The Effect of Endogeneity and Measurement Error Bias On Models of the Risk of Child Stunting

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Abstract

The impact of endogeneity and measurement error on models that estimate the risk of child stunting is demonstrated. Stunting occurs when poor living environments cause short physical stature and is a major health problem in developing countries. The literature modelling the effect of various policies on the risk of stunting suffers from uncertainty about the strength of income versus maternal education effects. Results are based on a household survey from Papua New Guinea, where repeated within-year observations on households allows calculation of each variable's reliability ratio. Both measurement error and endogeneity bias are shown to affect conclusions about whether raising incomes or maternal education is the best way to reduce the risk of stunting.

Keywords: Endogeneity, Errors-in-variables, Stunting

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1. Introduction

Stunting, whereby poor living environments cause short physical stature, is a major health problem affecting over 200 million children in developing countries [4]. Stunting causes increased risk of sickness and death and retards mental development [2,7]. These problems can persist across generations because young girls who grow poorly usually become stunted women, and these women are more likely to give birth to underweight babies who themselves have a higher risk of becoming stunted [19]. Simulating the effect of various policies on the risk of stunting is therefore a major concern of nutritionists and other health scientists [3,12]. Recently, economists have also turned their attention to modelling the effect that various social and economic variables have on the growth of children [1,10].

The aim of this paper is to show the impact that endogeneity and measurement error bias have on empirical models of the risk of child stunting. These statistical problems may contribute to uncertainty in the literature about the effect that different policies have in reducing the risk of stunting. In particular, there is debate about whether general economic development policies to raise incomes are better than more targeted interventions, which try to improve variables like mother's education [13,14,18,20]. Indeed, some commentators claim that improving mother's education is the most influential of any investments that developing countries can make, in part because of the effect on child health and subsequent development [17].

The problem of endogeneity occurs because household income (or total expenditures) and child health are likely to be jointly determined because time spent in market work may subtract from time spent caring for children [18]. The problem of measurement error occurs because stunting depends on the history of nutrient intakes and sicknesses but variables available to simulate the risk of stunting may refer only to recent periods. For example, measured income (or expenditure) usually refers to the past week, fortnight, or month, and so is likely to be a noisy measure of the permanent income that is hypothesised to affect stunting [18].

2. Empirical Approach

In this study a Linear Probability Model (LPM) of the risk of stunting for young children is estimated using household survey data from the developing country of Papua New Guinea (PNG). Three different estimators are used: Ordinary Least Squares (OLS), which corrects for neither endogeneity nor measurement error; errors-in-variables regression (EIVREG), which corrects for measurement error; and Instrumental Variables (IV), which corrects for both problems. The EIVREG estimator uses repeated within-year observations on households to calculate each variable's *reliability ratio* – one minus the ratio of the measurement error variance to the total variance. These reliability ratios allow regression estimates to be corrected for the attenuation caused by errors-in-variables, see [5]. In contrast, the IV estimator uses data on household and agricultural assets as the instruments for potentially endogenous household total expenditures.

The underlying theoretical model assumes that households maximise a utility function, which depends on the consumption of commodities and leisure as well as on the quality and quantity of children. Households are constrained by budget and time endowments and by a production function relating health outputs (e.g., stunting) to inputs (e.g., nutrient intakes, utilisation of health facilities and antenatal health care) and exogenous individual and household characteristics [18]. Several of the inputs, such as nutrient intakes and health care, are endogenous so estimates such as prices and service quality are needed to purge the estimates of bias but most socio-economic surveys lack these details [15]. Therefore, the approach used here follows most econometric studies of child health by focusing on the reduced-form demand for child health that depends on child characteristics such as age and sex, x_j, household characteristics such as income and indicators of parental human capital (e.g., schooling and stature), x_h, community characteristics x_c, and a child-specific random error reflecting heterogeneity in individual healthiness e_j,

$$D_h = h\left(x_j, x_h, x_c, e_j\right). \tag{1}$$

One of the main household characteristics included in x_h is (instrumented) expenditure, which acts as a measure of permanent income, so strictly speaking, equation (1) is a quasi-reduced form model because it does not include the exogenous determinants of income (such as productive assets), see [11]. However, equations like (1) are the basis of most econometric models of child health.

