ASIAN ECONOMIC JOURNAL
Journal of the East Asian Economic Association

Asian Economic Journal 2014, Vol. 28 No. 1, 81–104

Socioeconomic Determinants of Child Health: Empirical Evidence from Indonesia*

Subha Mani†

Received 1 March 2011; accepted 16 July 2013

This paper characterizes the socioeconomic determinants of child health using height-for-age z-score (HAZ), a long-run measure of chronic nutritional deficiency. We construct a panel data that follows children between ages 3 and 59 months in 1993 through the 1997 and 2000 waves of the Indonesian Family Life Survey. We use this data to identify the various child-level, household-level and community-level factors that affect children's health. Our findings indicate that household income has a large and statistically significant role in explaining improvements in HAZ. We also find a strong positive association between parental height and HAZ. At the community level, we find that provision of electricity and the availability of paved roads are positively associated with improvements in HAZ. Finally, in comparison to community-level factors, household-level characteristics play a large role in explaining the variation in HAZ. These findings suggest that policies that address the demand-side constraints have greater potential to improve children's health outcomes in the future.

Keywords: child health, panel data, Indonesia, height.

JEL classification codes: I10, 012, R20, D10.

doi: 10.1111/asej.12026

I. Introduction

Chronic malnourishment experienced at a young age is associated with poor cognitive development, fewer grades of schooling completed, and lower wage earnings in the long run (Stein *et al*., 2003, 2006, 2008; Hoddinott *et al*., 2008, 2010; Victora *et al*., 2008; Behrman *et al*., 2009; Maluccio *et al*., 2009). Furthermore, most of the permanent deficits in height attainment, a long-run measure of chronic malnutrition, occur during early life, with only partial catch-up potential in the future (Adair, 1999; Hoddinott and Kinsey, 2001; Mani, 2012). Therefore,

*Financial support was provided by the Grand Challenges Canada (Grant 0072-03 to the Grantee, The Trustees of the University of Pennsylvania), United Nations University-World Institute for Development Economics Research and the College of Letters, Arts, and Sciences, University of Southern California. I would like to thank John Hoddinott, Jeffrey B. Nugent, seminar participants at the University of Melbourne, Monash University, and the University of Southern California for helpful comments and suggestions. I am especially indebted to John Strauss for guidance, continuous encouragement, and support. All remaining errors are mine.
†Mani: Department of Economics and Center for International Policy Studies, Fordham University; Population Studies Center, University of Pennsylvania. Email: smani@fordham.edu.

identifying the socioeconomic determinants that shape a child's future physical and economic well-being is crucial.

The most widely-used indicators of child health are height-for-age z-score (HAZ), weight-for-height z-score (WHZ) and weight-for-age z-score (WAZ).[1] Among these three indicators, HAZ is identified as a long-run measure of health as it captures the entire stock of nutrition accumulated since birth (Waterlow, 1988). Stunting is a form of health deprivation, where children's observed height is at least two standard deviations below the height of a well-nourished child in the reference population and, therefore, remains a serious source of concern among policy-makers in several developing countries, including Indonesia.

During 1990–1996, Indonesia experienced a period of rapid economic growth, with average growth in GDP per capita remaining around 6 percent. Despite such high levels of economic growth, 40.6 percent of children under the age of 5 suffered from chronic nutritional deficiencies; that is, they were identified as being stunted. Indonesia suffered a sharp reversal in its economic performance in late 1997 and early 1998. The sudden depreciation of the Indonesian rupiah led to an increase in the relative price of tradable goods, especially foodstuffs. Nominal prices of food increased, resulting in 150-percent inflation within months. However, by 2000, Indonesia witnessed rapid recovery in the growth rate of GDP per capita, along with lower inflation rates. During the recovery period, the country also witnessed significant declines in the percentage of stunted children. However, in absolute terms, the percentage of children suffering from chronic nutritional deficiencies still remained high, at 35.1 percent.

The goal of the present paper is to identify the socioeconomic determinants of HAZ, an important measure of long-run health among children. Panel data are constructed to follow children between the ages of 3 and 59 months (under the age of 5 years) in 1993 through the 1997 and 2000 waves of the Indonesian Family Life Survey (IFLS). The panel structure of the data allows us to identify both time-invariant (example: parental height) and time-varying (example: household income) factors that influence child health. In addition, without focusing directly on any specific intervention, we attempt to provide evidence on the relative role of the household vis-a-vis the community in improving child health.

We estimate a static conditional health demand function to identify the determinants of child health. Our findings indicate that at the household level, parental height and household income are important determinants of child health. A 1-cm increase in mother's height is associated with a 0.047 standard deviation improvement in the child's HAZ. Similarly, a 1-cm increase in father's height corresponds to a 0.034 standard deviation improvement in the child's HAZ. Household income has a large and statistically significant role in explaining improvements in child health in Indonesia, where a 100-percent increase in real per capita

1 HAZ is standardized height calculated using the 1977 National Center for Health Services (NCHS) tables drawn from the US population conditional upon age (in months) and sex. WHZ and WAZ are standardized weights calculated using the 1977 NCHS tables drawn from the US population conditional upon height in centimeters and age, respectively.

household consumption expenditure is associated with a 0.24 standard deviation improvement in HAZ. At the community level, we find that provision of electricity and availability of paved roads are associated with 0.0025 and 0.11 standard deviation increase in HAZ, respectively. Finally, in comparison to community-level factors, household characteristics play a larger role in explaining the variation in HAZ.

The present paper contributes to the existing literature in several ways. First, growing evidence shows that early life health status is a significant determinant of lifetime well-being (Victora *et al*., 2008; Behrman *et al*., 2009; Maluccio *et al*., 2009). As a result, there is great interest and need for studies that identify the determinants of health among children. Second, this paper examines the relative role of the household vis-a-vis the community in improving child health. Third, we capture the independent effect of family background characteristics on child health, controlling for community-level unobservables such as political connections that are likely to confound the parameter estimates on both household-level covariates as well as community-level covariates (Rosenzweig and Wolpin, 1986; Ghuman *et al*., 2005). Finally, we treat our measure of long-run household income, captured by the logarithm of real per capita household consumption expenditure (PCE), as endogenous.

The rest of the paper is organized as follows. The conceptual framework used for analysis is outlined in Section II. A complete description of the data is provided in Section III. The main regression results are discussed in Section IV. Finally, concluding remarks follow in Section V.

II. Conceptual Framework

A theoretical model of determinants of child health is outlined here as a means for guiding the variables that appear as regressors in the empirical specification. This section draws upon earlier work done by Behrman and Deolalikar (1988) and Thomas and Strauss (1992).

