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Socioeconomic Determinants of Child Health – Empirical Evidence from Indonesia

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Abstract

This paper characterizes the socioeconomic determinants of child health using height-for-age z-score – a long-run measure of chronic nutritional deficiency. We construct a panel data that follows children between 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 height-for-age z-scores (HAZ). We also find a strong positive association between parental height and HAZ. At the community level, we find that provision of electricity and availability of a paved road is positively associated with improvements in HAZ. Finally, in comparison to community level factors, household level characteristics have a large role in explaining the variation in HAZ. These findings suggest that policies that address the demand side constraints will have a greater potential to improve children's health outcomes in the future.

Keywords: Child health, Panel data, Indonesia, Height

JEL Classification: I 10, 0 12, R 20, D 10

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1 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). Further, most of the permanent deficits in height attainments – a long-run measure of chronic malnutrition occurs during early life with only partial catch-up potential in the future (Hoddinott and Kinsey, 2001; Adair, 1999; Mani, 2011). It is therefore crucial to identify the socioeconomic determinants that shape a child's future physical and economic well-being.

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 2 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, when average growth in GDP per capita remained around 6%. Despite such high levels of economic growth, 40.6% of children under the age of 5 suffered from chronic nutritional deficiencies, that is, were identified as being stunted. Shortly after the period of rapid economic growth, Indonesia suffered a sharp reversal in its economic performance during 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 price of food increased resulting in 150% 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%.

The goal of this paper is to identify the socioeconomic determinants of height-for-age z-

[1] HAZ is standardized height calculated using the 1977 NCHS (National Center for Health Services) tables drawn from the United States population conditional upon age (in months) and sex. WHZ and WAZ are standardized weights calculated using the 1977 NCHS tables drawn from the U.S. population conditional upon height in cm and age respectively.

score (HAZ), an important measure of long-run health among children. A panel data is constructed following children between 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 (ex: parental height) and time-varying (ex: household income) factors that influence child health. In addition, without focusing directly on any specific intervention, we attempt to provide some 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 0.04 standard deviation (s.d) improvement in the child's HAZ. Similarly, a 1 cm increase in father's height corresponds to a 0.03 s.d. 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% increase in real per capita household consumption expenditure is associated with 0.24 s.d. improvement in HAZ. At the community level, we find that provision of electricity and availability of paved road is associated with 0.0025 and 0.11 s.d. increase in HAZ. Finally, in comparison to community level factors, household characteristics have a larger role in explaining the variation in HAZ.

This paper contributes to the existing literature in several ways. First, growing evidence shows that early life health status is a significant determinant of life-time 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 estimate 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 2. A complete description of the data is provided in Section 3. The main regression results are discussed in Section 4. Finally, concluding remarks follow in Section 5.

2 Conceptual Framework

A theoretical model of determinants of child health is outlined here as 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:

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

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

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

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

[2]Becker (1981) writes on page 21 "*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.*"

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

The child health production function (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 parent's time spent caring for the child, T_t^C. We assume that there are no substitutes available for parent's 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 mother's time is spent breastfeeding the child between ages 0-3 years, taking the child for immunizations, playing, talking and engaging the child in daily routines known as early childhood stimulation; all of these affect children's health outcomes in crucial ways (Barrera, 1991; Grantham McGregor et. al, 1997, 2007). Further, time-use surveys from 22 countries suggest that mothers spend 100 minutes per day on unpaid child care activities; whereas, fathers spend only 40 minutes per day on these activities (Miranda, 2011). As a result, any change in the price of time spent caring for the child, that is, 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 facility, availability of immunization and electricity in the community and other infrastructure. Time-varying demographic characteristics such as the child's age, D_t also influences 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) - (a) labor income - $w_t T_t^W$ where w_t is the hourly wage rate and T_t^W is hours worked, and (b) 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 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, spending time in 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 (3) and the time constraint (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 (1) subject to an income constraint and the time constraint combined in (5) and child health production function specified in (2). Using simple first-order conditions, we can obtain the vector of conditional market purchased health input demand functions M_t^* and conditional non-market health input demand function, T_t^{C*} as:

[3] Barrera, 1990 shows that 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.

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

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

Where, the demand for these health inputs (M_t^* and T_t^{C*}) depends upon the price of market purchased consumption goods, price of market purchased health inputs, price of parent's 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 preference parameter.

After Thomas, Strauss and Henriques (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) since – (a) empirically income is more difficult to measure and is subject to greater measurement error bias compared to consumption expenditure, and (b) as noted in Behrman and Knowles (1999) page 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, Strauss and Henriques (1990), Thomas and Strauss (1992), and Behrman and Skoufias (2004) and several others, we obtain the static conditional health demand function in (8) by replacing M_t and T_t^C in equation (2) by M_t^* and T_t^{C*}:

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

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

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

H_{it}, is the child's height-for-age z-score 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 cm and father's height in cm. Age and gender capture age-gender specific differences in the accumulation of child health. Measures of parental schooling are included to capture parent's rearing and caring practices that influence the choice of health inputs. Measures of parental height capture differences in mother's and father's genetic endowments. All height measurements are recorded to the nearest 0.1 cm (or 1 mm).

