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**How Reliable are Household Expenditures
as a Proxy for Permanent Income?
Implications for the Income-Nutrition Relationship**

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Abstract

Measurement error in short-run expenditures from household surveys may attenuate estimated effects of permanent income on economic outcomes. Repeated observations on households during the year are used to calculate reliability ratios and estimate errors in variables regressions of the impact of income on calorie intakes. In contrast to influential studies finding no effect of income, the results suggest significant nutritional responses to income in poor countries.

Keywords

income
measurement error
nutrition

JEL codes

C2; I3; O1

1. Introduction

Short-run expenditures observed over one to two weeks by household surveys are often used as a proxy for permanent income. Classical measurement error in this proxy may attenuate regression estimates of the effects of income on dependent variables, causing understated effects of economic growth. One example is nutrition, with influential studies claiming that calorie intakes of people in poor countries are unresponsive to changes in income (Behrman and Deolalikar, 1987). If higher incomes do not raise calorie intakes ‘growth-pessimism’ may result because of the wedge driven between affluence and a key component of human development – having adequate nutrition (Deaton, 1997). Indifference about nutritional consequences of short-term income shocks also may result, since zero elasticities imply that households adjust along other margins while keeping calorie intakes constant.

Given the importance of nutrition, close scrutiny is paid to calorie measures, since calculating calorie *availability* (rather than *intakes*) from household surveys seems to overstate the elasticity of calories with respect to income (Bouis and Haddad, 1992). Errors in reported expenditures are correlated, by construction, with calorie availability calculated from the same data, causing bias. Calorie intake data from nutritional surveys, such as 24-hour dietary recall, are better for estimating the relationship between income and calories. But less attention is paid to the quality of income measures. Typically, household expenditures are used as a proxy for permanent income. But expenditures are likely to be a noisy measure of long-run resources, especially when surveys use only a short observation period. Classical measurement error in this proxy may attenuate regression estimates of the effects of household income on calorie intakes.

In this note, we provide an example of this attenuation bias, using a specially designed survey with intra-year repeated observations. We follow an influential study that related calorie intakes to per capita expenditures, household size and women’s school years (Behrman and Wolfe, 1984). Using these explanatory variables in an ordinary least squares (OLS) model on our data, the elasticity of calorie intakes with respect to income is close to zero, at 0.14. Using the repeated observations on households during the year to calculate reliability ratios for each explanatory variable lets us estimate an errors-in-variables regression (EIVREG) that corrects for attenuation bias. The EIVREG estimate suggests a three times larger elasticity of calories with respect to income, of 0.40. Moreover, the EIVREG estimate lies within upper and lower bounds calculated from (biased) calorie availability data, while the OLS estimate is outside the bounds. Overall, these results suggest a significant effect of income on nutrition in poor countries.

2. Methods

Three estimators are used: OLS and instrumental variables (IV), which need no explanation, and the regression estimator corrected for attenuation (EIVREG) which is based on the following model relating an outcome vector \mathbf{y} to a matrix of explanatory variables \mathbf{X}^*

$$\mathbf{y} = \mathbf{X}^*\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (1)$$

$$\mathbf{X} = \mathbf{X}^* + \mathbf{U} \quad (2)$$

where \mathbf{X}^* are the true values, \mathbf{X} the observed values, $\boldsymbol{\varepsilon}$ are white noise disturbances, and \mathbf{U} are the measurement errors.¹ The moment matrix of the observed \mathbf{X} is $\hat{\boldsymbol{\Sigma}} = (1/N)\mathbf{X}'\mathbf{X}$ and $\boldsymbol{\Omega}$ is the covariance matrix of the measurement errors. With white noise errors, a consistent error estimator, $\hat{\boldsymbol{\Omega}}$ is the Hadamard product of the moment matrix and $(1-\lambda_i)$, where λ_i is the reliability ratio for the i th variable, showing the proportion of the variation in the observed variable due to variation in the true value, $\sigma_{x^*}^2/(\sigma_{x^*}^2 + \sigma_U^2)$. An estimate of λ_i is obtained from the correlation coefficient for two observations on the same variable (x^1 and x^2 where $x^i = x^* + u^i$):

$$r_{(x^1, x^2)} = \frac{\text{cov}(x^* + u^1, x^* + u^2)}{\sqrt{\text{var}(x^* + u^1) \bullet \text{var}(x^* + u^2)}} = \frac{\text{var}(x^*)}{\sqrt{\text{var}(x^1) \bullet \text{var}(x^2)}} = \frac{\sigma_{x^*}^2}{(\sigma_{x^*}^2 + \sigma_U^2)} \quad (3)$$