The dependent variable in the model is the 0-1 indicator variable of whether an individual child is stunted, which is defined as having a height (standardised for age and sex) that is more than two-standard deviations below the median height in the reference population.[1] The child characteristics included in the model are the child's gender and age, where age is entered as a string of dummy variables for each 12-month age bracket. It is expected that the estimated risk of stunting will rise with increasing age because of the increased growth retardation in the early years of life for children in developing countries [15]. The household characteristics included in the model are (log) per capita expenditures, (log) household size, and the years of schooling and height of the child's mother. A regional dummy variable is also included to indicate the children living in communities in the high altitude zone (≥1200m) where stunting is especially widespread because of a combination of dietary, environmental and genetic factors, see [16].

Two of the estimation methods used (OLS and IV) are well know so need no description but the regression estimator corrected for attenuation (EIVREG) is less well known so it is described here, also see [9]. Let the model to be estimated be:

$$\mathbf{y} = \mathbf{X}^* b + e$$
$$\mathbf{X} = \mathbf{X}^* + \mathbf{U}$$

where **X*** are the true values, **X** the observed values and **U** the measurement errors. Let $\hat{\boldsymbol{\Sigma}} = (1/N)\mathbf{X}'\mathbf{X}$ denote the moment matrix of the observed **X** matrix and **Ω** the covariance matrix of the measurement errors in the **X** variables. With white noise measurement errors, $\hat{\boldsymbol{\Omega}}$ is a consistent estimator of **Ω**, obtained as the Hadamard product of the moment matrix $\hat{\boldsymbol{\Sigma}}$ and a diagonal matrix with elements (1-l_i), where l_i is the reliability ratio of the *i*th variable (here denoted as *x* (=*x**+*u*)). This reliability ratio is the proportion of the variation in *x* that is due to variation in the true value, $s^2_{x^*}/(s^2_{x^*} + s^2_u)$. If $\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is the OLS estimator, then the estimator corrected for attenuation is $\hat{b} \equiv \hat{\Sigma}_*^{-1}\hat{\Sigma}\mathbf{b}$ where $\hat{\boldsymbol{\Sigma}}_* = \hat{\boldsymbol{\Sigma}} - \hat{\boldsymbol{\Omega}}$.

3. Data

The data come from the 1996 Papua New Guinea Household Survey, which covered a random sample of 1200 households in 120 rural and urban communities. The sample was clustered, stratified and weighted, so all results presented here take account of these sample design effects. Each household was visited twice over a two-week period and on each visit anthropometric measurements (height and weight) were made on all children below age five (*n*=969), and on the available parents (usually mothers) of these children. The age of each child and demographic and educational information on other household members was also recorded. The expenditure estimates made by the survey cover all food and other frequent expenses during the two-week interview period, plus infrequent expenses (obtained from a 12-

month recall) and an estimate of the flow of services from durable assets and owner-occupied dwellings. Complete data are available on 729 children and their households.

One-sixth of the survey clusters were chosen as a “longitudinal sub-sample” and households in these clusters were revisited approximately seven months after the first interviews. All parts of the survey, including the expenditure recall, were gathered again during these revisits. The correlation between these two sets of observations on the same household in different months allows the reliability ratio of each variable to be established. Let x^1 be the first observation on a given household’s expenditures, and x^2 be a repeated observation on the same household, some months later. Then if errors are assumed to be white noise,

$$\begin{aligned} r_{(x^1,x^2)} &= \frac{\operatorname{cov}\left(x^* + u^1,\ x^* + u^2\right)}{\sqrt{\operatorname{var}\left(x^* + u^1\right) \bullet \operatorname{var}\left(x^* + u^2\right)}} \\ &= \frac{\operatorname{var}\left(x^*\right)}{\sqrt{\operatorname{var}\left(x^1\right) \bullet \operatorname{var}\left(x^2\right)}} \end{aligned}$$

because u^1 and u^2 are uncorrelated with each other and with the true values. The correlation coefficient gives the ratio of the variance in the true variable to the (geometric) average variance of the repeatedly observed variables. Hence the correlation serves as an estimate of the reliability ratio for that particular variable in the full sample, as long as the households in the longitudinal sub-sample are representative of the full sample.[2]