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 value of 35 food items consumed including purchased, self-produced 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 non-linearities 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 km), 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 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, Suriastini and Thomas (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 on 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, Table 3 we control for the time-invariant community level unobservables through the inclusion of community fixed-effects.[6]

3 Data

The data used in this paper comes from the 1993, 1997 and 2000 waves of the Indonesian Family Life Survey (IFLS). The IFLS collects extensive information at the individual,

[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.

household, and 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 et. al, 1995, 2000; 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 the 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 the late 1998. A 25% sub-sample of the original IFLS1 households were contacted in late 1998 with the aim of analyzing the immediate impact of the 1997-98 economic and financial crisis. The fourth wave of the IFLS was fielded in 2000 (IFLS3). A total of 10435 households were interviewed in 2000. Of these, 6661 were original IFLS1 households and 3774 households were split-off households. The sample surveyed in 1993-94 represented 83% 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, capture the cultural socio-economic diversity of Indonesia, and yet be cost-effective given the size and the terrain of the country. A total of 321 enumeration areas (EAs)/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 (municipality) 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 in 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 details in the mini-CFS questionnaire from Strauss et. al 2004]. Second, to do 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, since many households have moved over time into new communities that were not initially surveyed in 1993. Hence, in order 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 variable. 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 which 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 id level.

Despite the availability of one more wave of data from the Indonesian Family Life Survey administered in 2007, we restrict our sample to only include children under the age of 5 years in 1993 followed through 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 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 attained body size as an adult (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 Indonesian Family Life Survey is only available in 2007, by which a majority of these children are likely to have attained their final heights and can no longer be influenced by

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

[8] The kecamatan and kabupatan codes are based on BPS (Indonesian Central Bureau of Statistics) codification that can be easily linked to other nationally representation 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 kabupatans over time, I use the 1999 BPS codes that define the kecamatan and kabuptan codes for all IFLS communities from all three years of the survey.

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. Further, 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 and 2000 waves of the Indonesian Family Life Survey when surrounding socioeconomic factors have the potential to influence a childs growth process.

Table 1 shows trends in mean height-for-age z-scores and the percentage of children classified as stunted over the three waves of the IFLS. We find that mean height-for-age z-score 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 the children remain chronically malnourished in 2000. Table 2 provides the mean and standard deviation of variables used in the empirical specification.

4 Results

Ordinary least square estimates of the determinants of child health are presented in columns 1 and 2 in Table 3, where household's long-run resource availability is captured using log (PCE) in column 1, Table 3 and total household assets in column 2, Table 3. The preferred 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. Whereas, 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, since 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 chi-squared 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 chi-square 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 uses the pooled sample of boys and girls together controlling for age, gender, and interactions thereof to account for age-gender specific differences in health outcomes.

The coefficient on the male dummy reported in column 4, Table 3 has a negative sign, suggesting that females 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, since 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. Also, Levine and Ames (2003) show that even in the aftermath of the crisis, girls did not fare worse than boys.

The relationship between height-for-age z-score and age in months is non-linear and the coefficient on the spline variables captures this non-linearity; indicating that z-scores decline till 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 male dummy captures the age-gender specific changes in health outcomes. Overall, females have higher

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

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

z-scores compared to their male counterparts.

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 (cm), father's height in cm, and log of real per capita consumption expenditure. Measures of parental schooling capture the efficiency with which health inputs are transformed into health output (Barrera, 1990; 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 though 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 though suggest 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 centimeter increase in mother's height (father's height) is associated with a 0.047 (0.034) standard deviation improvement in z-scores (column 4, Table 3). These results are consistent with earlier findings in the literature (Ghuman et. al, 2005; Thomas, Strauss, and Henriques, 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. Since 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

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

3 and 4 of Table 3 where log(PCE) is instrumented with the sum of household productive assets, unproductive assets, and unearned income (that 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 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) is 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 non-linear effects on child health. To capture this non-linearity, we include a spline in the measure of household income at the sample median. The preferred IV specification is re-estimated with the non-linear measures of log(PCE). The two measures of log(PCE) in the non-linear 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 non-linear 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 the use of cross-sectional data since community fixed-effects would also sweep out the community level variables included in the empirical

[12] The F statistic 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; Thomas et. al, 1990 all find a strong positive effect of per capita consumption expenditure in determining child health.

specification, as in Ghuman et. al, 2005.[14]

Among the community level time-varying characteristics, we find that 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 4, Table 3). The effect though is statistically significant only at the 10% significance level. Although, this result might seem surprising and counter-intuitive at a 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, Peterson and Grant, 1989 and Boius, 1991 find that urban households in Indonesia are more likely to choose high quality better 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 of rice which result 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, 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.

