Health And Labor Market Outcomes: Evidence From Indonesia*

Shailender Swaminathan and Lee Lillard*****
(University of Michigan)

Abstract

In this paper we model health as a latent variable to predict effects of health on wages and labor force participation. We jointly model the health, wage and labor force participation accounting for potential endogeneity of health and sample selection bias. Health is modeled as a latent variable of which multiple discrete indicators are observed. Multiple measures on wages allow us to control for measurement error in wage. We find that for women, after controlling for education and age, no effects of latent health are found on wages. However, the results do suggest that the estimates are sensitive to measurement of health. In participation equations a strong effect of health is observed when we do not control for wage rates. After controlling for wage rates, the effects of health are roughly halved but continue to remain strong predictors of participation. We compare results for women with those for men, for whom we find strong impacts of latent health on both wages and labor force participation.

---

* This research was supported by grants from the National Institute of Aging, NIH (NIA). The authors thank George Jacobson, Duncan Thomas, John Bound, Charlie Brown and Stan Panis for comments on an earlier version. All errors remain our own.
** Research Associate, Institute for Social Research, University of Michigan, Ann Arbor. Please direct all correspondence to: sswamin@umich.edu
*** My mentor and friend Lee Lillard died on December 2, 2000. Lillard was Professor of Economics, University of Michigan, Ann Arbor, and Senior Research Scientist at the Institute for Social Research.

1. Introduction

"We have next to consider the conditions on which depend health and strength, physical, mental and moral. They are the basis of industrial efficiency, on which the production of material wealth depends; while conversely the chief importance of material wealth lies in the fact that, when wisely used, it increases the health and strength, physical, mental and moral of the human race." A. *Marshall (1890)*

The global gains in health documented in the 20th century constitute, arguably, humankind's most dramatic achievement (WHO 1999). Health gains have intrinsic value, but there are reasons for assessing the economic consequences of better health: Conquering poverty constitutes a central goal of development policy at the beginning of the 21st century. Despite rapid economic growth, over a billion humans still exist in absolute, degrading poverty. Because ill health and low productivity of its members may trap families in poverty, sustained investment in the health of the poor could provide a policy lever for alleviating persistent poverty. In recent years, investment in human resources has been a major topic of interest for research in developing countries. It is widely believed and shown that investments in education yield high returns on productivity. However, in a developing country context returns to investments in health could also be high. Levels of health are known to be low and hence the returns to health could be high. Knowledge of the nature and links between health and labor market outcomes is also important for policy. If public investment in health infrastructure yields benefits in terms of higher productivity, then those benefits belong in evaluations of health programs (Strauss and Thomas, 1998). In two separate review articles, Strauss and Thomas (1998) and Behrman (1999) summarize studies examining the effect of health on productivity. Most studies use anthropometric measures–height and body mass index. Some use morbidity, and most examine the effects on wages, with a few focusing on effects on labor force participation. Both reviews conclude that there is suggestive evidence of a link, but that the magnitude and path of effect are not clear.

In this paper we study the interrelationships between health, wages and labor force participation in Indonesia. We model health as a latent variable, and use information on multiple indicators of health simultaneously. The idea of structural modeling of latent variable models was restricted initially to continuous indicators (as in Joreskog 1973). Muthen (1983) developed the model to include categorical as well as continuous indicators of the latent variable. In this paper, we develop a structural model that includes latent variables as regressors in both discrete and continuous outcome models. Full Information Maximum Likelihood Methods are proposed to account for the twin problems of endogeneity of and measurement error in the right hand side variables. The estimation techniques proposed are then applied to a sample of individuals in Indonesia to estimate the effects of health on wages and labor force participation, and the effect of wages on labor force participation. We jointly estimate the health, wage and labor force participation equations accounting for potential measurement error and endogeneity of wages and health status. For women, we find significant impacts of health on labor force participation, but no impact on wages. While, a substantial part of the impact of health on labor force participation is due to the healthier earning higher wages, independent health impacts on participation remain even after controlling for wage. For men, we find significant beneficial impacts of health status on both wages and labor force participation and positive impacts of wages on labor force participation.

Some Background

Health and Labor Market Outcomes

Two labor market indicators most often evaluated in studies of health and labor outcomes are wages and labor force participation. Continuing to participate in the labor force (at older ages) is important since that would decrease the size of the dependent population and increase resources available to further invest in human capital, thus propelling economic development. In this context, it is important to ascertain the extent to which health status affects labor force participation behavior at older ages.

Some of the earliest models linking health to productivity are the theoretical efficiency wage models (Leibenstein, 1957). The models argue that at low levels of nutrition there is an increasing, monotonic relationship between nutrition and productivity. Dasgupta (1997) provides recent evidence that the efficiency wage models remain relevant today. Schultz and Tansel (1997) use the number of days of work lost due to disability to estimate the impact of health on labor market outcomes in Ghana and Cote d'Ivoire. They find significant effects of health on wage rates. Thomas and Strauss (1997) estimate the effect of nutritional indicators on wage rates in urban Brazil and find that some of the nutrition indicators have strong impacts on wages of men but not the wages for women.

A prediction of the efficiency wage models is that employers have an incentive to raise wages above the minimum supply price of labor and exclude those in poor health from the labor market. Thus, there should exist a positive relationship between health and labor force participation. We could also consider utility maximizing individuals who might value health directly (health is part of the utility function) in addition to gaining utility from the consumption of goods and leisure. One implication of such a utility function is that if health and leisure are complements, then better health may raise the marginal rate of substitution between goods and leisure and so individuals may be less likely to participate in the labor market. Thus the direct effect of health on labor force participation may be negative. There are relatively few studies that have analyzed the impacts of health on labor force participation. The few that have analyzed the impacts of health do not control for wages. It is thus difficult to interpret the coefficient on health in the labor force participation equation in all of these studies. In analyzing impacts of health on labor force participation using HRS data, Bound et.al (1996) find that self-reported measures of health have positive and significant effects on labor force participation. They find that the lower labor force participation rates of blacks (relative to whites) can be explained by differences in health status. In our model, both wages and health affect labor force participation.

In evaluating the effects of health on labor market outcomes, two issues have dominated current research on the topic: measurement of health and endogeneity/simultaneity problems. We now turn to a discussion of some of the current thinking on such issues.

Measurement of Health

While there is consensus in the literature that the number of years of schooling is a reasonably good indicator of educational attainment, no similar agreement exists for health. While height, weight, and BMI have been used extensively as indicators of health, they really more reflect nutritional status. The concept of health is far more complex and is, in fact, multi-dimensional (Ware et al., 1980). Strauss and Thomas (1998) have argued that health is composed of distinct components that must be measured and interpreted separately. These multiple components are likely to affect labor outcomes differently. Thomas and Strauss (1997) use separate indicators of health (height, BMI, etc) to estimate their separate impacts on productivity.

The use of self-report measures of health has a long history and widespread application. These questions have either been global, asking about a respondent's general health status (GHS), or have focused on specific health complaints. Strauss and Thomas (1998) argue that "good" health may not mean the same thing to everybody and there is seldom an explicit reference group. Thus reports of general health are likely to be related to socio-economic characteristics, including wages and income. Strauss and Thomas (1998) conclude "... in the context of labor incomes, there are good reasons to be concerned that GHS may be contaminated with measurement error which is correlated with socio-economic characteristics, including income".