Figure 1 reports the reliability ratios for the four household and parental characteristics included in the model – the log of annual per capita expenditures (PCE), log household size, mother’s years of schooling, and mother’s height. It is clear that maternal height and schooling levels are measured with the greatest reliability (r=0.93-0.96) because for adults these variables are unlikely to change over a six month period so the imperfect reliability only reflects observer error. On the other hand, per capita annual expenditures are measured with the least reliability (*r*=0.66) because a large component of the measured variable is a short-term (i.e., two-week) recall of food and other frequent expenses, and households are evidently unable to perfectly smooth their consumption over the months of the year.[3] The instability in household size is also interesting, but may be particular to PNG because it is a tradition in that country to host extended family members for visits that can last many months so measured household size will depend on whether any of these long-term guests have recently arrived or departed.

4. Results

The estimation results are reported in Table 1, along with the means and standard deviations of the explanatory variables. The other notable descriptive statistics are that the average height of children in PNG is only 92.3 percent of the median height in the U.S. for the same age and sex. Just over 47 percent of children in PNG are defined as stunted, corresponding to a population total of 240,000, so the setting is one where stunting is a significant problem.

The OLS estimates in the second column of Table 1 are subject to both errors-in-variables and endogeneity biases. With those caveats in mind, the results suggest that the risk of stunting falls with increases in any of the following variables: per capita expenditures, household size, mother’s schooling, and mother’s height. The risk of stunting is generally higher for older children and for children in the high altitude regions, while the gender of the child makes no difference.

These results seem to support both sides of the debate about whether general economic development policies or more targeted interventions are better ways to tackle the problem of stunting. However, using the OLS estimates to simulate the effect of increases in either household incomes or mother's schooling suggests that the investment in schooling would have a more beneficial effect. Raising the years of schooling of all mothers by one standard deviation (an increase of 3.7 years) would see the incidence of child stunting in PNG fall to 40.4 percent, with a reduction of 35,000 in the number of stunted children. In contrast, a one standard deviation increase in (log) per capita expenditures would only reduce the stunting rate to 43.5 percent (a fall of 20,000 in the number of stunted children).

The results change greatly once account is taken of difference in the reliabilities of measuring the explanatory variables, using the EIVREG estimator. The estimated effect of per capita expenditures almost doubles, while the effect of maternal education falls slightly. After a standard deviation rise in expenditures the risk of stunting is only 40.0 percent (a fall of 37,500 in the number of stunted children), while a standard deviation increase in maternal schooling only reduces the number of stunted children by 30,500 (a stunting rate of 41.3 percent). It is apparent from the EIVREG results that the low reliability of measuring variables like per capita expenditures and household size can cause a large downward bias in their estimated effect on the risk of stunting, in contrast to the effect on more reliably measured variables like maternal schooling and height.

The treatment of both measurement error and endogeneity biases, using the IV estimator, results in a further rise in the estimated effect of per capita expenditures and a fall in the effect of maternal schooling and height. The instruments used include the total floor area and number of rooms in the dwelling, a dummy for whether the dwelling roof was iron, dummies for whether any household durable goods or agricultural capital goods were owned, a quadratic in the (log) total value of durable goods owned. These instruments raise the R^2 in the first stage regression for ln (PCE) from 0.27 to 0.48 while the *F*-test for excluding the instruments is $F_{(7,81)}$=19.8. A test of the over-identifying restrictions supported the validity of the instruments, with $\chi^2_{(6)}$=6.9.

