054)
10th	--------	-0.0510	-0.0794
		(0.0219)	(0.0058)

Note: Standard errors are reported in parenthesis.

APPENDIX 1

REVIEW OF LITERATURE ON INSTRUMENTAL VARIABLES FOR EDUCATION

Recently, much attention has focused on supply-side sources of variation in schooling, attributable to such features as the minimum school leaving age, tuition costs, or the geographic proximity of school. As in standard market settings, variables from the supply side are an obvious source of identifying information for estimating demand-side parameters.

Angrist and Krueger's (1991) landmark study of compulsory schooling and education, which uses an individual's quarter of birth (interacted with year of birth or state of birth in some specification) as an instrument for schooling. As a result of institutional feature that everyone starts school in September of the year he turns six, individuals born earlier in the year reach the minimum school-leaving are at a lower grade then people born later in the year, allowing those who want to drop out as soon as legally possible to leave school with less education. Assuming that quarter of birth is independent of taste and ability factors, this phenomenon generates exogenous variation in education that can be used in an IV estimation scheme. However, Bound, Jaeger and Backer (1995) pointed out that several of Angrist and Krueger's IV models (specifically, those use interaction between quarter of birth and state of birth as predictors for education) include large number of weak instruments, and are therefore biased toward the corresponding OLS estimates. Staiger and Stock (1997) used quarter of birth interacted with state and year of birth and controls are same as used by Angrist and Krueger, plus indicators for state of birth.

Two subsequent studies by Card (1995) and Conneely and Uusitalo (1997) examine the schooling and earning differentials associated with growing up near a college or university and Card found IV estimator is substantially above the corresponding OLS estimator, although rather imprecise. Consistent with the idea that accessibility matters more for individuals on the margin of continuing their education, college proximity is found to have a bigger effect for children of less educated parents. This suggests an alternative specification that uses interaction of college proximity with family background variables as instruments for schooling and includes college proximity as a direct control variable. The IV estimate from this interacted specification is somewhat lower than the estimate using college proximity alone, but still about 30 percent above the OLS estimate.

Harmon and Walker (1995) used changes in the legal minimum school-leaving age as instruments for completed education. Ichino and Winter-Ebmer (1998) focuses on the disruptive effects of World War II on the schooling of children in Austria and Germany born between 1930 and 1935. They argued that WW II had strong effect on the educational attainment of children who reached their early teens during the war and lived in countries directly subject to hostilities. Using data for 14 countries they find relatively big differences in completed education for children in the 1930-35 cohort in countries most heavily affected by war (e.g. Germany, Austria and UK) but relatively small differences for this cohort in other countries (e.g. USA and Ireland). Lemieux and Card (1998) also uses cohort-specific differences in educational attainment attributable to WW II.

Meghir and Palm (1999) examine educational and earning outcomes of Swedish men born in the late 1940s and early 1950s who were affected by the introduction of a new education system that raised the minimum years of schooling by 2 and instituted other changes. Their reduced-form models suggest that average years of schooling are about 0.8 years higher for men who attended the reformed school than for those who did not, controlling for year of birth, father's schooling and country of residence.

In data from developing countries, Maluccio (1997) applies school proximity idea to data from the rural Philipines. DuFlo (1998) examined the education and earning trends associated with a school building program in Indonesia in the 1970s. She used interaction of year of birth with program intensity in the district of birth as instruments for schooling.

Another pair of studies by Anrist and Krueger (1992, 1995) examines the effect of "draft avoidance" behaviour on the education and earning of men who were at high risk of being drafted under the lottery system used during the Vietnam War.

Callan and Harmon (1999) and Brunello and Miniaci (1999) used institutional changes in Ireland and Italy that potentially affected schooling as instruments for schooling.

APPENDIX 2

INTERPRETATION OF COFFICIENTS

The estimated parameters of equation (11) and (13) show the effects of schooling, IQ and unobservable on health.

1. The partial effect of change in years of education on health is given by c2+c6u1. Suppose the coefficient c2 is positive and significant while c6 is not significant, then this would imply that education has an influence on health after controlling for the effects of unobservables and that the effect of additional education does not dependent upon the level of unobservables. So additional education through education programs would have positive effect on health.

2. The effect of unobservables on health is given by $c5+c6S_1$. A significant estimated c5 combined with and insignificant c6 would imply that the unobservables in the education equation, like IQ, personality and genetic factors or time preference would have an influence on health after controlling for the direct effect of education. At the same time, the effect of unobservable will not depend upon level of education.

   If c5 were positive, unobservable which lead the individuals to invest more in education would also lead to better health.

3. If both c2 and c5 are both positive and significant, then the effect of extra years of education varies with the value of unobservable. In this case, the extra education would be more effective at improving the health of those with higher positive u_1.

4. The partial effect of change in IQ on health is given by c3+c7S1t. Suppose the coefficient c3 is positive and significant while c7 is not significant, then this would imply that IQ has an influence on health after controlling for the effects of schooling and that the effect of IQ does not dependent upon the years of schooling.

5. If both c3 and c7 are positive and significant, then it means the IQ does effects health and this effect varies with years of schooling.

6. If c2, c3 and c5 are all significant, then all schooling, IQ and unobservable are important determinants of health.