A commonly used set of measures involves nutrition-based indicators: nutrient intakes, height and body mass index. Strauss and Thomas (1998) conclude that nutrient intakes are often likely to be measured with error that is both random and systematic. Behrman (1999) summarizes the studies using such indicators. Haddad and Bouis (1991) estimate market wage functions for adults (pooling men and women) and they control for three health variables: individual level calorie intake, BMI and height. They find a strong effect of height on market wages in part of rural Philippines, but not of BMI nor of current calorie intake. A general problem with this approach to measuring health (through say height) is that height is often thought to be a measure of net child nutrition. Thus finding impacts of height on productivity (Thomas and Strauss, 1997) might reveal not more than the existence of an effect of a life-cycle impact of early child health on later child outcomes. We discuss more on this aspect later, but suffice it to say here that impacts of nutrition on productivity need to be interpreted carefully.

The preceding discussion suggests that there is no consensus on what true health status really is. Broadly, there are two categories of health questions in many household surveys. The first is self-reported health measures and the second are clinical evaluations of health. As Bound (1991) argues several self-reported measures are likely to suffer from systematic measurement error. While less likely to suffer from systematic error, the clinical evaluation measures do not reflect work capacity. Strauss and Thomas (1996) conclude, "For many social indicators, such as health status, "truth" is very difficult to measure, and in a survey setting, we will probably have to rely on self-reports. It will be worth investing resources in learning how to collect more reliable data on social indicators and in better understanding how to interpret the existing data". A promising set of self-reported measures has to do with an individual's ability to function at particular tasks, such as performing certain vigorous activities, walking uphill or bending. Such self-reported measures of physical functioning have been used in the analyses of health of the elderly in the United States[2] but have only recently been used in developing countries. In this paper, we use reports on such self-reported measures of health that are probably the most "objective" among the several types of self-reports available in surveys. We thus use a measure of health that reflects capacity of health and also one that is most

[2] For example, Manning, Newhouse and Ware (1982)

"objective" among self-reports. We model these self-reports as discrete, ordinal indicators of latent health and use the latent health measure to predict wage and labor force participation.

Endogeneity of Health

When estimating the effect of health on productivity the problem of endogeneity of health has to be addressed. There are two sources of endogeneity, (1) correlation in unmeasured factors in the health and productivity equations due to (say) unmeasured ability (Strauss and Thomas, 1998). (2) There is the potential reverse causality (simultaneous feedback) from higher productivity to better nutrition and hence health (Deolalikar, 1988). The problem in accounting for endogeneity is again the availability of good instruments. Strauss and Thomas (1998), comment on the lack of good instruments in addressing the problem. While there are reasons to believe the contemporaneous feedback from higher wages to better current nutrition, it is difficult to think of reasons to expect a contemporaneous feedback from current wage to physical limitations. It is conceivable that a long-run measure of income will predict current ability to perform specified tasks. Hence, in this paper we focus only on endogeneity caused from spurious correlation between health and labor market outcome and not on the simultaneous feedback possibility.

To summarize, two econometric problems have plagued estimation of the relationship between health and labor market outcomes: measurement error and endogeneity. The other more general, but important question is what is health? What are the dimensions of health that affect labor outcomes? It is not our intent in this paper to find the relative importance of separate dimensions of health on productivity. However, we contribute to the literature in at least two ways.

First, we develop an econometric approach that models health as a latent variable[3], and use the latent variable to predict wages and labor force participation. The approach accounts for the standard econometric problems noted in this literature: measurement error, endogeneity and sample selection.[4] Second, we estimate the relative importance of economic factors (say wages) and health as determinants of labor force participation. The methods developed are then applied to data from the Indonesian Family Life Survey (1993). In section 2 we outline the empirical model, section 3 discusses estimation, data are presented in section 4, results in section 5 and we conclude in section 6.

2. Empirical Model

We first outline some of the key characteristics of the overall model. We jointly model the wage, participation and health equations. Health affects wages, and health and wage affect participation. Detail specifications of the model are discussed later. Health is modeled as a latent variable[5] of which multiple indicators are observed.

It is a function of individual, household and community level covariates such as per-capita number of hospitals in the community. The underlying latent index function for health is given by

$$hlth_i^* = b_1 ' X_{hi} + d_{hi}$$

[3] We use information on separate discrete indicators of health

[4] Wages are observed only for individuals that participate in the labor market.

The wage equation is a function of health, and a set of other individual and community level covariates (the vector X_{wi}). As detailed below w^* is the true wage which we identify using the multiple wage measures.

$$w^* = a_1 hlth_i^* + a_2' X_{wi} + e_w$$

Labor force participation is modeled as a probit so that a woman is more likely to work if

$$y_i^* = b_1 w^* + b_2 hlth_i^* + b_3' X_{pi} + l_1 e_w + l_2 d_{hi} + v_i$$

where l_1 is parameter that accounts for correlation in wage and LFP equations,

l_2 is parameter that accounts for correlation in health and LFP equations

$LFP = 1$ if $y_i^* > 0$

$LFP = 0$ if $y_i^* \leq 0$

the underlying propensity to work y_i^* is greater than zero and does not work otherwise. Labor force participation is a function of wage, health and other individual and household characteristics (the vector X_{pi})s.

The literature (Heckman 1974) has stressed the potential biases in wage equations if sample selection is not accounted for. We jointly model the wage and participation equation using community level instruments in the wage equation to identify the correlation between e_w and v_i. Instruments in the wage equation also aid in predicting wages for women not currently employed and in accounting for potential measurement error in wage rates. An important feature of our study is that we are able to model labor force participation as a function of the true wage, w^*. We exploit multiple measures of wage rates available in the data set to purge the observed wages of the measurement error part, and thus are able to derive unbiased estimates of the wage coefficient in the labor force participation equation.

Strauss and Thomas (1998) point out that one of the subtle issues in deriving unbiased health coefficients in wage equations is the potential correlation between unmeasured effects in the wage and health equations (say, due to ability). We use the availability of instruments in the wage equation to jointly model the health and wage equations explicitly accounting for the correlation in the residuals d_h and e_w. We now discuss in more detail each of our 3 sub-models: measurement model for wage, labor force participation model, and the measurement model for health.

The Measurement model for wage

We use information on multiple measures on wage rates to address the issue of measurement error in wages. Work by Duncan and Hill (1985), Bound et.al (1989) documents the presence of serious measurement error in wages in studies of developed country.

---

[5] We tested and rejected the presence of separate factors for upper and lower body functional limitations and so in results presented here use only a single factor.

The IFLS provides data from which we can derive two wage measures for an individual who works. The first hourly wage measure[6]is derived from data on monthly earnings so that

$$\log(W_{1i}) = w_i^* + u_{1i}$$

$$W_{1i} = \frac{\text{Monthly earnings}}{\text{Hours last week} * 4} \qquad u_1 \sim N(0, s_{u_1}^2)$$