We assume that the household derives utility from only three things: market purchased food and non-food consumption goods, C_t; time spent in leisure activities such as eating, sleeping or gardening, T_t^L; and children's health, H_t. The satisfaction derived from C_t, T_t^L, and H_t can vary across parents due to differences in tastes and preferences and this unobserved heterogeneity in preferences is captured through the term θ_{pt}.[2] Parents choose to maximize the following utility function:

$$Max : U = u\left[C_t, T_t^L, H_t; \theta_{pt}\right] \tag{1}$$

2 Becker (1981, p. 21) writes: '*A more complicated and more realistic version of the theory recognizes that each person allocates time as well as money income to different activities, receives income from time spent working in the market place and receives utility from time spent eating, sleeping, watching television, gardening, and participating in many other activities*.'

subject to the child health production function (2), an income constraint (3) and a time constraint (4):

$$H_t = f\left(M_t, T_t^C; I_t, D_t, \theta_{ct}, \theta_c, \mu_{ht}, \mu_h, G\right) \tag{2}$$

$$P_t^c C_t + P_t^m M_t = w_t T_t^W + \pi_t \tag{3}$$

$$T_t = T_t^L + T_t^C + T_t^W. \tag{4}$$

The child health production function (Equation 2) depicts the evolution of child health, H_t, which depends upon a vector of market-purchased health inputs, M_t, which includes food, medicine and vitamins that are necessary for the maintenance and improvement of child health. We assume that the household derives no direct utility from the consumption of market-purchased health inputs except via its use in the accumulation of child health. An important health input that cannot be purchased from the market is parents' time spent caring for a child, T_t^C. We assume that there are no substitutes available for parents' time. Once again, the household derives no direct utility from spending time caring for the child except via its use in accumulating child health. Some of a mother's time is spent breastfeeding the child between ages 0 and 3 years, taking the child for immunizations, playing, talking and engaging the child in daily routines (i.e. early childhood stimulation); all of these activities affect children's health outcomes in crucial ways (Barrera, 1990b; Grantham McGregor *et al*., 1997, 2007). Furthermore, time-use surveys from 22 countries suggest that mothers spend 100 min per day on unpaid child-care activities, whereas fathers spend only 40 min per day on these activities (Miranda, 2011). As a result, any change in the price of time spent caring for a child, that is, the wage rate, affects child health through both an income effect (augmented through changes in earnings) and a substitution effect (affected by trade-offs between caring for the child and working for wages). The net effect of change in the wage rate on child health will be positive if the income effect outweighs the substitution effect and will be negative if the substitution effect outweighs the income effect.

Child health also depends upon I_t, a vector of community-level infrastructure variables that characterize the environment where the child lives and includes variables such as availability of water and sanitation facilities, availability of immunization and electricity in the community, and other infrastructure. Time-varying demographic characteristics such as the child's age, D_t, also influence the production process. Time-varying health shocks like occurrence of fever and diarrhea are captured in θ_{ct}. All information about the child, including the child's gender and time-invariant health endowments like the child's innate ability to absorb nutrients and fight diseases, is summarized in θ_c. Household-specific time-varying and time-invariant demographics and background characteristics, such as parents' age and education which have considerable influence over the choice of health inputs, are captured through the terms μ_{ht} and μ_h, respectively.[3] Finally, G summarizes information about all genetic endowments capturing genotype[4] and phenotype[5] influences on child health.

The household has two sources of income (Equation 3): (i) labor income, $w_t T_t^W$, where w_t is the hourly wage rate and T_t^W is hours worked; and (ii) non-labor income, π_t, capturing farm and non-farm profits. This total income is then used to meet household expenditure on market-purchased consumption goods (C_t) and market-purchased health inputs (M_t). P_t^c is the vector of prices of food and non-food consumption goods and P_t^m is a vector of the price of market-purchased health inputs. The household is also constrained by parents' total time endowment, T_t. This time has to be divided between working for wages, T_t^W, leisure activities such as sleeping or eating, T_t^L, and spending time caring for the child, T_t^C. An important implication of the trade-off between work and other activities is that money income is no longer pre-determined for the household but, rather, depends upon the amount of time chosen to work. We can combine the income constraint (Equation 3) and the time constraint (Equation 4) by re-writing the budget constraint as follows:

$$P_t^c C_t + P_t^m M_t + w_t T_t^C + w_t T_t^L = w_t T_t + \pi_t, \tag{5}$$

where $w_t T_t^L$ captures the opportunity cost of leisure time and, similarly, $w_t T_t^C$ captures the opportunity cost of time spent caring for the child.

The household maximizes utility (Equation 1) subject to an income constraint and the time constraint combined in Equation (5) and child health production function specified in Equation (2). Using simple first-order conditions, we can obtain the vector of conditional market-purchased health input demand functions, M_t^*, and the conditional non-market health input demand function, T_t^{C*}, as:

$$M_t^* = m\left(P_t^c, P_t^m, w_t, I_t, X_t, D_t, \theta_{ct}, \theta_c, \mu_{ht}, \mu_h, G, \theta_{pt}\right) \tag{6}$$

$$T_t^{C*} = m\left(P_t^c, P_t^m, w_t, I_t, X_t, D_t, \theta_{ct}, \theta_c, \mu_{ht}, \mu_h, G, \theta_{pt}\right). \tag{7}$$

The demand for these health inputs, (M_t^* and T_t^{C*}), depends upon the price of market-purchased consumption goods, the price of market-purchased health inputs, the price of parents' time spent caring for the child (wage rate), pre-allocated infrastructure, household per capita consumption expenditure (X_t), demographic characteristics, household rearing and caring practices, parental and child characteristics, and a preference parameter.

3 Barrera (1990a) shows that a mother's education affects child health through both an allocative effect and an efficiency effect.

4 Genotype influences include genetic endowments that are passed from the parents to the child via their DNA.

5 Phenotype influences capture all observable characteristics of an individual, such as shape, size, color and behavior that result from the interaction of genotype influences with the environment.

Following Thomas *et al*. (1990), it has become much more standard to condition the demand function on real per capita household consumption expenditure and not total income (income from wages and profits) because: (i) empirically, income is more difficult to measure and is subject to greater measurement error bias compared to consumption expenditure; and (ii) as noted in Behrman and Knowles (1999, p. 14), 'If some consumption smoothing is possible, expenditures are likely to be a better measure than income. Therefore, we use predicted expenditures per household member for all our estimates'. Following Thomas *et al*. (1990), Thomas and Strauss (1992), Behrman and Skoufias (2004) and several others, we obtain the static conditional health demand function in Equation (8) by replacing M_t and T_t^C in Equation (2) by M_t^* and T_t^{C*}:

$$H_t^* = h\left(P_t^c, P_t^m, w_t, I_t, X_t, D_t, \theta_{ct}, \theta_c, \mu_{ht}, \mu_h, G, \theta_{pt}\right). \tag{8}$$

The empirical counterpart of the static conditional health demand function can be written as follows:

$$H_{it} = \beta_0 + \sum_{j=1}^{R} \beta_j^X X_{jit} + \sum_{j=1}^{S} \beta_j^Z Z_{ji} + \varepsilon_c + \varepsilon_{it} \tag{9}$$

Here, H_{it} is the child's HAZ at time t, where subscript i refers to the individual and subscript t refers to time. The Xs capture time-varying regressors and the Zs capture the inclusion of time-invariant regressors. The choice of the right-hand side variables is guided by the conditional health demand function specified in Equation (8). At the individual level, we control for a number of factors: age of the child, a male dummy which takes a value 1 if male and 0 otherwise, mother's completed grades of schooling, father's completed grades of schooling, mother's height in centimeters and father's height in centimeters. Age and gender capture age–gender specific differences in the accumulation of child health. Measures of parental schooling are included to capture parents' rearing and caring practices that influence the choice of health inputs. Measures of parental height capture differences in mothers' and fathers' genetic endowments.