because u^1 and u^2 are assumed uncorrelated with each other and with the true values. Hence, the correlation coefficient gives the ratio of the variance in the true variable to the (geometric) average variance of the repeatedly observed variables. This empirical reliability ratio is used by the EIVREG estimator. Specifically, if $\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is the OLS estimator, then the EIVREG estimator, correcting for attenuation, is $\hat{\boldsymbol{\beta}} \equiv \hat{\boldsymbol{\Sigma}}_*^{-1}\hat{\boldsymbol{\Sigma}}\mathbf{b}$ where $\hat{\boldsymbol{\Sigma}}_* = \hat{\boldsymbol{\Sigma}} - \hat{\boldsymbol{\Omega}}$ (Iwata, 1992).

Other ways that multiple observations can mitigate measurement error are to average them or to use the second observation as an instrument for the first observation. The EIVREG approach has two advantages: it requires only a sub-sample be revisited to form reliability ratios for correcting attenuation bias in the full sample while the other approaches require all respondents to be revisited;

¹ The nutritional efficiency-wage hypothesis claims that income depends on calories, so $\boldsymbol{\varepsilon}$ could be correlated with \mathbf{X}^* due to simultaneity. But Subramanian and Deaton (1996) show the costs of food energy for daily work activities are much too low for this reverse causation to be plausible. The same result holds in the current data, with the extra 600 calories needed for a day's physical work costing less than three percent of the minimum daily wage.

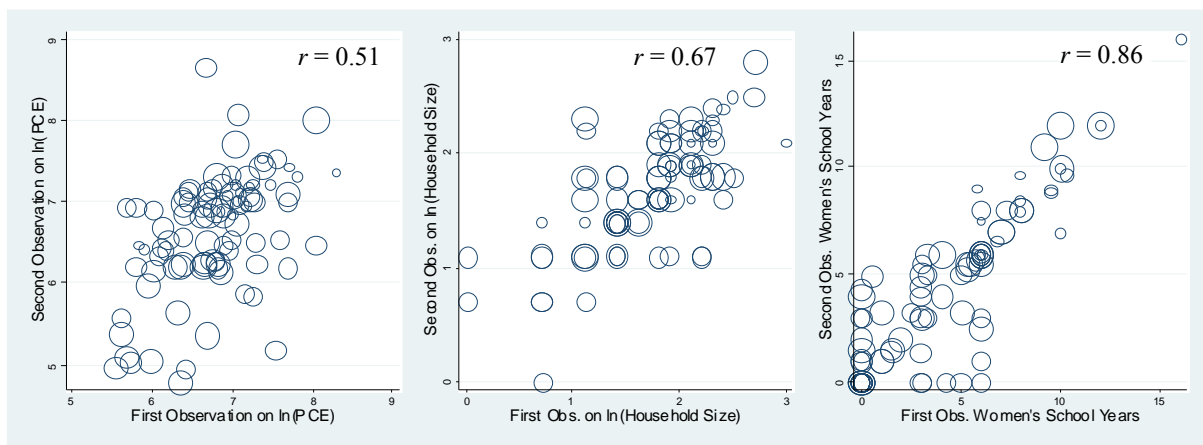
and, it focuses attention on the differing reliabilities of *all* of the explanatory variables. When IV is used, the focus is often on a single mis-measured variable when in fact all variables likely have some error, and imperfect reliability will appear in the form of a weaker instrument (lower first stage R^2) which distracts attention from the fundamental problem of measurement error.

3. Data and Results

We use a 1996 living standards survey from the developing country of Papua New Guinea (PNG).² The unusual feature of the survey is that households were visited up to four times per year. On the first visit a 24-hour dietary recall was carried out, along with the collection of basic demographic data. The start of the expenditure recall period was also signaled by this first interview. Households were revisited two weeks later and asked about their expenditures (and own-production) in the period since the first interview, along with a longer term (unbounded) recall of less frequently occurring expenditures. Measurement error in these expenditure data should be uncorrelated with errors in the 24-hour calorie intakes, which occurred earlier. The interviews were staggered throughout the year so seasonality in the 24-hour calorie intakes (which were collected just at the first interview) is unlikely.