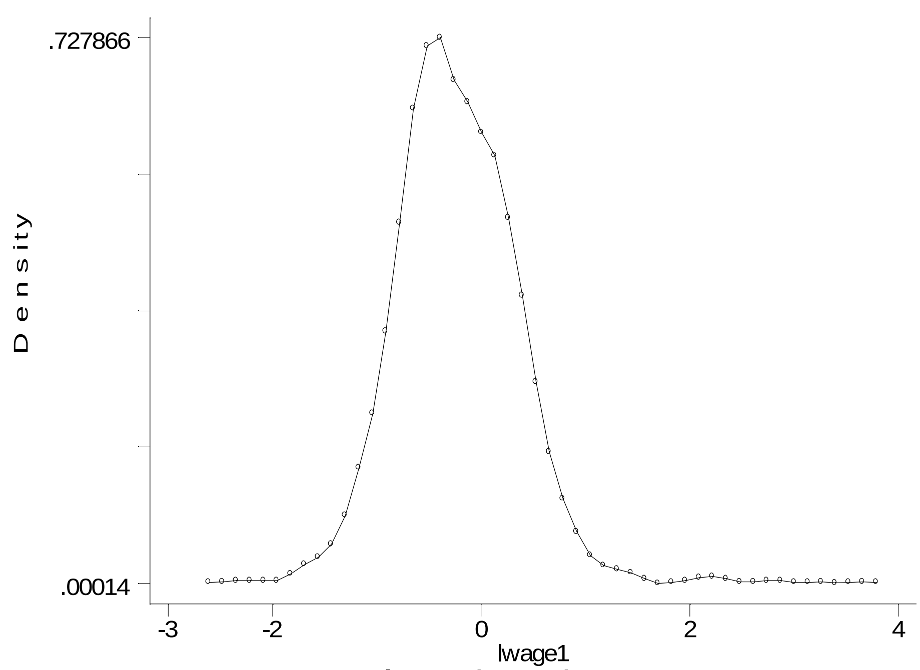
The second wage measure is derived from annual earnings data so that

$$\log(W_{2i}) = c_2 + w_i^* + u_{2i} \qquad u_2 \sim N(0, s_{u_2}^2)$$

$$W_{2i} = \frac{\text{Annual earnings}}{\text{Normal hours per week} * \text{weeks per year}}$$

w_i^* is the true wage rate, u_{1i} is the measurement error for the first wage measure and u_{2i} is the measurement error for the second wage equation. c_2 is the shifter in the second wage equation. The error terms are normally distributed so that
Non-parametric plotting of the observed log wages supports the normality assumption made on the distribution of the error terms[7].

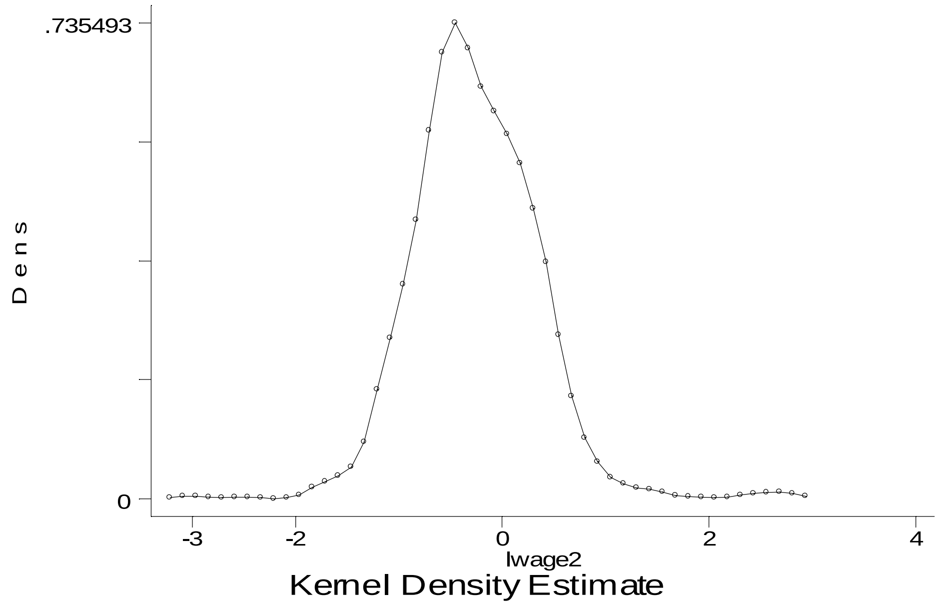
LOG (WAGE 1)



Kernel Density Estimate

[6] Wage rates are in 1000's of rupiah. In 1993 the exchange rate between the rupiah and the dollar was approximately 1400 rupiah to the dollar.
[7] Around the mean the average wage rate is approximately 70 cents per hour in 1993.

LOG (WAGE 2)



A crucial assumption in using multiple measures of the same variable is that the measurement error components, u_1 and u_2, have to be uncorrelated. We assume that most of the measurement error part can be attributed to random factors such as the date of interview[8]. On the other hand most of the measurement error in the second wage measure may be attributed to factors such as poor recall[9]. If the measurement error bias is to be eliminated then it is also important that the measurement error is uncorrelated with the true wage. As Bound et.al, (1989) report this does not appear to be the case in the United States. However, if the assumptions of zero correlation between the measurement error and true wage is violated, then we are likely to observe substantial differences in IV estimates from those obtained using multiple measures on wages. This is an issue to which we will return to again in the description of the results.

In addition to latent health status, regressors in the wage equation include potential labor force experience[10] and education. Community level labor demand conditions such as the existence of a factory in the community, the average community level wage rates for women in factories (conditional on a factory existing), and the number of credit facilities in the community are included as instruments in the wage equation.

---

[8] For example, if an individual is interviewed in a week when there are national/state holidays she is likely to report fewer hours worked in the last week than an otherwise identical individual who is interviewed in a week when there are no holidays. It is also conceivable that a woman interviewed on (say) Monday reports less hours worked in the last week (with the overlapping weekend) than a woman interviewed on (say) Saturday.

[9] Individuals are asked to report earnings in the last one year prior to the survey and the number of weeks in the last year prior to the survey. The problem is likely to be especially severe for the self-employed workers for whom a regular filing system might not exist.

Labor Force Participation (LFP)

LFP is modeled as a probit. The latent "propensity to work" index is a function of "true" wages, latent health, non-labor income, the number of young kids, labor force experience and marital status. Marital status, non-labor income and the number of young kids serve as identifying instruments to identify selection into the labor force.

The parameter l_1 accounts for potential selection into the labor force and l_2 accounts for any correlation between the health and labor force participation equations.

$$y_i^* = b_1 w^* + b_2 hlth_i^* + b_3' X_{pi} + l_1 e_w + l_2 d_{hi} + v_i$$
$$LFP = 1 \quad \text{if } y_i^* > 0$$
$$LFP = 0 \quad \text{if } y_i^* \leq 0$$

A key feature of this model is that health has both a direct and indirect (through wages) on labor force participation, Strauss and Thomas (1998). In trying to separate the direct and indirect effects of health on LFP it is crucial that both wages and health are measured without error. Having more than one variable measured with error implies that even assuming random measurement error, it is difficult if not impossible to sign the direction of the bias on either the health or wage coefficients. Having multiple measures on wages and health allows us to identify the measurement error in wage and health respectively.

The Measurement Model for Health

The underlying continuous aggregate latent index of physical limitation measured imperfectly by the multiple indicators is given by the regression equation

$$hlth_i^* = b_1' X_{hi} + d_{hi}$$

(X is a vector of covariates that affects latent health). Note that the * symbol is used to denote unobserved latent variables. There are seven (multiple) indicators of immobility, each with a regression equation relating the $j-th$ indicator Ind_{ij}^* to the aggregate latent index. In matrix notation this is given by,

$$\begin{array}{l} \text{Carry heavy load 20 meters} \\ \text{Sit on floor with bent knees} \\ \text{Walk for five kilometers} \\ \text{Bow} \\ \text{Stand from sitting in chair} \\ \text{Stand from sitting on floor} \\ \text{Draw pail of water} \end{array} \qquad \underline{Ind}_i^* = \begin{bmatrix} 0 \\ l_{02} \\ l_{03} \\ l_{04} \\ l_{05} \\ l_{06} \\ l_{07} \end{bmatrix} + \begin{bmatrix} 1 \\ l_{12} \\ l_{13} \\ l_{14} \\ l_{15} \\ l_{16} \\ l_{17} \end{bmatrix} * hlth_i^* + \begin{bmatrix} u_{1i} \\ u_{2i} \\ u_{3i} \\ u_{4i} \\ u_{5i} \\ u_{6i} \\ u_{7i} \end{bmatrix}$$

These seven indicators are not observed directly, but an ordinal ranking of immobility is given for each – the threshold responses. As the underlying $j-th$ indicator passes successively higher thresholds, successively greater immobility is reported in the verbal response. One of the factor loadings, l_{1j} is normalized to equal one for identification.