At the household level, we control for a measure of household expenditure using log of real per capita household consumption expenditure (PCE). Detailed data on food and non-food consumption is available from the household questionnaire. Total household expenditure is obtained as the sum of food and non-food expenditure, where food expenditure is obtained as the sum of the value of 35 food items consumed, including purchased food, self-produced food and food received. Non-food expenditure is computed as the sum of non-food items purchased, such as clothing, furniture and school uniforms. Total household consumption expenditure is divided by household size to capture the per-person resource availability in the household. We use the logarithm of real per capita household consumption expenditure to capture nonlinearities in the relationship between household expenditure and child health. Total household expenditure on all market purchased goods are jointly determined with the demand for health inputs. Hence, in the empirical work to follow we will treat real per capita household expenditure as endogenous.

At the community level, we control for a series of time-varying observables such as price of market purchased health inputs (distance to health center in kilometers), price of market purchased consumption goods (price of rice, price of condensed milk and price of cooking oil), price of time spent in leisure activities and child-care activities (male and female wage rate capture differences in mother's and father's opportunity cost of time), and community infrastructure variables (number of health posts, percentage of households with electricity in the community and a dummy variable which takes a value 1 if a paved road is available in the community, 0 otherwise).

There are two sources of unobservables in the empirical specification, ε_{it} and ε_c, where ε_{it} is the time-varying i.i.d. error term and ε_c is the time-invariant community-specific unobservable that affects child health. The time-invariant community level unobservables include factors such as geographic differences in access, cultural differences in child rearing and caring practices, and political connections, all of which are unobserved to the econometrician. These unobservables are likely to influence the placement of community-level time-varying resources in a selective manner, confounding the true impact of the community-level time-varying infrastructure variables on child health. For example, Frankenberg and Thomas (2001) and Frankenberg *et al*. (2005) show that midwives in Indonesia were carefully targeted to poor remote communities where observed health status among children and adults were poor. If all infrastructure placement decisions were solely based on observable characteristics then such placement would pose no econometric difficulty. If, however, the placement of community infrastructure is related to characteristics that are unobserved, such as political connections or geographic differences in access, then failure to account for such nonrandom placement will generally bias the coefficient estimates of the community-level time-varying variables. The direction of bias on the community-level time-varying variables is negative if the placement rule is pro-poor and positive if the placement rule is pro-rich. Hence, to obtain unbiased estimates on the community-level time-varying characteristics reported in column 4 of Table 3, we control for the time-invariant community-level unobservables through the inclusion of community fixed effects.[6]

III. Data

The data used in this paper come from the 1993, 1997 and 2000 waves the IFLS. The IFLS collects extensive information at the individual, household and

6 There are not enough observations with at least two children from the same mother or household to separately control for household-specific time-invariant unobservables and, hence, we treat the time-invariant unobservables at the household level as random.

community level. The survey includes modules on measures of health, household composition, labor and non-labor income, farm and non-farm assets, pregnancy, schooling, consumption expenditure, contraceptive use, sibling information and immunization (see Frankenberg and Thomas (2000) and Strauss *et al.* (2004) for more details on sample selection and survey instruments).

The IFLS is an ongoing longitudinal survey, the first wave of which was fielded during late 1993 and early 1994 (IFLS1). In IFLS1, 7224 households were interviewed. The first follow-up wave was surveyed during the second half of 1997 (IFLS2), just before the major economic and financial crisis in Indonesia. In IFLS2, 7629 households were interviewed, of which 6752 were original IFLS1 households and 877 were split-off households. The third wave (IFLS2+) was a special follow-up survey fielded during late 1998. A 25-percent subsample of the original IFLS1 households were contacted in late 1998 with the aim of analyzing the immediate impact of the 1997–1998 economic and financial crisis. The fourth wave of the IFLS was fielded in 2000 (IFLS3). A total of 10 435 households were interviewed in 2000. Of these, 6661 were original IFLS1 households and 3774 households were split-off households. The sample surveyed in 1993–1994 represented 83 percent of the Indonesian population living in 13 of Indonesia's 27 provinces at the time. The 13 provinces are spread across the islands of Java, Bali, Kalimantan, Sumatra, West Nusa Tenggara and Sulawesi. Provinces were selected to maximize representation of the population and capture the cultural socioeconomic diversity of Indonesia, and yet be cost-effective given the size and the terrain of the country. A total of 321 enumeration areas (EA)/communities were selected from these 13 provinces for final survey purposes.

Location information for all respondents is available at four administrative unit levels in Indonesia (from smallest to the largest): community, kecamatan (subdistrict), kabupatan (district) and province. One would ideally like to use the community-level code as the location variable to remove any location-specific time-invariant unobservables from the model and also to control for community-level time-varying characteristics on the right-hand side of the empirical specification. There are two challenges in using the original community codes as the location variable in this study. First, community-level data is only available for respondents residing in the 321 original IFLS communities. The IFLS did not collect detailed community-level information for mover households, except for some communities in 2000 (see Strauss *et al.* (2004)). Second, for any community/location-specific fixed effects, data must be available on multiple children residing in the same community. It becomes particularly hard to obtain observations on multiple children from the same community during the follow-up surveys, because many households have moved over time into new communities that were not initially surveyed in 1993. Hence, to be able to match households with community-level information in all three waves of the survey, and estimate fixed-effects models to remove the time-invariant community-level unobservables, we use the following decision rule to create the 'location' variable.

The 'location' variable created here is assigned a community code whenever there are 5 or more children residing in the same community.[7] In cases where this criterion fails, the 'location' variable is assigned the code corresponding to the next level of aggregation, (i.e. the kecamatan)[8] code following the same rules. Similarly, the kabupatan and, lastly, the province codes are assigned to the location variable in order to obtain at least 5 children from each of the newly-created location variables. This new aggregation of the geographic units helps us combine household-level and community-level information and also allows the use of fixed-effects estimation techniques at the location level. It is this 'location' variable that captures geographic information corresponding to each household in all three waves of the IFLS. All community-level characteristics reported in the tables vary at the location level created in this paper and not at the original community i.d. level.

Despite the availability of one more wave of data from the IFLS administered in 2007, we restrict our sample to only include children under the age of 5 years in 1993 following them through to the 1997 and 2000 but not the 2007 waves of the IFLS. There are several reasons for doing this. First, Martorell and Habicht (1986) and Satyanarayana *et al*. (1989) point out that a decline in growth in height during the first few years of life largely determines the small stature exhibited by adults in developing countries. Second, height measured at a young age is strongly correlated with adult body size (Spurr, 1988; Martorell, 1995). Third, the average age of a child in our sample in 1993 is 3 years. By 2000, the average age of a child in our sample is 10 years. The next wave of the IFLS is only available for 2007, by which time a majority of these children are likely to have reached their final height and can no longer be influenced by the socioeconomic factors collected at the time of the survey. In addition, the literature on human biology indicates that most of the growth in height that occurs during adolescence (ages 13 and above) is caused by individual-specific growth spurts that occur at a different time for each child as they enter puberty. The height gain observed among children in adolescence is further attributable to only these unobserved individual-specific growth spurts and not their socioeconomic environment. Consequently, it limits what we can learn from estimating conditional demand functions for this sample. Furthermore, height gains during pubertal growth spurts are not enough to reverse the negative consequences of early life stunting among children (Satyanarayana *et al*., 1980, 1989). For these reasons, we restrict our analysis to only follow children under the age of 5 years in 1993 through the 1997

7 It is usually the case that fewer than 5 children are found only in communities that were not the original IFLS1 communities and are communities where mover households resided.