The bounded expenditure recall was repeated six months later, when the demographic data were also recollected.³ The two observations on the same household allow reliability ratios to be calculated. These are shown in Figure 1 for (log) per capita expenditures (PCE) and household size, and for women's years of schooling (circle sizes reflect sampling weights).⁴

Figure 1: Reliability Ratios



² Details on the survey and downloads are available at: <http://go.worldbank.org/CJ9LIGVJ00>.

³ The full sample had 1200 households but only a randomly chosen subset of survey clusters were revisited after six months. This subset provides the reliability ratios for the sample of $n=620$ used here.

⁴ These same three variables are used by Behrman and Wolfe (1984) in their influential study showing almost no effect of income on calories.

The correlation coefficients range from 0.51 for log PCE to 0.86 for women's schooling. The low correlation between the two reports on the same household's expenditures reflects the difficulty of measuring this complex variable with just a short observation period. Low reliability of this proxy for permanent income is likely to be a general feature of developing country data. For example, McKenzie (2010) reports six monthly autocorrelations for expenditure in four developing countries that average only 0.36 and notes that autocorrelations in survey measures of household income and consumption are often in the 0.2 to 0.3 range.

It is apparent that (log) household size is also subject to measurement error, with a correlation between the two reports of only 0.67. This is consistent with Halliday (2010) finding noisy estimates of demographic variables from surveys measuring evolving household structure just at a point in-time. There is greater reliability in survey measures of women's school years, with a correlation between the two reports of 0.86 – consistent with evidence from resurveys and twin studies that the reliability of schooling measures is in the 0.8-0.9 range.

The OLS estimate of the elasticity of calorie intakes with respect to income is 0.14, with a standard error of 0.03 (Table 1).⁵ This elasticity suggests a low response of calorie intakes to income changes. This is not because the PNG population was already well nourished, since the survey data suggest that 42 percent of the population had fewer calories than required. There is no evidence of non-linearity in the calorie-income relationship since a squared log PCE term was statistically insignificant ($p < 0.17$).⁶ The estimates also show lower per capita calorie intakes in larger households – consistent with Behrman and Wolfe (1984) – but women's schooling has no effect (which differs from Behrman and Wolfe).

The OLS estimate of the income elasticity appears to suffer considerable attenuation bias. Specifically, the EIVREG estimate of the income elasticity of calorie intakes is three times as large, at 0.40 (bootstrapped standard error of 0.16). This is the largest change for any of the three regressors in the model. In fact, household size and women's schooling are statistically insignificant after accounting for the differing reliabilities of the regressors. It appears that the estimated effect of income on nutrition is especially susceptible to measurement error amongst the right-hand side variables.

⁵ All standard errors are bootstrapped and account for the weighting, clustering and stratification of the sample.

⁶ This contrasts with the Behrman and Wolfe (1984) study whose specification is followed here, where a quadratic income term was statistically significant. In that study (for Nicaragua in the late 1970s) the calorie-income elasticity was 0.06 at mean income levels.

Table 1: Regression Estimates of the Determinants of Log Per Capita Calorie Intakes

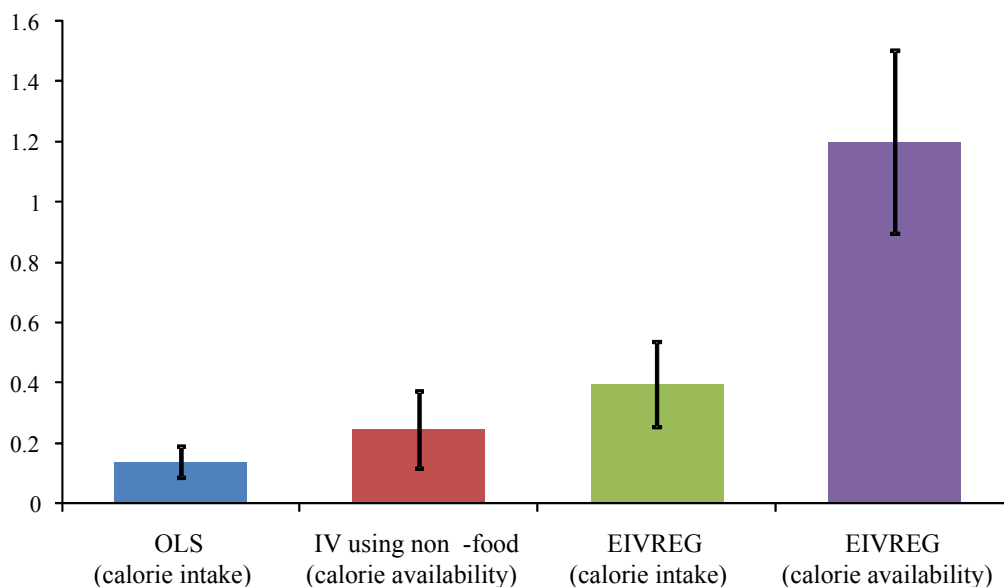
	Reliability ratio	OLS	EIVREG
log per capita expenditure	0.51	0.138 (0.026)**	0.396 (0.159)**
log household size	0.67	-0.105 (0.045)*	0.031 (0.191)
Women's years of schooling	0.86	0.009 (0.008)	-0.023 (0.027)
Constant		6.647 (0.220)**	4.808 (1.294)**
R-squared		0.13	0.24