When the IV results are used to simulate the effect of a standard deviation increase in per capita expenditures, the predicted incidence of stunting falls to 36.0 percent, with the number of stunted children falling by almost one-quarter (a population total of approximately 58,000). In contrast, a standard deviation increase in mother's years of schooling reduces the stunting rate to only 43.2 percent, which corresponds to only 21,000 fewer children stunted. Further evidence for the significant effect of household economic resources (i.e., incomes or expenditures) on the risk of stunting comes from the significant effect of household size in decreasing the risk of stunting. This effect implies that there are economies of scale, with the increase in disposable income that may result from sharing housing expenses with more people meaning that more resources are available to improve the health and nutrition of children.

Conclusions

Using household survey data from the developing country of Papua New Guinea, this paper has show that endogeneity and measurement error bias both have significant effects on empirical models of the risk of child stunting. If these statistical problems are not dealt with appropriately, simulated increases in household incomes show disappointing effects in terms of reducing the risk of stunting, while simulated increases in maternal schooling appear more beneficial. But once corrections are made for the endogeneity and imperfect reliability in the measurement of household incomes, simulated increases in incomes appear to exert a more powerful effect on the risk of stunting than do simulated increases in schooling.

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Table 1: Linear Probability Models of the Determinants of Stunting in Papua New Guinea