8 The kecamatan and kabupatan codes are based on Indonesian Central Bureau of Statistics (BPS) codification that can be easily linked to other national data like the SUSENAS. The definition of a kecamatan and a kabupatan continue to change over time. In order to use systematic codes of the kecamatan and kabupatan over time, I use the 1999 BPS codes that define the kecamatan and kabuptan codes for all IFLS communities from all 3 years of the survey.

Table 1 Summary statistics on height-for-age z-score

Years	*Observations*	*HAZ < −2*	*Mean*	*Mean difference (years)*
1993	1819	40.62	−1.62	−0.133*** (1997–1993)
		(0.01)	(0.03)	(0.03)
1997	1819	42.05	−1.75	0.077*** (2000–1997)
		(0.01)	(0.02)	(0.01)
2000	1819	38.64	−1.68	−0.055*** (2000–1993)
		(0.01)	(0.02)	(0.03)

Notes: Standard errors reported in parenthesis are robust to clustering at the household level. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2 Summary statistics

Variables	*Mean*	*Std. dev*
Height-for-age z-score (HAZ)	−1.68	1.30
Height in cm	105.86	19.42
Mother's height (in cm)	150.5	5.1
Father's height (in cm)	161.3	5.3
Mother's schooling (in completed grades)	5.96	3.93
Father's schooling (in completed grades)	6.90	4.33
Log (PCE): log of real per capita household consumption expenditure	9.87	0.76
Total assets: square root of real per capita household total assets	4.48	3.78
Distance to the health center (in km)	5.07	4.58
Electricity: percentage of households with electricity	76.68	26.92
Male wage rate	6.55	0.52
Female wage rate	6.19	0.84
Price of rice	0.85	0.20
Price of condensed milk	5.17	1.51
Price of cooking oil	1.74	0.43
Dummy for paved road	0.74	0.43
Number of health posts	6.67	4.73

Notes: Number of observations: 5457.

and 2000 waves of the IFLS when surrounding socioeconomic factors have the potential to influence a child's growth process.

Table 1 shows trends in mean HAZ and the percentage of children classified as stunted over the three waves of the IFLS. We find that the mean HAZ worsens until 1997 and then improves during 1997–2000. The percentage of children classified as stunted also increases between 1993 and 1997 and then declines between 1997 and 2000. Yet, in absolute terms, more than one-third of children remain chronically malnourished in 2000. Table 2 provides the mean and standard deviation of variables used in the empirical specification.

IV. Results

Ordinary least square estimates of the determinants of child health are presented in columns 1 and 2 of Table 3, where households' long-run resource availability is captured using log(PCE) in column 1, Table 3 and total assets in column 2, Table 3. The preferred instrumental variable (IV) estimates for log(PCE) are reported in columns 3 and 4 of Table 3. The results reported in column 3, Table 3 include the full set of community/location interacted time dummies to control for all possible time-varying community-level factors both observable and unobservable to the econometrician at date t. In contrast in column 4, Table 3 we replace these community interacted time dummies with actual community level time-varying observable characteristics such as price of food consumption goods, distance to health center and other observables reported in column 4, Table 3. While the estimates reported in both columns 3 and 4 of Table 3 result in unbiased estimates for the household and child-level characteristics, there is no information on observable time-varying community characteristics in column 3, which are presented in column 4, Table 3. The estimates reported in column 4, Table 3 are more useful for policy prescription, because they identify the impact of various community characteristics on child health.[9] White's heteroskedasticity robust standard errors adjusted for clustering at the individual level are reported in Table 3 (Wooldridge, 2002).

We assume that the coefficient estimates on the right-hand side variables do not differ by gender. To check this assumption, we report the results from pooling the male and female sample together. The χ^2 test of pooling results in a value of 32.46 (p-value = 0.05) and favors separating the sample for boys from girls. However, a χ^2 test on all the right-hand side variables except the age and gender-interacted coefficients results in a value of 24.79 (p-value = 0.16), which further suggests that the gender-specific differences in the determinants of child health only come from the presence of age and gender-specific differences in growth of height. Hence, the preferred estimates reported in Table 3 use the pooled sample of boys and girls together, controlling for age, gender and interactions thereof to account for age and gender-specific differences in children's health outcomes.

The coefficient on the male dummy reported in column 4, Table 3 has a negative sign, suggesting that female children have better health than male children. This result is striking when compared to other Asian countries like India and Bangladesh which exhibit comparable levels of stunting, where one finds large significant gender differentials in favor of boys vis-a-vis girls. For Indonesia, this is not particularly surprising, because the country does not traditionally suffer from large gender differential investments in human capital accumulation. In examining mortality rates, Kevane and Levine (2001) find no evidence of 'missing girls'; that is, daughters are not likely to suffer from higher rates of mortality as compared to sons. Levine and Ames (2003) show that even in the aftermath of the crisis, girls did not fare worse than boys.

9 The terms location and community are used interchangeably throughout the paper.

Table 3 Determinants of Height-for-age z-score

Covariates	*(1) OLS HAZ*	*(2) OLS HAZ*	*(3) IV HAZ*	*(4) IV HAZ*
Male dummy	−0.765***	−0.764***	−0.788**	−0.684**
	(0.28)	(0.28)	(0.30)	(0.28)
Spline in age in months (< 24 months)	−0.078***	−0.077***	−0.079***	−0.077***
	(0.009)	(0.009)	(0.01)	(0.009)
Spline in age in months (> = 24 months)	−0.001	−0.0013	−0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.0008)
Spline in age in months (< 24)*male dummy	0.033***	0.033***	0.035**	0.030**
	(0.01)	(0.01)	(0.01)	(0.01)
Spline in age in months (> = 24)*male dummy	−0.002***	−0.002***	−0.002**	−0.002***
	(0.0009)	(0.001)	(0.001)	(0.001)
Mother's height	0.047***	0.048***	0.047***	0.047***
	(0.004)	(0.004)	(0.003)	(0.003)
Father's height	0.036***	0.035***	0.035***	0.034***
	(0.003)	(0.003)	(0.003)	(0.003)
Mother's schooling	0.015**	0.016**	0.009	0.008
	(0.007)	(0.007)	(0.006)	(0.006)
Father's schooling	0.0026	0.0024	−0.001	−0.002
	(0.006)	(0.006)	(0.005)	(0.005)
log(PCE)	0.088***		0.247***	0.247***
	(0.03)		(0.08)	(0.07)
Total assets		0.015***		
		(0.005)		
Price of rice				0.303*
				(0.16)
Price of cooking oil				−0.094**
				(0.04)
Price of condensed milk				−0.003
				(0.01)
Rural dummy				0.023
				(0.18)
Rural dummy*price of rice				−0.308*
				(0.18)
Number of health posts				0.018
				(0.01)
Distance to health center				0.007
				(0.005)
Electricity				0.0025**
				(0.001)
Dummy for paved road				0.117*
				(0.06)
Male wage rate				0.0127
				(0.05)
Female wage rate				0.0135
				(0.03)
Observations	5457	5457	5457	5457
Location interacted time fixed-effects	Yes	Yes	Yes	No
Location fixed-effects	Yes	Yes	Yes	Yes
R^2	0.13	0.13	0.11	0.11
Kleibergen–Paap rk Wald *F*-statistic			161.19	174.13