The conditional likelihood is simply the probability of the observed response conditional on the observed covariates and the unmeasured individual component part d_{hi}. The vector X_i includes education dummies, age splines and an indicator variable for whether the individual suffers from diabetes. Each of the indicator specific residuals (measurement error) is assumed normal with unit variance, $s_{u_j} = 1 \; \forall \; j = 1, 7$.
Health is modeled as a latent variable of which we observe multiple discrete indicators. This kind of data is typical of most surveys in which responses to health questions are discrete. To minimize the impact of systematic measurement error in our measure of health, we use indicators of health that ask the respondent his/her ability to perform particular activities. Strauss and Thomas (1998) argue that such measures are more "objective" measures of health status than other measures such as self-reported measures of health. It is important that such is the case, since the latent variable model discussed below is based on the premise that measurement errors in the indicators are random.[11]
The Multiple-Indicator-Multiple-Cause (MIMC) framework in which we model health enables us in identifying the measurement error in health as detailed below. Since the indicators that we use are "objective" we can assume that the measurement errors are random. However, since we use $hlth_i^*$ as a regressor in the wage and labor force participation equations, we only use the measurement error-free part of health. $l_{1j}'s$ are the factor loadings. In estimation we normalize the factor loadings on one of the indicators to equal one and the rest of the factor loadings are estimated relative to the normalized indicator.

Latent health status is a function of individual, household and community level covariates and a normally distributed individual specific unobserved heterogeneity component. In an attempt to control for endogeneity bias in estimates of health on labor market outcomes, we take advantage of community level instruments. We require variables that affect health, but not wages or labor force participation directly. We use health infrastructure variables such as nearness to hospital and doctors as instruments for health.

3. Estimation

For any given observation (individual), conditional on the measured covariates and on the heterogeneity components, the outcomes for each health indicator, wages and labor force participation are independent, and the joint probability of any combination of outcomes is the product of the probabilities of individual outcomes.

I) Likelihood Function for Health Model

The probability of the ordinal rankings values (or verbal responses) conditional of the measured and unmeasured covariates (X_i and d_i) is given by the 'conditional' likelihood $L_j\left(X_i, d_i\right)$ for each indicator.

[11] Muthen (1983) applies the model in the context of self-reported anxiety measures. The assumption of random measurement errors with such measures is arguable.

$$
\mathrm{L}_{\mathrm{j}}\left(X_i, d_{hi}\right) = \begin{cases} \text{Verbal} & \text{Threshold Response} & \text{Cond'l Likelihood } \mathrm{L}_{\mathrm{j}}\left(X_i, d_{hi}\right) \\ \text{Unable to do} & t_{\mathrm{j}2} < Ind_{ij}^* & 1-\Phi\left(t_{\mathrm{j}2} - l_{\mathrm{j}}\left(b_1'X_i + d_{hi}\right)\right) \\ \text{With difficulty} & t_{\mathrm{j}1} < Ind_{ij}^* < t_{\mathrm{j}2} & \Phi\left(t_{\mathrm{j}2} - l_{\mathrm{j}}\left(b_1'X_i + d_{hi}\right)\right) - \Phi\left(t_{\mathrm{j}1} - l_{\mathrm{j}}\left(b_1'X_i + d_{hi}\right)\right) \\ \text{Easily} & Ind_{ij}^* < t_{\mathrm{j}1} & \Phi\left(t_{\mathrm{j}1} - l_{\mathrm{j}}\left(b_1'X_i + d_{hi}\right)\right) \end{cases}
$$

Conditional on d, the multiple (7) indicators are independent for a person, so we obtain the conditional likelihood function for a give person as the product of the seven indicators.

$$
L_h(X_h, d_h) = \prod_{j=1}^{7} L_{ij}(X_h, d_h)
$$

II) Likelihood function for wage model

Wages are measured with error and so the true wage w^* is not observed. Error-ridden measures of wage W_{1i} and $\mathrm{W}_{2\mathrm{i}}$ are observed.

$$
\begin{aligned}
& w^* = a_1 hlth_i^* + a_2' X_{wi} + e_w \\
& and \\
& \log(W_{1i}) = w_i^* + u_{1i} \\
& \log(W_{2i}) = c_2 + w_i^* + u_{2i}
\end{aligned}
$$

We can write down the reduced form for the two wage equations

$$
\begin{aligned}
& \log(W_{1i}) = a_1(b' X + d) + a_2 X_w + e_w + u_{1i} \\
& \log(W_{2i}) = c_2 + a_1(b' X + d) + a_2 X_w + e_w + u_{2i}
\end{aligned}
$$

The conditional likelihood[12] function for the wage model (conditional on d and e_w) can be written as:

$$
\begin{aligned}
L_w(d, e_w, X_h, X_w) = & \frac{1}{s_{u_1}} f\left(\frac{\log(w_1) - (a_1(b' X + d) + a_2 X_w + e_w)}{s_{u_1}}\right) * \\
& \frac{1}{s_{u_2}} f\left(\frac{\log(w_2) - (a_1(b' X + d) + a_2 X_w + c_2 + e_w)}{s_{u_2}}\right)
\end{aligned}
$$

[12] Alternatively, we can use the multivariate normal covariance matrix to estimate the wage equation.

III) Likelihood function for the labor force participation model

$$y_i^* = b_1 w^* + b_2 hlth_i^* + b_3' X_{pi} + l_1 e_w + l_2 d_{hi} + v_i$$

$$LFP = 1 \quad \text{if } y_i^* > 0$$

$$LFP = 0 \quad \text{if } y_i^* \le 0$$

We write the reduced form for the latent index function of the labor force participation equation

$$y_i^* = b_1(a_1(b' X_h + d_{hi}) + a_2' X_{wi} + e_w) + b_2(b' X_h + d_{hi}) + b_3' X_{pi} + l_1 e_w + l_2 d_{hi} + n_i$$

$$n_i \sim N(0,1)$$

$$LFP = 1 \quad \text{if } y_i^* > 0$$

$$LFP = 0 \quad \text{if } y_i^* \le 0$$

The conditional likelihood function for the labor force participation model is then:

$$L_p(d_h, e_w, X_h, X_w, X_p) = \Phi(-(1-2LFP)\begin{bmatrix} b_1(a_1(b' X_h + d_h) + a_2' X_{wi} + e_w) + \\ b_2(b' X_h + d_h) + b_3' X_{pi} + l_1 e_w + l_2 d_h \end{bmatrix}$$

IV) Joint Estimation of Full Model

A critical assumption in the behavioral model is that all correlation, either among different health indicators for a given person or among processes (say health and wage) is captured by the heterogeneity components. Conditional on the unmeasured components there is no remaining correlation. Given this the joint conditional likelihood for the set of observed outcomes for all processes is the product of the individual conditional likelihoods. The vector of unmeasured components is assumed to be jointly normal.
We can write the joint marginal likelihood of the full model as the product of the joint conditional likelihoods after integrating over the full range of the unmeasured components d and e_w.
The joint marginal likelihood is:

$$L = \int_{d}\int_{e_w} L_{ij}(X_h, d_h) * L_w(d, e_w, X_h, X_w) * L_p(d_h, e_w, X_h, X_w, X_p) dF(d_h, e_w),$$

$$dF(d_h, e_w) = \frac{1}{s_{d_h} s_{e_w}} f\left(\frac{d_h}{s_{d_h}}, \frac{e_w}{s_{e_w}}\right)$$

Estimation is based on maximization of the joint marginal likelihood function.