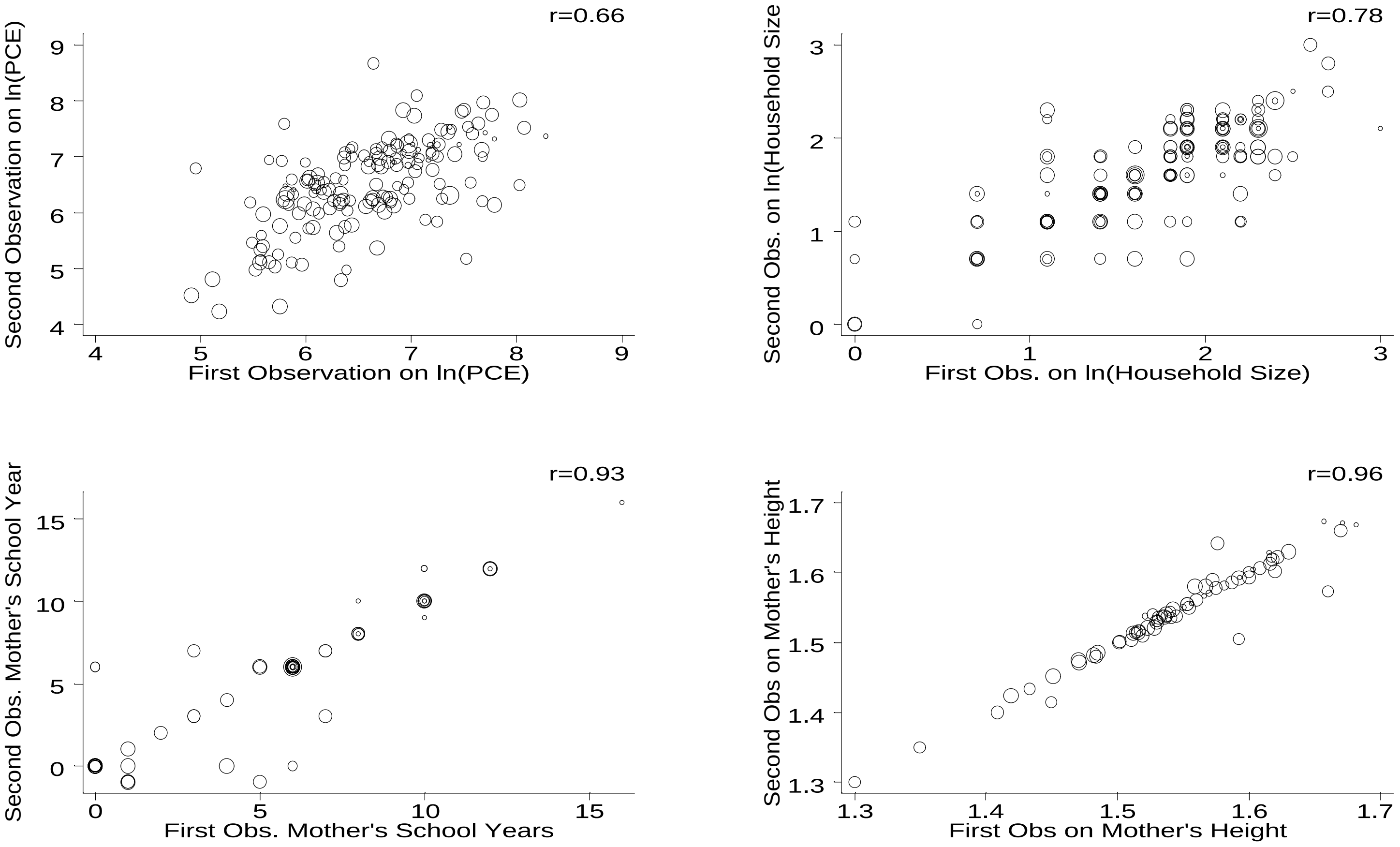
	Mean[a]	*OLS*	*EIVREG*	*IV*
ln (PCE)*[b]	6.23	-0.052	-0.096	-0.148
	[0.76]	(1.75)	(1.87)	(2.33)
ln (household size)	1.88	-0.088	-0.135	-0.126
	[0.43]	(2.01)	(2.34)	(2.79)
Mother’s school years	3.15	-0.018	-0.016	-0.011
	[3.74]	(2.85)	(2.32)	(1.53)
Mother’s height (cm)	152.98	-0.014	-0.013	-0.011
	[6.66]	(4.08)	(4.27)	(2.86)
Highlands dummy var.	0.35	0.198	0.210	0.227
	[0.48]	(3.59)	(5.32)	(3.65)
Child 12-24 month dummy	0.21	0.254	0.259	0.264
	[0.41]	(2.91)	(5.15)	(2.89)
Child 25-36 month dummy	0.21	0.289	0.289	0.289
	[0.41]	(3.36)	(5.75)	(3.27)
Child 37-48 month dummy	0.22	0.231	0.235	0.238
	[0.41]	(2.99)	(4.70)	(3.08)
Child ≥ 48 month dummy	0.13	0.316	0.319	0.317
	[0.33]	(3.62)	(5.47)	(3.60)
Male child dummy	0.54	0.022	0.028	0.032
	[0.50]	(0.60)	(0.82)	(0.84)
Constant		2.464	2.399	2.086
		(4.80)	(5.09)	(3.39)
R^2		0.192	0.200	0.175
F-test $_{(10,78)}$		17.56	17.18	14.27

Note: Dependent variable is binary taking a value of 1 if the child is stunted (height-for-age more than two standard deviations below the median in the reference population) and 0 otherwise. N=729.
Numbers in ( ) are t-statistics, corrected for clustering, sampling weights and stratification.
Endogenous variables are indicated by *.

[a] Weighted estimates, with weights reflecting the number of households represented by each observation and standard deviations in [ ].

[b] Kina per year, at national average prices, where the value of the regional poverty line is used as the spatial price deflator and K1.3=US$1 in 1996.

Figure 1: Comparison of Two Reports on Each Variable



Notes

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[1] The reference standards come from North American multiethnic data of the National Center for Health Statistics (NCHS) but they are applicable to developing countries (and recommended by the World Health Organization) because children from high-income households in those countries show the same age-related body stature (Gross, *et. al.*, 1996).

[2] Gibson (1999) shows that there is no statistically significant difference between the average value of household characteristics for the longitudinal sub-sample compared with the remaining households.

[3] Items covered by short-term recall comprise 81 percent of the average household budget.