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors reported in parenthesis are robust to clustering at the individual level. In (3), log(PCE) is instrumented with total assets. The F statistic on the excluded instruments is 161.19. In (4), log(PCE) is instrumented with total assets. The F on the excluded instruments is 174.14. The first-stage regression estimates for column 4 are reported in Appendix Table A1.

The relationship between HAZ and age in months is nonlinear and the coefficient on the spline variables captures this nonlinearity, indicating that z-scores decline until the age of 24 months and then improve and remain steady and or unchanged after 48 months.[10] The interaction terms between the spline variables and the male dummy capture the age and gender-specific changes in health outcomes.

Household characteristics included in the regression model are: mother's completed grades of schooling, father's completed grades of schooling, mother's height in centimeters, father's height in centimeters, and log of real per capita consumption expenditure. Measures of parental schooling capture the efficiency with which health inputs are transformed into health outputs (Barrera, 1990a; Strauss and Thomas, 1998; Fedorov and Sahn, 2005). The coefficient estimates on mother's completed grades of schooling and father's completed grades of schooling reported in column 1, Table 3 show an expected positive relationship between parental schooling and child health. Every additional year of mother's schooling increases z-scores by 0.015 (column 1, Table 3) standard deviations. Father's schooling has a positive, although insignificant impact on z-scores. The positive correlation between household per capita consumption expenditure and mother's schooling is likely to have biased the coefficient estimate on mother's schooling upwards in column 1, Table 3. The preferred IV estimates reported in column 4, Table 3 suggest, however, that neither of the parental schooling variables have a statistically significant impact on child health.

Measures of parental height capture the impact of genetic endowments on child health (Strauss and Thomas, 1998). Mother's height in centimeters and father's height in centimeters capture the role of parent-specific genetic endowments on child health.[11] Every 1-cm increase in mother's height (father's height) is associated with a 0.047 (0.034) standard deviation improvement in HAZ (column 4, Table 3). These results are consistent with earlier findings in the literature (Ghuman *et al.*, 2005; Thomas *et al.*, 1991).

The final household characteristic included in the regression specification is household income. Logarithm of real per capita household consumption expenditure [log (PCE)] is used to capture the household's access to resources in the long run. OLS estimates of log(PCE) from column 1, Table 3 can be both biased upwards due to its correlation with time-invariant household-specific unobservables and biased downwards due to measurement error in data. Because assets are exogenously determined in a static model we replace log(PCE) with total assets in column 2 of Table 3. The coefficient estimates on log(PCE) and assets reported in Table 3 suggest that children residing in households with higher income enjoy better health. The IV estimates of log(PCE) is reported in columns 3 and 4 of Table 3 where log(PCE) is instrumented with the sum of household

10 This is consistent with much of the literature on health outcomes (see Strauss *et al.*, 2004).

11 See Thomas and Strauss (1992) for discussion on the role played by parent-specific genetic endowments in explaining child health.

productive assets, unproductive assets and unearned income (which sum up to total assets), which are assumed to be exogenous in a static model. The coefficient estimate on log(PCE) increases from 0.08 (column 1, Table 3) to 0.24 (columns 3 and 4, Table 3), showing that IV estimates of income have a much larger impact on current health status. The increase in the coefficient estimate of log(PCE) from OLS to IV regressions indicates that OLS estimates of log(PCE) are likely to be biased downward due to measurement error and not biased upwards due to omitted variables.[12] The role of income is largely consistent with most related work examining the determinants of child health.[13] Household income can also possibly have nonlinear effects on child health. To capture this nonlinearity, we include a spline in the measure of household income at the sample median. The preferred IV specification is re-estimated with the nonlinear measures of log(PCE). The two measures of log(PCE) in the nonlinear specification are not significantly different from each other. A chi2 test on the two measures of log(PCE) is 0.48 (p-value = 0.48), rejecting any nonlinear effect of log(PCE) on child health.

The role of time-varying community/location characteristics is also important in determining child health. In the presence of endogenous program placement effects, failure to take into account the correlation between community infrastructure variables and community-level time-invariant unobservables can bias coefficient estimates on the community characteristics (Rosenzweig and Wolpin, 1986; Frankenberg *et al.*, 2005). To address this issue the preferred IV estimates include location fixed effects that allow us to identify the exogenous impact of the time-varying community-level characteristics on child health. These estimates are valid under the assumption that the time-varying community-level unobservables that affect program placement are uncorrelated with the community-level observable characteristics. The panel structure of our data allows us to obtain unbiased parameter estimates on both the family background characteristics as well as time-varying community characteristics controlling for community-level fixed effects (see column 4, Table 3). This is usually not possible with cross-sectional data because community fixed effects would also sweep out the community-level variables included in the empirical specification, as in Ghuman *et al.* (2005).[14]

Among the community-level time-varying characteristics, we find that an increase in the price of rice is associated with improvements in child health in urban areas (0.303), while it has a negative impact in rural areas (–0.005) (column

12 The F-statistics on the excluded instruments in the first-stage regression for the IV estimates reported in Table 3 are appended at the end of Table 3, and the complete first-stage regression estimates are summarized in Appendix Table A1.

13 Thomas *et al.* (1991), Thomas and Strauss (1992), Haddad *et al.* (2003), Glick and Sahn (1998), Sahn (1994) and Thomas *et al.* (1990) all find a strong positive effect of per capita consumption expenditure in determining child health.

14 Ghuman *et al.* (2005) are able to obtain reliable estimates of the household-specific observables as they control for village fixed effects.

4, Table 3). The effect, however, is statistically significant only at the 10-percent significance level. Although this result might seem surprising and counterintuitive at first glance, it is not so in the context of Indonesia. For instance, Alderman and Timmer (1980) find a higher income elasticity of demand with respect to rice consumption in rural Indonesia compared to urban areas. Ito *et al*. (1989) and Bouis (1991) find that urban households in Indonesia are more likely to choose high quality, more nutritious substitutes for rice. These findings suggest that rural Indonesians are more price sensitive and, hence, are likely to witness a decline in child health that is affected by an increase in rice price, whereas urban Indonesians are able to find more nutritious substitutes for rice, which results in improvements in child HAZ, as observed here. Finally, urban households in Indonesia allocate only one-fifth of their household budget share to staples (primarily rice), while rural households allocate two-fifths of their household budget share to staples; consequently, the substitution effect of an increase in rice price is greater for rural areas, as observed here (Thomas *et al*., 1999).