4. Data

We use data from the 1993 Indonesian Family Life Survey for our analysis. Frankenberg and Karoly (1993) provide an overview of the survey. The survey covered about 7200 household spread across 13 provinces on the islands of Java, Sumatra, Bali, West Nusa Tenggara, Kalimantan and Sulawesi. Together these provinces encompass 83 % of the

Indonesian population and much of its heterogeneity. Additionally, extensive community and facility data accompany the household data. Village leaders and heads of the village women's group provided information in each of the 321 enumeration areas from which the households were drawn. In our paper we make use of information provided on nine indicators of functional health limitations. Several questions were asked of the health status of the individuals including general health status, morbidity, and physical limitations at performing select activities. This latter measure is just beginning to be fielded in developing countries and the validity of such measures has been already tested in data from developed countries. As discussed in the introduction, the reports to the physical limitations are likely to be the most objective indicators of health status. Summary statistics on the health responses are provided in the table 1 below.

Table 1

Functional Health Indicator	% Respond Unable to do	% Respond With difficulty	%Respond Easily
Carry heavy load 20 m	3.64	6.62	89.75
Sweep floor or yard	1.52		98.48
Walk 5 km	7.41	11.78	80.81
Bow, squat or kneel	.87	3.46	95.67
Stand from sitting on chair	1.7		98.3
Go to bathroom without help	.69		99.31
Stand from sitting on floor	.55	2.81	96.64
Draw pail of water	1.7	2.15	96.16
Dress without help	.62		99.38

Even though responses to all the nine functional limitation questions were asked in three categories we collapsed the responses as falling in two categories in cases when there was less than .5% falling in any one category.

We used only individuals who worked in either the self-employed or wage market in our analysis. Information on wages was not provided for individuals that were family workers and these individuals were dropped from analysis. As covariates, we used individual and household level variables provided in the household module of the survey. We merged community level information to the household data set to get information on health and labor demand conditions in the community.

5. Results

Effects of Individual, Family and Community Level Covariates on Latent Health

Table 2 presents estimates of the covariates in the health equation. Estimates for women and men are presented separately. The outcome is the latent index for *poor health*. Health worsens with age, while education has beneficial effects on health for both men and women. The community level infrastructure variables include a dummy variable for whether a hospital exists in the community and the number of health centers per 1000 household heads in the community. While the former variable predicts health of women, the latter is a significant predictor of the health of both men and women. These community level variables will be used as instruments in predicting the effects of health on wages and labor force participation. The heterogeneity component s_d is strongly significant. This suggests that there are unmeasured factors (such as innate healthiness) that affect all the health indicators.

Table 2: Effects of Individual, Family and Community Level Covariates on Latent Health

Variable	Women	Men
Constant	-2.2338 ***	-4.2188 ***
	(0.1314)	(0.2363)
Age less than 30 (splines)	-0.0084 **	-0.0038
	(0.0038)	(0.0055)
Age 30-50 (splines)	0.0396 ***	0.0399 ***
	(0.0026)	(0.0035)
Age >50 (splines)	0.0491 ***	0.1260 ***
	(0.0027)	(0.0063)
Education0-6 (splines)	-0.0460 ***	0.0283 ***
	(0.0063)	(0.0077)
Education 610 (splines)	0.0156	-0.0078
	(0.0112)	(0.0160)
Education gt10 (splines)	-0.0494 ***	-0.1097 ***
	(0.0137)	(0.0163)
Dummy for hospital in village	-0.0706	-0.4361 ***
	(0.0496)	(0.0706)
Number of health centers per 1000 HH heads	-0.0409 ***	-0.0695 ***
	(0.0109)	(0.0148)
urban	-0.0081	-0.0946 ***
	(0.0225)	(0.0322)
s_d	1.4736 ***	2.0055 ***
	(0.0601)	(0.0980)

*** Significant at 1%, ** Significant at 5 %, Significant at 10 %,

Health Equation: Factor Loadings and Thresholds

The factor loading on one of the indicators (walk with load 20 m) has been normalized to equal one to set the scale. The rest of the factor loadings are estimated relative to this normalized loading. The ordinal response thresholds are also estimated after normalizing the lower threshold for each indicator to equal zero.

Table 3

	Factor Loadings	Lower threshold	Upper threshold
Carry heavy load 20 meters	1.0000	0.0000	0.9281 *** (0.0428)
Sweep the floor or yard	1.0932 *** (0.0892)	0.0000	0.6873 *** (0.0731)
Walk for five kilometers	0.8511 *** (0.0534)	0.0000	0.9013 *** (0.0338)
Bow, squat, kneel	1.1793 *** (0.0808)	0.0000	0.7991 *** (0.0559)
Stand from sitting on chair	1.0970 *** (0.0686)	0.0000	1.2043 *** (0.0854)
Go to bathroom without help	1.5306 *** (0.1713)	-	-
Stand from sitting on floor	1.2116 *** (0.0997)	0.0000	1.1493 *** (0.1551)
Can you draw pail of water	1.2200 *** (0.1056)	0.0000	0.7337 *** (0.1423)
Can you dress without help	1.0460 *** (0.0752)	0.0000	1.4502 *** (0.1461)

The fraction of residual variance that is measurement error (the variance of the u_{ij}'s relative to total residual variance) is roughly between 25 to 30 percent as can be calculated from:

$$MeasurementError = 1/\,s^{2}_{\mathrm{Re}\,sidual(j)}$$

$$where$$

$$s^{2}_{\mathrm{Re}\,sidual(j)} = l^{2}_{1j}\,s^{2}_{d} + 1$$

Results in table 3 suggest two things. First, that there is measurement error in all of the health indicators. Second, they suggest that the separate measures are not equally reliable[13]. For example walking five kilometers is the least reliable measure.

Thus, using either each indicator separately in labor outcome equations or even summing the measures (say to get the total number of limitations) is likely to introduce an element of measurement error in the analysis.

Results – Wage Equation: Measurement error in wages

Results in table 4 reveals that about 30 % of the unmeasured variation in wages is due to measurement error[14]. The fraction that is measurement error is greater for measure 1 than measure 2. There is a difference in means of wage rates for men but not for the women.

[13] By the reliability of a indicator we mean the degree to which the indicator reflects the construct (in this case latent health) that it is meant to.

[14] Fraction of residual that is measurement error in $wage_i = s^{2}_{ui} / (s^{2}_{ui} + s^{2}_{e_w})$, for $i = 1,2$

There is more measurement error in the wage measure calculated from annual earnings than the wage measure calculated from monthly earnings.

Table 4

Variable	Women	Men
Residual variation in true wage (std.dev)	1.1477 ***	1.1072 ***
	(0.0461)	(0.0420)
Measurement error Wage1 (std. dev)	0.4564 ***	0.5090 ***
	(0.0150)	(0.0077)
Measurement error Wage2 (std. dev)	0.6327 ***	0.5781 ***
	(0.0105)	(0.0079)
Wage 2 intercept shift	-0.0254	-0.0679 ***
	(0.0185)	(0.0131)

Parameters of the Wage Equation

Estimates for women are presented in table 5 and estimates for men are presented in table 6. We include as covariates in the wage equation, piecewise linear splines in education and experience, labor demand conditions, an urban dummy and health.