Notes: $N = 620$. Bootstrapped standard errors in () take account of survey weights, clustering and stratification. **= $p < 0.01$, *= $p < 0.05$.

Bounds can be placed on the true elasticity, using calorie *availability* data derived from the household food expenditures. Regressions using such data will be subject to both attenuation bias, from the noisy estimates of permanent income, and to upward bias from the errors in calories and total expenditures being positively correlated (both are constructed from the same food expenditure data). A lower bound comes from using IV, with non-food expenditures as the instrument for total expenditures (Subramanian and Deaton, 1996). The reason is that, conditional on the true value of income, a positive regression error implies that food expenditure (and hence calorie availability) is above its predicted value so non-food expenditure must be below its predicted value. Hence, error in the instrument is correlated with the regression disturbances, biasing the IV estimates downwards. An upper bound uses EIVREG to remove only the attenuation bias from the income-calorie availability regression, leaving the upward correlated errors bias.

These bounds are illustrated in Figure 2, along with the OLS and EIVREG estimates of the elasticity of calorie *intakes* with respect to income. The lower bound estimate, from using non-food as the instrument, is 0.245 (± 0.065). This is above the OLS estimate when using calorie intakes, suggesting that the OLS estimate is unlikely to be true. The upper bound, using EIVREG to remove attenuation bias while leaving the upward correlated error bias, is 1.198 (± 0.155). The income elasticity estimate from using EIVREG on calorie intakes lies within these bounds, lending support to this estimate of the true but unknown elasticity.

Figure 2: Bounding Estimates of Elasticity of Calories with respect to Income



4. Conclusions

In this note we report an example where measurement errors in survey estimates of total expenditures create attenuation bias when estimating the elasticity of calorie intakes with respect to household incomes. The effect of these measurement errors is mitigated here by using a survey where repeated within-year observations allow reliability ratios to be calculated. A general lesson to draw from this example, and from previous literature, is that the proxies used for a complex variable like permanent income may be less reliable than the empirical measures for other variables like schooling. Therefore, correcting for measurement error should have a larger effect on estimated income elasticities than on elasticities for other determinants of calories. In this example, after mitigating the effect of attenuation bias, the estimated effect of income on calories is three times larger than in the uncorrected estimates.

Regression studies of the determinants of many other desirable outcomes use short-run estimates of household expenditures as an empirical proxy for permanent income. Our results suggest that the estimated effect of incomes on these outcomes also may be understated, due to the same attenuation bias found here. For example, when we use the same survey to study effects of household incomes on child height (as an indicator of long-term health and nutritional status) the estimated effect using EIVREG is three times larger than the effect when using OLS.

References

- Behrman, J and Deolalikar, A. (1987) 'Will developing country nutrition improve with income? A case study for rural South India' *Journal of Political Economy* 95(3): 492-507.
- Behrman, J and Wolfe, B. (1984) 'More evidence on nutrition demand: income seems over-rated and women's schooling underemphasized' *Journal of Development Economics* 14(1): 105-128.
- Bouis, H. and Haddad, L. (1992) 'Are estimates of calorie income elasticities too high? A recalibration of the plausible range' *Journal of Development Economics* 39(4): 333-364.
- Halliday, T. (2010) 'Mismeasured household size and its implications for the identification of economies of scale' *Oxford Bulletin of Economics and Statistics* 72(2): 246-262.
- Iwata, S. (1992) 'Errors-in-variables regression using estimated latent variables' *Econometric Reviews* 11(2): 195-200.
- McKenzie, D. (2010) 'Beyond baseline and follow-up: the case for more T in experiments' *BREAD Working Paper* No. 291, Bureau for Research and Economic Analysis of Development, December.
- Subramanian, S. and Deaton, A. (1996) 'The demand for food and calories' *Journal of Political Economy* 104(1): 133-162.