An increase in the price of cooking oil is associated with a decline in child health (column 4, Table 3). Expenditure on cooking oil may not be a large proportion of total household consumption expenditure but reflects spending on essential consumption goods. One important consumption good aimed only for children is condensed milk; it is also included in the regression results. The advantage of using condensed milk is that it does not need refrigeration, an important advantage in a country where not all households own a refrigerator. The price of condensed milk has a positive but insignificant impact in determining child health. We acknowledge that a range of consumption goods must be included in the right-hand side. However, data constraints do not allow us to control for prices of more consumption goods.

In addition, included in the regressions are prices of health inputs as captured by distance to health center, and price of parents' time as captured by male and female-specific hourly wage rates in a community. None of these have a statistically significant impact on child health. We find some degree of positive correlation between male and female wage rates (the Spearman rank correlation coefficient is 0.47; see Appendix Table A2) weakening the independent effect of these variables on child HAZ. However, notice that in Appendix Table A2, the correlation coefficient between all the community variables is fairly small and, hence, there is no evidence of multicollinearity.

Measures of community infrastructure availability such as the number of health posts (access to health care), presence of paved roads (access to bigger cities) and measure of electricity (storage facility) are used as additional control variables. The number of health posts in a community has a positive but insignificant impact on child health. Measures for presence of paved roads and measure of electricity in the community are both positively associated with improvements in child health. Children residing in communities with a paved road have 0.11 standard deviation higher z-scores compared to their counterparts residing in communities without a paved road. Similarly, children residing in communities with greater prevalence of electricity on average gain a 0.0025 standard deviation improvement in z-scores.

A number of the community-level time-varying factors, such as male and female wage rates, number of health posts, distance to health center and price of condensed milk, have no significant impact on child health. One possible explanation for this is that a lot of the variation in the community time-varying variables in our panel comes from variation across communities that gets picked up by the community fixed effects rather than variation over time within communities. To check for this we decompose the variation in the community variables into two parts: the proportion of variation across communities and the proportion of variation within communities. We regress the community-level male wage rate on the full set of community dummies and obtain an associated R^2 of 0.70. This R^2 tells us that 70 percent of the variation in male wages is coming from variation across communities and that only 30 percent of the variation in male wages comes from variation within the community. We conduct a similar exercise for all the time-varying community variables where the proportion of across and within community variation is given in Appendix Table A3. Notice that for all the community variables that are insignificant in column 4, Table 3, the majority of the variation in these variables is coming from variation across communities which gets picked up by the community fixed effects, leaving out the limited over time variation to be picked by the community level variables included in column 4, Table 3.

Using the final preferred estimates reported in column 4, Table 3, we conduct a simple simulation exercise to outline the policy implications of this paper. Notice that the coefficient estimate reported in column 4, Table 3 suggests that a 1-cm increase in mother's height (father's height) is associated with a 0.047 (0.034) standard deviation improvement in child HAZ. First, the average mother's height in our sample is 150.53 cm and the average height of a mother whose children are not stunted is 151.58 cm. Now, if we were to assume that all mothers in our sample have the height of a well-nourished child's mother then average mother's height in the sample would increase by 1 cm and, as a result, the predicted HAZ will also increase by 0.047 standard deviations. A similar policy simulation can be conducted with father's height; that is, if all children in our sample were to now have the height of a well-nourished child's father's height then the predicted HAZ for children would increase by 0.034 standard deviations. Second, access to paved roads increases the predicted HAZ by 0.117 standard deviations. In our sample, only 80 percent of households have access to paved roads. Now if all households were to have access to paved roads, that is, the variable paved road now takes a value of 1 for everyone in the sample, then the predicted HAZ will increase further by 0.023 standard deviations. Finally, we can simulate the impact 100 percent access to electricity on the predicted HAZ. We find that increasing access to electricity from 75 to 100 percent in Indonesia will increase predicted HAZ by 0.06 standard deviations.

Table 4 Household vs. Community Characteristics

Covariates	*(1) OLS HAZ*	*(2) IV HAZ*	*(3) IV HAZ*	*(4) IV HAZ*	*(5) IV HAZ*
Individual characteristics	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	Yes	Yes	Yes	Yes
Community characteristics	No	No	No	Yes	Yes
R^2	0.03	0.15	0.11	0.16	0.11
F statistic on household characteristics		640.76	415.46	516.45	414.46
F statistic on community characteristics				64.17	30.81
Observations	5457	5457	5457	5457	5457
Location interacted time fixed-effects	No	No	Yes	No	No
Location fixed-effects	No	No	Yes	No	Yes

Notes: Standard errors reported in parenthesis are robust to clustering at the individual level. *** significant at 1%, ** significant at 5%, * significant at 10% level.

The findings in the paper suggest that governments and policy-makers need to guide investments in programs and policies that lead to improvements in household income, parents' height (through improvements in children's height today which will have intergenerational effects), access to paved roads and electricity that will lead to improvements in HAZ.

In Table 4, we make an attempt to uncover the relative contribution of the various individual-level, household-level and community-level factors in explaining the variation in child health. The first specification reported in column 1, Table 4 is an OLS specification with only child-level controls, excluding both household and community-level controls. The R^2 reported in column 1, Table 4 indicates that only 3 percent of the variation in HAZ can be explained through individual-level controls such as age and gender. The second specification reported in column 2, Table 4 is an IV specification including child-level and household-level factors but excluding all community-level factors. As we include household characteristics such as measures of parental height, parental education and household income on the right-hand side; the R^2 reported in column 2, Table 4 increases to 0.15, depicting that a large proportion of the variation in children's health can be explained through differences in household resources. The third specification reported in column 3, Table 4 is an IV specification that not only includes child-level and household-level observable factors, but also includes community-level time-varying and time-invariant controls through the inclusion of the location dummies and the location-interacted time dummies controlling for both endogenous program placement effects and community time-varying factors. These controls result in an R^2 of 0.11, indicating that not much of the explained variation in HAZ comes from variation in community-level factors. The specification reported in column 3, Table 4 is theoretically appropriate except that from a policy point of view, it does not have information on the influence of community-level factors on child health. The fourth specification reported in column 4, Table 4 is an IV specification with individual-level, household-level and community-level controls but does not address the problem of endogenous program placement. As we add community-level observables in column 4, Table 4 the R^2 only increases marginally to 0.16, depicting that only a very small proportion of the variation in children's health comes from variation in community resources. The changes in the R^2 across specifications suggest that in comparison to community characteristics, household characteristics are more powerful in explaining variation in children's health. The last specification reported in column 5, Table 4 is an IV specification with the full set of individual, household and community-level controls. It also includes a set of community/location dummies to sweep out the program placement effects and results in an R^2 of 0.11; this is closer to the R-square reported in column 2, Table 4 with only the household-level and child-level controls.