Column 1 in table 5 presents results when health is assumed exogenous in the wage equation. Column 2 allows potential endogeneity of health[15] but does not account for selection bias, column 3 accounts for selection bias, and estimates a reduced form selection equation jointly with the wage equation, column 4 allows health (but not wage) to have a direct effect on the LFP equation and finally column 5 allows a direct effect of both health and wage in the LFP equation. Numerous studies in developing countries have almost universally demonstrated the beneficial impacts of education on earnings (Psacharopoulos, 1989). For both women and men, there are increasing returns to higher levels of education. Health however has no effect on wage rates for women. While surprising, the literature has been consistent in not finding strong health impacts for women. This may partly be a reflection of the kinds of jobs that women undertake.

We find that for men, strong impacts of health are found in all of the specifications. An important feature of our study is that we show the sensitivity of estimates of health on wages allowing for different specifications for the labor force participation equation. While the effect of health for women is not significant in any of the specifications, the magnitudes of health impacts differ across the specifications. For men, the effects of health differ across the specifications. What seems surprising is the almost 10 fold increase in the effects of health between columns 2 and 3. This difference is caused by a negative correlation (of 0.4) in unmeasured factors in the health and wage equations (see results in appendix). The result implies that an individual with greater ability at earning higher wages has less ability in improving his own health. While certainly plausible, the large negative (bad health and higher wages are positively correlated) correlation does not accord with what we might expect. A separate argument has been that individuals that discount the future (make less investments today) are likely to have higher current wages but poorer current health.

[15] By allowing correlation in the random components (e_w and d_h) in the wage and health equations respectively.

Table 5: Parameters of the true wage equation: Women

	0-Corr	Corr-HlthWg	+ Selection	+Hlth-LFP	+Wg-LFP
Cons_w	-2.5143 ***	-2.8091 ***	-3.1843 ***	-2.7963 *	-2.6570 **
	(0.2436)	(0.6539)	(1.0637)	(1.4662)	(1.0595)
Education0-6 (splines)	0.0501 ***	0.0503 ***	0.0455 ***	0.0512 ***	0.0280 **
	(0.0131)	(0.0132)	(0.0130)	(0.0150)	(0.0129)
Education 610 (splines)	0.1354 ***	0.1418 ***	0.1545 ***	0.1461 ***	0.1437 ***
	(0.0288)	(0.0311)	(0.0359)	(0.0374)	(0.0319)
Education gt10 (splines)	0.2067 ***	0.2034 ***	0.1918 ***	0.1920 ***	0.2160 ***
	(0.0365)	(0.0372)	(0.0364)	(0.0430)	(0.0410)
Factory Exists Dummy	0.0810	0.0787	0.0833	0.0781	-0.0139
	(0.0707)	(0.0697)	(0.0676)	(0.0690)	(0.0563)
Number of factories	0.0284	0.0289	0.0272	0.0301	0.0296
	(0.0326)	(0.0321)	(0.0311)	(0.0316)	(0.0251)
Urban	0.4049 ***	0.3994 ***	0.3805 ***	0.3899 ***	0.4303 ***
	(0.0523)	(0.0516)	(0.0514)	(0.0510)	(0.0508)
Experience <20 (splines)	0.1118 ***	0.1084 ***	0.0925 ***	0.1043 ***	0.1284 ***
	(0.0237)	(0.0248)	(0.0229)	(0.0252)	(0.0239)
Experience >20 (splines)	-0.0048 **	-0.0006	0.0088	0.0005	-0.0052
	(0.0022)	(0.0091)	(0.0116)	(0.0167)	(0.0121)
Health	0.0204 *	-0.0846	-0.3406	-0.1103	-0.0149
	(0.0107)	(0.2274)	(0.2811)	(0.3941)	(0.2838)
Corr-Hlth-Wage	0.0000	0.1311	0.4319	0.1748	0.0613
		(0.2870)	(0.2750)	(0.4885)	(0.3648)

Table 6: Parameters of the true wage equation: Men

	0-Corr (# of limitations)	0-Corr	Corr-HlthWg	+ Selection	+hlth-LFP	+Wg-LFP
Cons_w	-2.5403 ***	-2.6510 ***	-3.8051 ***	-4.2986 ***	-3.6956 ***	-3.7334 ***
	(0.2178)	(0.2222)	(0.3165)	(0.4197)	(0.4709)	(0.4552)
Education0-6 (splines)	0.0849 ***	0.0861 ***	0.1057 ***	0.1212 ***	0.1067 ***	0.1057 ***
	(0.0083)	(0.0084)	(0.0094)	(0.0101)	(0.0101)	(0.0102)
Education 610 (splines)	0.0897 ***	0.0896 ***	0.1054 ***	0.1279 ***	0.0997 ***	0.0982 ***
	(0.0151)	(0.0153)	(0.0160)	(0.0173)	(0.0156)	(0.0154)
Education gt10 (splines)	0.1739 ***	0.1725 ***	0.1550 ***	0.1413 ***	0.1789 ***	0.1790 ***
	(0.0160)	(0.0162)	(0.0170)	(0.0175)	(0.0166)	(0.0168)
Factory	0.0796 *	0.0803 *	0.0892 *	0.0990 **	0.0845 *	0.0899 *
	(0.0465)	(0.0472)	(0.0471)	(0.0463)	(0.0465)	(0.0462)
# Factories	0.0670 ***	0.0663 ***	0.0616 ***	0.0587 ***	0.0680 ***	0.0661 ***
	(0.0208)	(0.0212)	(0.0212)	(0.0210)	(0.0208)	(0.0208)
Urban	0.4749 ***	0.4713 ***	0.4341 ***	0.4216 ***	0.4217 ***	0.4255 ***
	(0.0365)	(0.0371)	(0.0385)	(0.0415)	(0.0435)	(0.0432)
Experience <20 (splines)	0.1131 ***	0.1115 ***	0.0924 ***	0.0621 ***	0.0839 ***	0.0985 ***
	(0.0218)	(0.0222)	(0.0226)	(0.0222)	(0.0241)	(0.0235)
Experience >20 (splines)	-0.0016	-0.0001	0.0167 ***	0.0291 ***	0.0172 ***	0.0154 ***
	(0.0013)	(0.0013)	(0.0036)	(0.0045)	(0.0050)	(0.0047)
Health	-0.0147	-0.0227 ***	-0.2671 ***	-0.4020 ***	-0.2563 ***	-0.2374 ***
	(0.0164)	(0.0047)	(0.0473)	(0.0644)	(0.0739)	(0.0698)
Corr-Hlth-Wages	0.0000	0.0000	0.4517 ***	0.6040 ***	0.4385 ***	0.4046 ***
			(0.0666)	(0.0653)	(0.1052)	(0.1050)

Measurement of health and the Effects of Health on Wages

We hypothesized that measurement of health would have significant impacts on the estimates of health on labor outcomes. We now present results that reveal the sensitivity of estimates to measurement.

Even though health does not appear to have any impact on wages, we would still like to know whether there is an advantage to measuring health as a latent variable, instead of using a simple sum of the number of health limitations as a covariate. Results are presented in table 7. When using latent health and forcing no age effects on wages (column 1), we find that health when measured as a latent variable has impacts on wages even after controlling for education. However, when the total number of limitations is included as a regressor (column 2) we do not find significant impacts of health on wages. There is some evidence of a downward bias in estimates. As a caveat to using latent variables it is important to note that an advantage in using the number of limitations variable is that it allows us to that it allows us to explore non-linear impacts of health on wage. Thomas and Strauss (1997) show that the impacts of calories on wages are non-linear in a sample of individuals in urban Brazil.[16].

Table 7: Measurement of health and the Effects of Health on Wages: Women

	Latent Health	# Limitations
Cons_w	-1.6454 ***	-1.5710 ***
	(0.0537)	(0.0488)
Education0-6 (splines)	0.0527 ***	0.0565 ***
	(0.0116)	(0.0112)
Education 610 (splines)	0.1380 ***	0.1375 ***
	(0.0294)	(0.0287)
Education gt10 (splines)	0.1770 ***	0.1814 ***
	(0.0348)	(0.0338)
Factory Exists Dummy	0.0692	0.0673
	(0.0732)	(0.0712)
Number of factories	0.0237	0.0253
	(0.0335)	(0.0326)
Urban	0.4198 ***	0.4127 ***
	(0.0545)	(0.0529)
Experience <20 (splines)	0.0000	0.0000
Experience >20 (splines)	0.0000	0.0000
Health	-0.0352 ***	-0.0156
	(0.0118)	(0.0209)

[16] In results not presented here, we find that when piecewise linear splines in total limitations are included as regressors large effects of limitations on wage are found only when the number of limitations exceeds 6 (coefficient of 0.2 and a standard error on 0.98).

We take another approach to explore the sensitivity of estimates of health on wage. Given measurement error in health indicators we proposed a factor model to overcome the problem. It is easy to show that the factor model for health outlined in section 2 is identified using 3 indicators of health. In table 8 we present results that explore the consequences for health effects on wage when using different health indicator sets in the factor model. All results in table 8 are for men and assuming exogeneity of health. These results are shown to illustrate an important aspect of our analysis: the effects of health measurement on estimates. The results are revealing and suggest that estimates are fairly robust to using different health indicator sets. The result also suggests that using such a procedure of identifying measurement error is likely to work even when different questions about health limitations are asked (say in other surveys).

Table 8: Measurement of Health and Estimates of Health on Wage: Men

	All Health Indicators	3 Indicators [1]	5 Indicators [2]
Cons_w	-2.6510 ***	-2.6932 ***	-2.6269 ***
	(0.2222)	(0.2277)	(0.2241)
Education0-6 (splines)	0.0861 ***	0.0867 ***	0.0864 ***
	(0.0084)	(0.0085)	(0.0084)
Education 610 (splines)	0.0896 ***	0.0899 ***	0.0887 ***
	(0.0153)	(0.0153)	(0.0153)
Education gt10 (splines)	0.1725 ***	0.1721 ***	0.1733 ***
	(0.0162)	(0.0162)	(0.0162)
Factory	0.0803 *	0.0820 *	0.0807 *
	(0.0472)	(0.0473)	(0.0472)
# Factories	0.0663 ***	0.0654 ***	0.0669 ***
	(0.0212)	(0.0212)	(0.0211)
Urban	0.4713 ***	0.4715 ***	0.4711 ***
	(0.0371)	(0.0371)	(0.0371)
Experience <20 (splines)	0.1115 ***	0.1109 ***	0.1118 ***
	(0.0222)	(0.0222)	(0.0222)
Experience >20 (splines)	-0.0001	0.0005	-0.0005
	(0.0013)	(0.0015)	(0.0014)
Health	-0.0227 ***	-0.0276 ***	-0.0165 **
	(0.0047)	(0.0096)	(0.0078)

[1]Carry heavy load 20 meters, Sweep the floor or yard, Walk for five kilometers

[2] Carry heavy load 20 meters, Bow, Stand from sitting on chair, Go to bathroom without help, Stand from sitting on floor.

Results - Labor Force Participation Equation

In our study we explicitly account for the direct effect of health status on labor force participation in addition to the indirect impact operating through the effect of health on wages. Strauss and Thomas (1998) have argued that a direct effect of health status on wages may arise due to changing preferences for leisure. The other reason might be because of employers not employing those with very poor health status – a prediction of the efficiency wage hypothesis. Estimation of the labor force participation equation is made difficult by the presence of measurement error in the wage[17] and health measures. The implications and method of addressing the measurement error in health was discussed earlier and so now we focus on the issue of measurement error in wages.

. **Table 9: Labor Force Participation Equation: Women**

	No-hlth-wg	No-wg	Hlth+wg
Cons_LFP	-2.1777 ***	-5.3931 ***	-2.6056 ***
	(0.1594)	(0.5091)	(0.9229)
Education_06	0.0154	-0.0979 **	-0.0992 **
	(0.0408)	(0.0475)	(0.0479)
Education_610	0.1702 ***	-0.0518	-0.3301 ***
	(0.0524)	(0.0690)	(0.0960)
Age	0.0831 ***	0.0819 ***	0.0721 ***
	(0.0069)	(0.0078)	(0.0087)
Age squared	-0.0009 ***	-0.0004 ***	-0.0005 ***
	(0.0001)	(0.0001)	(0.0001)
Urban	0.0473	0.0089	-0.1945 ***
	(0.0336)	(0.0413)	(0.0647)
Never mar	-0.1824	-0.0416	-0.4745 **
	(0.1456)	(0.2031)	(0.2085)
Lambda1	0.2444 ***	0.3811 ***	0.4835 ***
	(0.0918)	(0.0949)	(0.1008)
Latent Hlth		-1.1149 ***	-0.4569 **
		(0.1695)	(0.2018)
Lambda2		1.0424 ***	0.3828 *
		(0.1719)	(0.2025)
Wage			0.4630 ***
			(0.1144)

Table 9 presents estimates of the LFP equation for women[18]. In column 1 we present results without controlling for either wages or health. Column 2 presents results controlling for health but not wage, and column 3 presents results controlling for both health and wage. Lambda1 is the parameter that accounts for selection into the labor force (see section 2). Lambda2 is the parameter that picks up the correlation (due to unmeasured factors) between the health and labor force participation equations. There is positive correlation in wage and participation[19] equations that accords with what we would expect. However, there is a negative correlation in

[17] In results not presented here we show that results are not altered significantly when using one measure of wage and using instruments for wage.
[18] Results for men are presented in table 1 in the appendix.
[19] Individuals with greater ability are more likely to participate in the labor market and have better health.

unmeasured factors in the health and LFP equations. This again suggests that individuals have different the attributes of an individual that lead to success in the labor market are different from the attributes that lead to better health of an individual. With no controls for health or wage (column 1), we find that the more educated are more likely to participate in the labor force. However after controlling for both health and wage we find that the more educated are less likely to participate in the labor force[20]. We find strong effects of latent health on LFP even after controlling education. This result is intuitive because the health indicators used in the latent health model are likely to impair movements of individuals to a large extent. These are limitations that quite literally can limit the ability of the individual to work. Not finding significant impacts of health on wages for women and finding small but significant effects for men suggest two things. First, wage rates could be determined over a long run period and thus maybe what we need to consider is a longer run measure[21] of health than current physical limitations. Second, it could imply that women work in relatively less taxing occupations than men. If the less educated women work in more physically demanding jobs then we might expect effects of health on wages for the illiterate women. In future analysis we propose to explore health-education interaction effects more fully.