Also, 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

[14]Ghuman et. al 2005, are able to obtain reliable estimates on the household specific observables as they control for village fixed-effects.

(spearman rank correlation coefficient is 0.47, see appendix Table A3) weakening the independent effect of these variables on child HAZ. Though notice that in appendix Table A3, 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. 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 communities without a paved road. Similarly, children residing in communities with greater prevalence of electricity on average gain 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 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 community level male wage rate on the full set of community dummies and obtain an associated R-square of 0.70. This R-square tells us that 70% of the variation in male wages is coming from variation across communities and that only 30% of the variation in male wages is coming 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; 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 suggest that a 1 cm increase in mothers height (fathers height) is associated with a 0.047 (0.034) s.d. improvement in child height-for-age z-score. First, the average mothers height in our sample is 150.53 cm and the average height of mothers whose children are not stunted is 151.58 cm. Now, if we were to assume that all mothers in our sample were to have the height of a well nourished childs mother then average mothers height in the sample would increase by 1 cm and as a result, predicted height-for-age z-score (HAZ) will also increase by 0.047 s.d. A similar policy simulation can be conducted with fathers height, that is, if all children in our sample were to now have the height of a well-nourished childs fathers height then predicted height-for-age z-score for children would increase by 0.034 s.d. Second, access to paved roads increases predicted HAZ by 0.116 s.d. In our sample, only 80% 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 predicted HAZ will increase further by 0.023 s.d. Finally, we can simulate the impact a 100% access to electricity on predicted HAZ. We find that increasing access to electricity from 75% to 100% in Indonesia will increase predicted HAZ by 0.06 s.d.

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 childrens height today which will have intergenerational effects), access to paved roads and electricity that will lead to improvements in height-for-age z-scores.

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-square 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 in the right hand side; the R-square 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 via 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 a R-square 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, household 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-square 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-square 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 a R-square of 0.11; this is closer to the R-square reported in column 2, Table 4 with only the household 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 in the right hand side of the empirical specification. Using this as a guidance, 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. Though, 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.

5 Conclusion

This paper characterizes the socioeconomic determinants of child health using data on height-for-age z-score – a long-run measure of chronic nutritional deficiency. A panel data is constructed using observations on children initially between ages 3 and 59 months in 1993 followed through the 1997 and 2000 waves of the Indonesian Family Life Survey. 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 estimate of the impact of household income is biased downwards relative to IV results. We also find 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.

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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)

- Source: IFLS - 1993, 1997, and 2000; *** significant at 1%, ** significant at 5%, * significant at 10%

- Standard errors reported in parenthesis are robust to clustering at the household level

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 completed grades of schooling	5.96	3.93
Father's completed grades of schooling	6.90	4.33
Log of real per capita household consumption expenditure	9.87	0.76
Square root of real per capita household total assets	4.48	3.78
Distance to the community health center in km	5.07	4.58
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=1 if the community has paved road	0.74	0.43
Number of health posts in a community	6.67	4.73

- Source: IFLS - 1993, 1997, and 2000; No. of observations - 5457

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	-0.078***	-0.077***	-0.079***	-0.077***
(< 24 months)	(0.009)	(0.009)	(0.01)	(0.009)
Spline in age in months	-0.001	-0.0013	-0.001	0.001**
(>= 24 months)	(0.001)	(0.001)	(0.001)	(0.0008)
Spline in age in	0.033***	0.033***	0.035**	0.030**
months (< 24)*male dummy	(0.01)	(0.01)	(0.01)	(0.01)
Spline in age in	-0.002***	-0.002***	-0.002**	-0.002***
months (>= 24)*male dummy	(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				-0.308*
of rice				(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-square	0.13	0.13	0.11	0.11
Kleibergen-Paap rk Wald F statistic			161.19	174.13

Notes:

- Source: IFLS - 1993, 1997, and 2000; *** 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 household assets. The F statistic on the excluded instruments is 161.19
- In (5), log(PCE) is instrumented with total household assets. The F on the excluded instruments is 174.14
- The first-stage regression estimates for columns 3 and 4 are reported in table A.1 of the appendix

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-square	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

- Source: IFLS - 1993, 1997, and 2000; *** significant at 1%, ** significant at 5%, * significant at 10%

- Standard errors reported in parenthesis are robust to clustering at the individual level

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

- Source: IFLS - 1993, 1997, and 2000
- *** 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

- Source: IFLS - 1993, 1997, and 2000

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

- Source: IFLS - 1993, 1997, and 2000