The theoretical model outlined in the paper identifies the best specification as the one including the full set of time-varying and time-invariant community-level, household-level and individual-level factors as appropriate controls on the right-hand side of the empirical specification. Using this as a guide, we can say that both the specifications reported in columns 3 and 5 of Table 4 (analogous to the specifications reported in columns 3 and 4 of Table 3) are theoretically justified. However, there is more information (in the form of community-level time-varying factors) to learn from the empirical specification reported in column 5, Table 4 that is otherwise absorbed in the community-time fixed-effects reported in column 3, Table 4. Overall, changes in the value of R-square reported across specifications suggest that in comparison to community characteristics, household characteristics are more powerful in explaining variation in children's health.

V. Conclusion

This paper characterizes the socioeconomic determinants of child health using data on HAZ, a long-run measure of chronic nutritional deficiency. Panel data are constructed using observations on children initially between ages 3 and 59 months in 1993 followed through the 1997 and 2000 waves of the IFLS. A static conditional health demand function is estimated to obtain the parameter estimates on the various child-level, household-level and community-level factors that affect child health in Indonesia.

Our findings indicate that household income has a large and statistically significant role in explaining improvements in children's health. OLS estimates of the impact of household income are biased downwards relative to IV results. We also find a strong positive association between parental height and children's health. At the community level, we find that provision of electricity and availability of a paved road is positively associated with improvements in children's health. Finally, we find that in comparison to community-level factors, household-level characteristics are more important in explaining improvements in children's health. Finally, there is no evidence of gender-specific differences in the determinants of HAZ in Indonesia.

The key policy implication of this paper is that investment in programs that increase household income, parent's height (through investments in child height today) and community infrastructure are likely to improve children's health, and, consequently, their education and earnings in the long run. At the household level, government's can provide cash transfers and offer employment opportunities to augment household income. Finally, improvements in access to paved roads and electricity at the community level will contribute towards improving children's health.

Appendix

Table A1 First-stage regression results

Excluded and included instruments from the first-stage regressions	*coefficient estimates on the first-stage regressions variables reported in column 4, table 3*
excluded instruments	
Total assets	0.06***
	(0.004)
included instruments	
Male dummy	0.05
	(0.08)
Spline in age in months (< 24 months)	0.007**
	(0.002)
Spline in age in months (> = 24 months)	−0.001***
	(0.0004)
Spline in age in months (< 24)*male dummy	−0.003
	(0.004)
Spline in age in months (> = 24)*male dummy	0.0005
	(0.0004)
Mother's height	0.002
	(0.001)
Father's height	0.002
	(0.001)
Mother's schooling	0.02***
	(0.003)
Father's schooling	0.01***
	(0.003)
Price of rice	−0.22***
	(0.07)
Price of cooking oil	0.14***
	(0.02)
Price of condensed milk	0.003
	(0.007)
Rural dummy	−0.32***
	(0.08)
Rural dummy*price of rice	0.15*
	(0.08)
Number of health posts	−0.0003
	(0.002)
Distance to health center	−0.007
	(0.002)
Electricity	−0.0002
	(0.0005)
Dummy for paved road	0.004
	(0.02)
Male wage rate	0.06**
	(0.02)
Female wage rate	0.03**
	(0.01)
Observations	5457
Location fixed-effects	Yes
F statistic on the excluded instruments from the first-stage regressions	174.14

*** significant at 1%, ** significant at 5%, * significant at 10%.

Table A2 Matrix of Spearman Rank Correlation Coefficients

Variables	*Price of rice*	*Price of cooking oil*	*Price of condensed milk*	*Number of health posts*	*Distance to health center*	*Electricity*	*Dummy for paved road*	*Male wage rate*	*Female wage rate*
Price of rice	1								
Price of cooking oil	0.37	1							
Price of condensed milk	−0.11	0.05	1						
Number of health posts	0.10	0.05	0.06	1					
Distance to health center	0.11	0.045	−0.086	−0.29	1				
Electricity	0.23	0.085	−0.15	0.27	−0.12	1			
Dummy for paved road	0.10	0.062	−0.08	0.20	−0.20	0.35	1		
Male wage rate	0.15	0.17	0.0085	0.12	−0.14	0.33	0.22	1	
Female wage rate	0.037	0.0083	−0.077	0.10	−0.10	0.23	0.14	0.47	1

Table A3 Distribution of variation in community time varying characteristics

Community variables	*Proportion of variation across communities*	*Proportion of variation within communities*
Male wage rate	0.70	0.30
Female wage rate	0.68	0.32
Price of rice	0.45	0.55
Price of cooking oil	0.27	0.73
Price of condensed milk	0.55	0.45
Number of health posts	0.88	0.12
Distance to health center	0.51	0.49
Electricity	0.36	0.64
Dummy for paved road	0.39	0.61

References

Alderman H. and C. P. Timmer, 1980, Food policy and food demand in Indonesia, *Bulletin of Indonesia Economic Studies*, **16**, pp 83–93.

Adair, L. S., 1999, Filipino children exhibit catch-up growth from age 2 to 12 years. *Journal of Nutrition*, **129**, 1140–8.

Bouis, H., 1991, Rice in Asia: Is it becoming a commercial good?: Comment. *American Journal of Agricultural Economics*, **73**: 522–7.

Becker, G. S., 1981, *A Treatise on the Family*. NBER Books, National Bureau of Economic Research, Inc, number beck81–1.

Barrera, A., 1990a. The role of maternal schooling and it's interaction with public health programs in child health production function. *Journal of Development Economics*, **32**, 69–91.

Barrera, A., 1990b, The interactive effects of mother's schooling and unsupplemented breastfeeding on child health. *Journal of Development Economics*, **34**, 81–98.

Behrman, J. R. and A. B. Deolalikar, 1988, Health and nutrition, Handbook of Development Economics, In: *Handbook of Development Economics*, edition 1, volume 1 (eds Chenery H. and Srinivasan T.N.), pp. 631–711. Elsevier.

Behrman, J. R. and E. Skoufias, 2004, Correlates and determinants of child anthropometrics in Latin America: Background and overview of the symposium, *Economics and Human Biology*, **2**, pp. 335–51, December.

Behrman, J. R., M. C. Calderon, S. Preston, J. Hoddinott, R. Martorell and A. D. Stein, 2009, Nutritional supplementation of girls influences the growth of their children: Prospective study in Guatemala. *American Journal of Clinical Nutrition*, **90**, pp. 1372–9.

Behrman, J. R. and J. C. Knowles, 1999, Household income and child schooling in Vietnam. *World Bank Economic Review*, **13**, pp. 211–56.

Fedorov, L. and D. E. Sahn, 2005, Socioeconomic determinants of children's health in Russia: A longitudinal study. *Economic Development and Cultural Change*, **53**, pp. 479–500.

Frankenberg, E. and D. Thomas, 2000, The Indonesia family life survey (IFLS): Study design and results from Waves 1 and 2. *DRU-2238/1-NIA/NICHD*.

Frankenberg, E. and D. Thomas. 2001, Women's health and pregnancy outcomes: Do services make a difference?, *Demography*, **38**, 253–65.

Frankenberg, E., W. Suriastini and D. Thomas, 2005, Can expanding access to basic health care improve children's health status? Lesson's from Indonesia's 'midwife in the village' program. *Population Studies,* **59**, pp. 5–19.