6. Conclusion

Theoretical models such as the efficiency wage models predicted a strong relationship between health and labor market outcomes. Recent policy related work done at the World Bank (1993) also suggests that improving women's health can improve individual productivity and particularly, when combined with education and access to jobs can accelerate a nation's economic development. Despite a lot of evidence in favor of these beneficial impacts of health on labor outcomes, few empirical studies have addressed the issue. Measuring the effects of health on labor outcomes are seriously handicapped by measurement error in health status leading to biases in estimates. Indeed, the issue of how exactly one should measure health is a moot question. Thus, it should come as no surprise that the few studies on the subject have produced fairly inconsistent results. In measuring the impacts of health on labor force participation it is important to control for wages. Yet, almost no study explores the direct effect of health on labor force participation in addition to the indirect effect operation through wage rates. In this paper, we make use of unique data from the IFLS and put forward a new empirical strategy to address the issue of measurement error in health and wage. We develop an empirical model for health that accounts for the multiplicity of measures and also accounts for the presence of random measurement error in health. The MIMC framework in which we model health allows us to identify the measurement error in health. It also allows us to use simultaneously multiple measures of health indicators. In addition we explicitly model the discrete nature of the responses to health questions and the ordered threshold responses that are typical of responses given in most household surveys. We jointly model health, wage and labor force participation. This procedure accounts for the sample selection bias as well as the potential endogeneity of health in the wage equation.

[20] In future work on the same research we will interact health and education to see if the effect of health on LFP varies across education levels.
[21] The IFLS asked information on when the physical limitation was first felt and so it is conceivable that such a long-run measure of health could be constructed from the available data.

We summarize our main results. (a) We find that a substantial part of wage and health measures is contaminated with measurement error and thus results from studies that have been agnostic to problems of measurement error will need to be interpreted with caution. (b) We show that the use of multiple measures on wages and health is able to account for the potential measurement error in these two variables. (c) We find that using the latent variable methodology used in modeling health reduces the effect of measurement error bias.

The research accomplished in this study is an attempt to take advantage of the range of health indicators that are beginning to be gathered in household surveys in developing countries. We provide some evidence of health effects on labor force participation, but not very strong effects on wage rates. The results do suggest that there are likely to be spillover effects of government health spending on labor market outcomes of both women and men. One implication of the effect of measurement of health on estimates is that researchers should be cautious when interpreting their results. Further, specification of the functional form for the selection equation could have implications for magnitudes of health effects on wages. There is evidence of endogeneity of health even though the negative correlation between health and wage does appear surprising. Overall the research highlights the importance to consider a latent variable approach to measuring health. We suggest that such an approach to modeling health should complement rather than substitute more traditional approaches. The more traditional approaches (say using number of limitations) would allow us to explore non-linear impacts of health.

References

Behrman, J 1999. “Labor Markets in Developing Countries”. *Handbook of Labor Economics*, Volume 3. Chp. 43. Eds. O. Ashenfelter and D. Card. Elsevier Science.

Bound,J (1991), “Self-reported vs. Objective Measures of Health in Retirement Models”, *Journal of Human Resources* 26:106-138

Bound,J, Jaeger,J.A, and Baker,R (1995) “Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variables is Weak” *Journal of the American Statistical Association* 90:443-450.

Bound,J, Schoenbaum,M, Duncan,G and Rodgers.W (1989), “Measurement Error in Cross-Sectional and Longitudinal Labor Market Surveys: Results from Two Validation Studies,” *Working Paper 2884, National Bureau of Economic Research*.

Bound,J, Schoenbaum,M, and Waidmann,T (1986) “Race Differences in Labor Force Attachment and Disability Status”. *Gerontologist* 36,no.3 (1996): 311-321.

Dasgupta, Partha (1997) “Nutritional Status, the capacity for work and poverty traps” *Journal of Econometrics*, Vol. 77 (1) pp. 5-37.

Duncan,G and Hill,D. (1985), “*An Investigation of the Extent and Consequences of Measurement Error in Labor Economic Survey Data*,” *Journal of Labor Economics* 3:508-522.

Frankenberg, E. and L. Karoly. "The 1993 Indonesian Family Life Survey: Overview and Field Report." November, 1995. RAND,Santa Monica, CA.

Haddad, L.J, and Bouis,H (1991) “The impact of nutritional status on agricultural productivity” Wage evidence from the Philippines, Oxford Bulletin of Economics and Statistics,53,1:45-68

Heckman,J (1979) “Sample Selection Bias as a Specification Error”. *Econometrica*, 47.1:153-161.

Hill,A (1993)“Female Labor Force Participation in Developing and Developed Countries-Consideration of the Informal Sector”, *The Review of Economics and Statistics*,Volume 65, no3. pp. 459-468.

Joreskog, K.G (1973), “A General Method for Estimating a Linear Structural Equation System”, in *Structural Equation Modeling in the Social Sciences*. Eds. A.S Goldberger and O.D. Duncan. pp: 85 –112.

Leibenstein,H (1957) “Economic backwardness and economic growth: Studies in the theory of economic development. New York: Wiley & Sons.

Marshall, Alfred. 1890. “Principles of Economics: An Introductory Volume”.

Muthen, Bengt, 1983 “Latent Variable Structural Equation Modeling with Categorical Data” *Journal of Econometrics* 22. pp 43 – 65.

Schultz,T.Paul and Tansel,A "Wage and Labor Supply Effects of Illness in Cote d'Ivoire and Ghana." *Journal of Development Economics*, August 1997 53(2), pp 251-286.

Strauss,J and Thomas,D (1998) "Health, Nutrition and Economic Development" *Journal of Economic Literature*. Volume 36, # 2.

Strauss,J and Thomas,D (1996). "Human Resources: Empirical Modeling of Household and Family Decisions" in *Handbook of Development Economics*, Vol 3A. Eds.: Srinivasan, T.N and Behrman, J.

Thomas,D and Strauss,J (1997) "Health,Wealth and Wages of Men and Women in Urban Brazil" *Journal of Econometrics* 77, pp 159 – 185.

Ware,J, Allyson,D, and Robert,B (1980) "Conceptualization and measurement of health status for adults in the Health Insurance Study:Vol VI. Analysis of relationships among health status measures. R-1987/6-HEW, RAND, Santa Monica,CA.

Ware,J Allyson,D and Donald,C (1978) "General Health Perceptions, R-1987/5-HEW, RAND, Santa Monica,CA.

WHO. 1999. "Health and Development in the 20th Century", World Health Report. WHO, Geneva.

World Bank (1993) "World Development Report. Oxford: Oxford University Press.

Appendix

Table 1: Labor Force Participation Equation: Men

	No-hlth-wg	No-wg	Hlth+wg
Cons_LFP	0.0423	-6.7001 ***	-5.4018 ***
	(0.2532)	(0.8864)	(0.9885)
Education0-6 (splines)	-0.1633 **	0.0382	-0.0079
	(0.0777)	(0.0939)	(0.1021)
Education 610 (splines)	-0.1605 *	-0.1895	-0.3666 **
	(0.0920)	(0.1184)	(0.1651)
Age	0.1195 ***	-0.0016	-0.0103
	(0.0105)	(0.0195)	(0.0203)
Age squared	-0.0016 ***	0.0011 ***	0.0010 ***
	(0.0001)	(0.0003)	(0.0003)
Urban	-0.2773 ***	-0.5804 ***	-0.6751 ***
	(0.0600)	(0.0840)	(0.1093)
Never mar	-0.3174 ***	0.0156	-0.2015
	(0.0763)	(0.1542)	(0.2045)
Lambda1	-1.7097 ***	-1.2738 ***	-1.2823 ***
	(0.1250)	(0.1428)	(0.1420)
Latent Health		-1.8143 ***	-1.7017 ***
		(0.2266)	(0.2207)
Lambda2		1.5781 ***	1.4651 ***
		(0.2208)	(0.2144)
Wage			0.2265 *
			(0.1349)