Ghuman, S., J. R. Behrman, J. Borja, S. Gultiano and E. King, 2005, Family background, service providers, and early childhood development in Philippines: Proxies and interactions. *Economic Development and Cultural Change*, **54**, pp. 129–64.

Glick, P. and D. E. Sahn, 1998, Maternal labor supply and child nutrition in West Africa. *Oxford Bulletin of Economics and Statistics*, **60**, pp. 325–55.

Grantham-McGregor S. M., Y. B. Cheung, S. Cueto, P. Glewwe, L. Richter and B. Strupp, International Child Development Steering Group 2007, Child development in developing countries 1. Developmental potential in the first five years for children in developing countries. *Lancet*, **369**, 60–70.

Grantham-McGregor S. M., S. P. Walker, S. M. Chang and C. A. Powell, 1997, Effects of early childhood supplementation with and without stimulation on later development in stunted Jamaican children. *Americal Journal of Clinical Nutrition*, **66**, 247–53

Haddad, L., H. Alderman, S. Appleton, L. Song and Y. Yohannes, 2003, Reducing child malnutrition: How far does income growth take us? *World Bank Economic Review*, **17**, 107–31.

Hoddinott, J. and W. Kinsey, 2001, Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics*, **63**, 409–36.

Hoddinott, J., J. A. Maluccio, J. R. Behrman, R. Flores and R. Martorell, 2008, Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults, *Lancet*, **371**, 411–16.

Hoddinott, J., J. Maluccio, J. R. Behrman, R. Martorell, P. Melgar, A. R. Quisumbing, M. Ramirez-Zea, A. D. Stein and K. M. Yount, 2010, The consequences of early childhood growth failure over the life course. *International Food Policy Research Institute*, Washington, DC.

Ito, S., E. Wesley, F. Peterson and W. R. Grant, 1989, Rice in Asia: Is it becoming an inferior good? *American Journal of Agricultural Economics*, **71**, 33–42.

Kevane, M. and D. Levine, 2001, The changing status of daughters in Indonesia, *mimeo*.

Levine, D. and M. Ames, 2003, Gender bias and the Indonesian financial crisis: Were girls hit hardest? *Center for International and Development Economics Research*.

Maluccio, J. A., J. Hoddinott, J. R. Behrman, R. Martorell, A. Quisumbing and A. D. Stein. 2009. The impact of improving nutrition during early childhood on education among Guatemalan adults, *Economic Journal*, **119**, 734–63.

Mani, S., 2012, Is there complete, partial, or no recovery from childhood malnutrition? Empirical evidence from Indonesia. *Oxford Bulletin of Economics and Statistics*, **74**, 691–715.

Martorell, R., 1995, Promoting healthy growth: Rationale and benefits. In: *Child Growth and Nutrition in Developing Countries: Priorities for Action* eds Pinstrup-Andersen P., Pelletier D. and Alderman H.), pp. 15–31. Cornell University Press, Ithaca.

Martorell, R. and J. Habicht, 1986, Growth in early childhood in developing countries. In: *Human Growth, Methodology, Ecological, Genetic, and Nutritional Effects on Growth*, second edition (eds Falkner F. and Tanner J. M.), pp. 241–62. Plenum, New York.

Miranda, V., 2011, Cooking, caring and volunteering: Unpaid work around the world. OECD Social, Employment and Migration Working Papers, No. 116, OECD Publishing.

Rosenzweig, M. R. and K. I. Wolpin, 1986, Evaluating the effects of optimally distributed public programs: Child health and family planning interventions. *American Economic Review*, **76**, pp. 470–82.

Sahn, D., 1994, The contribution of income to improved nutrition in Cote de Ivoire. *Journal of African Economics*, **3**, 29–61.

Satyanarayana, K., A. Nadamuni Naidu and B. S. Narasinga Rao, 1980, Adolescent growth spurt among rural Indian boys in relation to their nutritional status in early childhood. *Annals of Human Biology*, **7**, 359–65.

Satyanarayana, K., G. Radhaiah, K. R. Mohan, B. V. Thimmayamma, N. P. Rao, B. S. Rao and S. Akella, 1989, The adolescent growth spurt of height among rural Indian boys in relation to childhood nutritional background: An 18 year longitudinal study. *Annals Human Biology*, **16**, 289–300.

Spurr, G. B., 1988, Body size, physical work capacity, and productivity in hard work: Is bigger better? In *Linear Growth Retardation in Less Developed Countries* (ed. Waterlow J.C.). Nestle Nutrition Workshop Series Volume 14. Raven Press, New York, NY.

Stein, A. D., H. X. Barnhart, M. Hickey, U. Ramakrishman, D. G. Schroeder and R. Martorell, 2003, Prospective study of protein-energy supplementation early in life and of growth in the subsequent generation in Guatemala, *American Journal of Clinical Nutrition*, **78**, 162–7.

Stein, A. D., M. Wang, A. DiGirolamo, R. Grajeda, U. Ramakrishnan, M. Ramirez-Zea, K. Yount and R. Martorell, 2008, Nutritional supplementation in early childhood, schooling and intellectual functioning in adulthood: A prospective study in Guatemala, *Archives of Pediatric and Adolescent Medicine*, **162**, 612–18.

Stein, A. D., M. Wang, M. Ramirez-Zea, R. Flores, R. Grajeda, P. Melgar, U. Ramakrishnan and R. Martorell, 2006, Exposure to a nutrition supplementation intervention in early childhood and risk factors for cardiovascular disease in adulthood: Evidence from Guatemala, *American Journal of Epidemiology*.

Strauss, J. and D. Thomas, 1998, Health, nutrition and economic Development, *Journal of Economic Literature*, **36**, 766–817.

Strauss, J., K. Beegle, A. Dwiyanto, Y. Herawati, D. Pattinasarany, E. Satriawan, B. Sikoki, Sukamdi and F. Witoelar, , 2004, Indonesian living standards – Before and after the financial crisis, *Rand Corporation*.

Thomas, D., J. Strauss and M. Henriques, 1990, Child survival, height for age, and household characteristics in Brazil. *Journal of Development Economics*, **33**, 197–234.

Thomas, D., J. Strauss, J. and M. Henriques, 1991, How does mother's education affect child height? *Journal of Human Resources*, **26**, 183–211.

Thomas, D. and J. Strauss,1992, Prices, infrastructure, household characteristics, and child height. *Journal of Development Economics*, **39**: 301–31.

Thomas, D., E. Frankenberg, K. Beegle and G. Teruel, 1999, Household budgets, household composition and the crisis in Indonesia: Evidence from longitudinal household survey data, UCLA working paper series.

Victora, C. G. , L. Adair, C. Fall, P. C. Hallal, R. Martorell, L. Richter and H. S. Sachdev, on behalf of the Maternal and Child Undernutrition Study Group. 2008. Undernutrition 2: Maternal and child undernutrition: Consequences for adult health and human capital, *The Lancet*, **371**, 340–57.

Waterlow, J., 1988, Linear growth retardation in less developed countries. *Nestle Nutrition workshop series vol. 14, chapters 1 and 2*.

Wooldridge, J., 2002, *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge.