Errors in Self-Reported Wages: The Role of Previous Earnings Volatility and Individual Characteristics

Randall Akee
Tufts University

November 3, 2009

Abstract

I report the measurement error in self-reported earnings for a developing country using a novel data set. The data set is representative of the wage sector employed in the Federated States of Micronesia (FSM) and provides a look at two cross-sections in 1993 and 1999; additionally, a subset of the two cross-sections may be linked to create a panel data set. Administrative data from FSM Social Security office are matched to the FSM Census data for the wage sector employed. I find that the error in annual self-reported earnings is centered on zero but less efficient than results from the US. Additionally the error is not classical in nature – I find evidence for mean reversion in the data. Using the individual earnings histories contained in the FSM Social Security data, I construct accurate measures of past deviations of administratively recorded earnings to identify the impact of prior years' earnings variability on the current reporting of earnings. Prior earnings volatility is an important determinant of the error in earnings for the current period. However, the effect of prior shocks diminish significantly over time - suggesting that first-differencing and fixed-effects techniques will not improve accuracy and may in fact exacerbate the measurement error. Efforts to bound the true coefficient work well even when there is non-classical measurement error.

Acknowledgement 1 *I am grateful to Holger Bonin, Nancy Chau, Barry Chiswick, Didier Fouarge, Lily Gataullina, Peter Gottschalk, Daniel Hamermesh, Joop Hartog, Yingyao Hu, David Jaeger, Melanie Khamis, Michael Levin, Domenic Malumchai, Miguel Portela, Holger Seebens, Kostas Tatsiramos, Mutlu Yuksel, Zhong Zhao and participants of NEUDC 2007 at Harvard University and the Sixth IZA/SOLE Transatlantic Meeting of Labor Economists. I am especially indebted to the FSM Statistics Office, Eneriko Suldan and the FSM Social Security Administration, Mr. Alexander Narruhn for assistance with the data. Any errors, omissions or oversights are my own.*

Keywords: Non-Classical Measurement Error, Developing Countries, Instrumental Variables, Bounding Coefficient Estimates

JEL Classification:C80, D01,O15

1 Introduction

In applied economic studies, one seldom knows the true extent of the measurement error contained in their variables. Data is normally provided from survey questionnaires that are asked of individuals or households. Individuals may misreport their earnings or there may be problems in the coding and transcription of these amounts. A typical assumption is that the errors are classical in nature. In this case measurement error simply increases the standard error in estimation when present in a left-hand side variable, but otherwise leave coefficients unbiased. When measurement error is present in a right hand side variable, the estimated coefficients suffer from attenuation bias and provide a lower bound for the true coefficient. A number of papers have shown that the assumption of classical measurement error in annual wage and salary earnings is not supported for the United States (Duncan and Hill, 1984; Bound and Krueger, 1991; Bound et al , 1994; Pischke, 1995). The nature of earnings reporting for wage sector employed in developing countries has so far gone unstudied.[1] Earnings in self-employment in business and agriculture are notoriously difficult to measure and are omitted from this research. I, instead, focus only on the accuracy of earnings reporting from within the wage sector of a developing country.

Previous research for the US have utilized special matched data sets which contain both administrative records of an individual's earnings and the self-reported earnings from survey data. Duncan and Hill (1985) find that when comparing annual earnings of workers in a single firm the errors are not classical in nature and that there are strong correlations between the errors and years of current job tenure. Bound and Krueger (1991) use a more nationally representative data set, the Current Population Survey matched to U.S. Social Security data, and find that errors in reporting are mean reverting and autocorrelated. These results clearly indicate that the assumption of classical measurement error in earnings data cannot be supported.

Bound and Krueger (1991) also examine the impact of first-differencing these error-ridden self-reported earnings measures and find that there is still a high degree of accuracy in panel data. They report measures of true variance to the total variance of 0.82 for men in cross section data and 0.65 in first-differenced data. Both figures suggest that while there is some loss of information, the accompanying decrease in accuracy is not as dramatic as previously expected. In a later study, which uses panel data created from the original Panel Study of Income Dynamics (PSID) study, the researchers find that the coefficient from a regression of the administrative record data on the self-reported value of earnings is 0.81 for males in the cross section data; the coefficient on the same variable in difference form is 0.76, which again implies very little accuracy loss (Bound et. al , 1994). Pischke (1995) specifically examines the impact of transitory versus permanent income changes on error reporting. He concludes that under reporting of changes in transitory earnings accounts for a large part of the error in earnings reported in his data.

[1] See De Mel et al (2007) for an examination of measurement error contained in reporting of business profits in Sri Lanka.

I contribute to this literature by examining errors in self-reported earnings for a developing country. Following Duncan and Hill (1984) and Bound and Krueger (1991) and Pischke (1995), I investigate the individual determinants of errors in self-reported annual wages. I have assembled data for the wage-sector employed in a developing country and I examine the quality of self-reporting of earnings in survey data. I investigate the role of previous earnings volatility, individual characteristics and employment tenure on errors in earnings reporting. My novel dataset matches Social Security data from the Federated States of Micronesia (FSM) with the FSM Census data for 1993 and 1999. In addition to these two cross section data sets, I can match individuals between the two census years and create a true panel for a subset of observations. Because the FSM Social Security data contains the complete wage-sector earnings histories for everyone in my samples, I can construct accurate measures of previous wage volatility. Finally, I also compute the tenure with current employer from the social security data for use in explaining measurement in earnings reports.

My findings on the whole are qualitatively similar to those for the US. On average the error in reporting earnings for the FSM is centered on zero and the correlation between the administrative records and self-reported records is 0.48 in the first year and 0.60 in the second year. I find that measurement errors are mean-reverting as well - this implies that individuals who have above (below) average wages are more likely to underreport (over report) their wages in the survey. I establish that earnings volatility in the short run has large explanatory power with regard to errors. A large positive shock to earnings in the previous year causes individuals to underreport their earnings in the current year. This result indicates that researchers should be concerned with accuracy of their earnings data if there have been significant shocks in the preceding year. Results from a first-differencing of the panel data fare much worse than the results from the US: I find a signal to total variance ratio of only 0.20 in the panel data when controlling for non-classical measurement error. I attribute this finding to the strongly time variant determinants of measurement error in self-reported wages; I find evidence that there is almost no correlation between the error terms over six years. Differencing the data only adds noise to the already noisy wage reports. I also find that, when a plausible instrument exists in the data, bounding the estimated coefficients can be a useful exercise even in the presence of non-classical measurement error.

The paper is organized as follows: the next section describes the data sets, sample selection and provides the sample means, correlations and reliability ratios. The third section provides an analysis of the determinants of measurement error. I examine the effect that individual characteristics, short-run changes in individual annual wages, and position in the household have on predicting measurement error. The fourth section shows the consequences of measurement error in a simple bivariate consumption regression when measurement error is classical, non-classical and when potential instruments are uncorrelated and correlated with measurement error. Finally, I provide an example of a bounding technique (Black et al, 2000) that may be of use in applied work even when measurement error is non-classical. Section five concludes.

2 Data Set Creation and Description

I utilize three separate data sets in this analysis - the 1994 and 2000 Census of Population and Housing for the Federated States of Micronesia (FSM) and the FSM Social Security Administration Earnings History data.[2] The first two data sets are a standard census data set with questions at the individual level such as income (sources and amounts), education, birth date, and employment information.[3] It is particularly fortunate that the census income questions distinguish between earnings from wage sector employment, self-employment and other government transfer payments and remittances. Therefore, I am confident that the measure of self-reported earnings from wage sector employment does not include other sources of income which have their own specific designation. Additionally, the census data is not top-coded on wage earnings.

The Social Security data provides earnings information on the wage sector employed.[4] Coverage is mandatory for all employers with one or more employees unless they participate in another Social Security program (primarily for foreign nationals employed in foreign ministries). This essentially covers everyone employed in the wage sector. The Social Security system was set up with US assistance when the FSM was a trust territory of the United States. Once the FSM became an independent nation in 1986, the FSM Social Security Administration was established and is completely separate from the US Social Security Administration. The Social Security Act or FSM Public Law 2-74 provides the principal guidelines for the program in the FSM. Workers and employers are each required to pay 6% of earnings up to a maximum of $5000 per quarter into the system. Similar to the FSM Census data, there is no top coding on the amount of employee earnings here either. Self-employed business owners are also covered with slightly different provisions, but are not included in the analysis that follows.

I match individuals between the census and social security data by the day, month and year of birth as well as sex and current state of residence. The Census data does not contain names or social security numbers; therefore, it

[2] I secured use of these data sets via an agreement with these specific FSM offices. The data, as such, is not public.

[3] The census asks respondents for information for the previous calendar year (1993 and 1999). I therefore match these years to the FSM Social Security Administration Earnings History data for the relevant years. In the tables to follow these cross-section data are denoted as the 1993 and 1999 samples.

[4] The FSM Social Security data on annual wage and salary earnings is taken to be an accurate record of the true annual earnings. Recent work has questioned this assumption, see Abowd and Stinson (2003). Their approach utilizes firm and individual effects to estimate a common error component between the survey and administrative data in order to estimate reliability ratios. Crucial to their analysis is the presence of two separate wage reports for an individual at multiple points in time; they utilize the Survey of Income and Program Participation (SIPP) and Detailed Earnings Records (DER) from the US Social Security Administration. In total they have 5 survey waves in their estimation. Unfortunately, I have only two waves for the same individual and my sample size is much smaller than theirs: they have a total of 137,361 individuals with 207,323 different jobs and 115,958 employers. Nevertheless, I treat the FSM Social security data as a significantly less noisy measure of annual wages and salary than the self-reported measure.

is not possible to match on these items. I take only single matches for this research; single matches are the cases where there is only one unique match between the census and social security data on the matching variables. Duplicate matches occurred, but it is not possible given the lack of further information to distinguish between true and false matches in these cases. Therefore, I restrict my analysis to include only the cases where there are unique matches. Table 1 provides information on the selection of the sample. For both the 1993 and 1999 samples, I use all of the observations for individuals that report wages in the current year. The number of successful matches are reported in row 2 of Table 1. I eliminate any duplicate matches; only unique matches are retained for this analysis. Third, the self-employed are removed from this data. Fourth, I remove any observations where the reported wage is zero. Missing education and other covariates further diminish the number of observations. The final sample size used for the primary analysis is given on row 7 of Table 1 - 2854 for the 1993 sample and 3142 for the 1999 sample.

Panel B of Table 1 provides information on the successful merging on social security data for the 1993-1999 panel. I merge the 1993 and 1999 samples which may have missing education or other covariates (step 5 from above) using their social security numbers. The total number of observations that I have merged successfully is 1357.

Table 2 provides differences in means between the samples and the population where both have been subject to the same data restrictions mentioned previously. In both years the mean of education and age are higher for my sample than for the population. These differences are not exceptionally large, however. The sex ratio appears constant and not significantly different over time. Marital status and English language usage appears higher in the samples for both years as compared to the population means. State of residence differs most dramatically for the state of Kosrae, which is overrepresented consistently in the sample data. Finally, the differences in reported income are approximately \$1000-1400 between the sample and population means. The sample consistently has a higher reported income than the population sample. The sample selection for the panel data appears qualitatively very similar to that of the 1993 and 1999 population.

2.1 Data Means

I present the means in Table 3 for the two cross-section samples used in the analysis that follows. The average value of reported wages is \$7288 in 1993, while the administrative reported amount is \$7524. In 1999, the average self-reported value of earnings is \$7958 which is higher than the average value of administrative record of earnings at \$7452.

The relationship between the true measure of wages and the self-reported wages is given below:

$$(1) \qquad X_1 = X^* + \epsilon$$

where $X^*$is the true value of wages and X_1 is the observed value and ϵ is the error term which may or may not be white noise. Subtracting out the true value of wages from both sides isolates the error term. I present this variable, the measurement error in wage reports, in row 5 of Table 3. This measure of differences in self-reported and administratively recorded earnings will be the primary variable of interest in this study. Positive values of the error term indicates that the individual has over reported his wages for the given year and vice versa. The 1993 sample indicates that there is on average an underreporting of wages while in 1999 there appears to be an over reporting of wages on average. However, both of these numbers are relatively small in log terms. Figures 1 and 2 provide the distributions of the measurement error for 1993 and 1999 respectively.

The next three variables will be used in a regression that explains measurement error. These deviations are based on a three year average of an individual's administratively recorded income. I construct the variables as follows: the average value of the administrative record of wages for the three years prior to the survey years 1993 (1990, 1991, 1992) and 1999 (1996, 1997, 1998) are computed. Then I compute the simple difference between the administrative wage data for that particular year and the three year average. These simple deviation terms measure how far above or below a particular year's wages were compared to the three year average. The data indicate that wages were on average above the three year average by about \$562 in 1992 and by only \$38 in 1991 (\$395 in 1998 and \$233 in 1997). The average wage income over these three years is \$6454 in 1993 and \$7097 in 1999. I repeat this exercise for a four year average and these four variables are presented in the next section below. These variables are computed on only 2557 observations in 1993 and 2859 observations in 1999. The sample size decreases because not everyone was continuously employed for the five total years examined (the four previous years plus the current year). Extending this analysis to six continuous years of employment loses substantially more observations.

The demographic variables provide a general picture of this sampled population. The two samples are remarkably similar for many of the basic demographic variables. The survey respondent's average age is approximately 40 years old and has about 12 years of schooling.[5] The proportion of males is constant at almost 70% in both samples. Marital status, family size and English language usage are also constant across the two samples. The two samples slightly diverge in their employment experience variables. In 1993, the average tenure with the current employer was almost 7 years; by 1999 the average tenure with the current employer was eleven and a half years. However, total labor market experience was higher on average for the first sample than for the later sample with a difference of five years on average. This indicates that while the 1993 sample of wage sector employed had a large amount of labor force experience they had changed employers fairly frequently. The 1999 sample, in

[5]According to the FSM Census, the average education level for the adult population in the FSM is approximately 10 years of education.

contrast, has had more experience with their current employer.

The geographic location variables indicate that the observations are drawn fairly evenly from all four FSM states, with slightly more observations coming from the capital state of Pohnpei.

Finally, I report one of the few household consumption variables contained in the FSM Census – household kerosene and electricity annual use in log values. The values tend to be quite stable over time at approximately $50 per year per household. These will be used later in a simple consumption regression to test the degree of bias when using earnings variables with measurement error.

2.2 Correlation

The correlation between the administrative record of earnings and self-reported earnings provides us with some information on the overall accuracy of the self-reported wage data. The correlation between the administrative record and the measurement error indicates whether the measurement error is classical or not. The third possible correlation is between the self-reported earnings and the error term. The first correlation is presented in Table 4 and shows the relationship between the self-reported earnings and the administratively recorded amount. While the two wage amounts are positively correlated, they are by no means perfectly so. In fact, they have a correlation coefficient of 0.48 in 1993 and 0.60 in 1999. This contrasts with earlier findings by Bound and Krueger (1991) who find that in the US the correlation is 0.88. The accuracy of reporting is lower than the US and generally this will hold for other FSM results as well. The two further columns restricts the data to women alone and to those employed in the government sector (municipal, state, federal and foreign). There does not appear to be very large differences between the total sample and these two sub-samples; women tend to have slightly less accurate self-reports in 1993 than 1999 on average and the government sector employed closely matches the overall correlation. The finding that the 1999 sample had self-reported wages that were more closely related to the administrative record than the 1993 sample may be driven by the longer tenure with current employer for the 1999 sample. In a later section, I will show that tenure with current employer plays a big role in reducing measurement error.

The second set of correlations indicate that the measurement error is not classical in nature. The correlation between the administrative record and the measurement error is not zero - there is a strong, negative relationship. Classical measurement error would entail no relationship between the administrative record and the error; measurement error should be white noise here. Bound and Krueger (1991) refer to this negative correlation as "mean-reverting" errors. In simple terms: the higher the true value of earnings, the more likely an individual is to under report her earnings and vice versa. The negative correlation holds for both years and for the two sub-samples of women and government sector employed.

The third correlation illustrates the relationship between the error term and the natural log of the self-reported earnings amount. This correlation is just a mechanical outcome of the way that the error is defined and the fact that we have already established a negative correlation between the true value of earnings and the error term.

2.3 Reliability Ratios

In this section, I report the reliability ratios from the two cross-sections and panel data. Reliability ratios indicate the magnitude of attenuation bias for coefficients in simple bivariate regressions. These ratios tell us how a change in our observed variable relates to a change in the true, underlying variable. Equation 1 describes the relationship between the true value of wages and the self-reported value. The reliability ratios relate the covariance of these two variables, X_1 and X^*, to the variance of the self-reported value of wages. As Bound and Krueger (1991) note, this is similar to running a regression of the true value on the self-reported value of wages. Therefore, when there is non-classical measurement error the reliability ratio is given by the following:

$$\text{(2)} \qquad \text{Reliability Ratio}_{Non-Classical} = \frac{Cov(X^*,X_1)}{Var(X_1)} = \frac{\sigma^2_{X^*}+\sigma_{X^*,\epsilon}}{\sigma^2_{X^*}+2\sigma_{X^*,\epsilon}+\sigma^2_\epsilon}$$

Under the assumption of classical measurement error, the term $\sigma_{X^*,\epsilon}$disappears and we have the following reliability ratio:

$$\text{(3)} \qquad \text{Reliability Ratio}_{Classical} = \frac{Cov(X^*,X_1)}{Var(X_1)} \frac{Cov(X^*,X_1)}{Var(X_1)} = \frac{\sigma^2_{X^*}}{\sigma^2_{X^*}+\sigma^2_\epsilon}$$

I present both measures in Panel B of Table 4 for comparison, even though, there is strong evidence that the measurement error in this data is non-classical. Assuming there is classical measurement error, the reliability ratio in 1993 is 0.45, while it is 0.58 in 1999.[6] The next reliability ratio accounts for the non-classical measurement error and we find that the ratio is 0.42 in 1993 and 0.67 in 1999. Inclusion of the covariance of the true measure and the error term in the reliability ratio further indicates that there is better reporting of earnings in 1999 than in 1993 in this data. The results for the two sub-samples of women and government sector employed are qualitatively similar to the total sample results; women tend to report slightly better than men in 1999 but not in 1993 and government employees are slightly less accurate in their reporting which is surprising.

Finally, in Panel C of Table 4, I report the reliability ratio for a first-differencing of the matched panel data for 1993-1999. Under the assumption of classical measurement error the signal to noise ratio is just 0.36. When I account for the non-classical measurement error, there is a significant drop in

[6] Bound and Krueger(1991) find a reliability ratio of 0.97 for men and 0.96 for women in their US study utilizing the Current Population Study. A later study by Bound et al (1994) finds a reliability ratio of 0.81 for the US using the Panel Study of Income Dynamics Validation data. Angrist and Krueger (1999) find a reliability ratio of 0.77 for hourly wages using CPS data for the US.

the reliability ratio to 0.20. The disappointing results for first-differencing are a result of the fact that misreporting of earnings does not appear to be time invariant in this population. Therefore, the differencing only exacerbates the measurement error. In later sections, I will discuss more thoroughly some of the determinants of misreporting of earnings and illustrate how they vary across time. Bound and Krueger (1991) found that first-differencing their data for adjacent years did not significantly diminish the reliability ratio as it remained in the 0.78 - 0.85 range.[7] The six year difference in the panel may be too long of a time span to effectively eliminate measurement error in reported earnings. I will show later that the determinants of measurement error decay quickly over time and after six years measurement is uncorrelated.

The Variance-Covariance Matrixfor the panel data is presented in Table 5 for the true wages in 1993 and 1999 and the errors in both years.[8] The covariance between the error in 1993 and 1999 is small at 0.079 which provides further evidence that the misreporting of earnings is not highly correlated across these six years. These results are also presented for the two sub-samples of women only and government sector employed. The correlation between these variables are provided in the bold italics above the diagonal. Examining the correlation between the true wages in 1993 and 1999 for the total sample indicates that there is not a great deal of mobility; this population has a correlation of 0.6 in wages over the six years which indicates that there is not a lot of movement in the distribution. A value of 1 would indicate no movement at all. Interestingly women tend to have lower mobility in the wage sector - they have a wage correlation of 0.707 over this six year time period.

3 Determinants of Measurement Error

In this section, I regress the measurement error on individual and household characteristics and previous income deviations to determine some causal factors in misreporting of wages in the FSM. This regression is identified if we first assume that all of the individual characteristics such as age, labor market experience, sex and marital status are fixed prior to the answering of the survey question. Second, in order to account for the unobserved labor market characteristics I include a proxy for unobserved labor market characteristics of the individual - the mean of administrative recorded wages for the previous three years. My contention is that controlling for the mean of the previous three years' wages (derived from the administrative records) controls for unobserved labor market characteristics and abilities and that the regression error term, ξ_t, is therefore white noise in the following regression:

$$MeasurementError = \epsilon_t = \beta_0 + \beta_1 age + \beta_2 education + \beta_3 sex + \beta_4 maritalstatus +$$

[7] Bound et al (1994) finds slightly smaller reliability ratio of 0.76 for annual earnings in a four year panel using the PSID Validation data. A first-differencing result for hourly wages, however, performs poorly with a reliability ratio of only 0.19 for the same data set.

[8] This Variance-Covariance matrix is computed using the 1357 observations in the matched 1993-1999 panel data.

$\beta_5 NetLaborMarketExperience + \beta_6 CurrentEmployerExperience + \beta_7 ThreeYearWageMean +$
$\beta_8 \mathrm{Si}\, mpleDifference1 + \beta_9 \mathrm{Si}\, mpleDifference2 + \beta_{10} Survey\, \mathrm{Re}\, spondent + \xi_t$

In the table that follows, a coefficient with a positive sign indicates that changes in that particular variable tends to increase the over reporting of wages relative to the true amount while a negative coefficient reduces the over reporting. The variables have been previously described in the data set creation section. Additionally, the measurement error, ϵ_t, is defined as in equation 1.

3.1 Regression Results

Column 1 of Table 6 provides the basic human capital variables and labor market experience. Most of the coefficients in this regression are not statistically significant. Currently married is statistically significant and has a moderating effect on reporting error with a negative value of 0.13. The coefficient on years of labor market experience net of current employer is positive and statistically significant as well. This indicates that individuals with longer experience in the labor market are more likely to over-report their wages relative to the true value. Column 2 of Table 6 provides a similar model with the years with current employer as a regressor. In this case, more years spent with the current employer has a moderating effect on misreporting of wages. Individuals that have had a stable, long-term employment history are less likely to misreport their wages. The R-squared increases in this regression and we see that the other variables (including currently married) are statistically insignificant.

The third column of the table adds in the measures of past wage volatility. In this model, I include the three year average of their wage and salary income (excluding the survey year). Additionally, the first two years' deviations from this three year average are included as additional regressors. These two additional variables indicate whether deviations from a short-run average of wages affects the reporting of wages in the current year. I find that an increase in the previous year's wages results in an underreporting of the current period's wages.[9] For instance, an individual with wages in the previous period that were $1000 above his three year average will underreport his wage in the current period by 0.04 log points. This is large given that the mean of measurement error for the 1999 sample is 0.04. For the 1993 sample, a similar increase in the previous year's wage relative to the three year average would result in an underreporting of wages in the current period by 0.057 log points. The finding that deviation in the previous period's wages is negatively related to the measurement error is consistent with mean-reversion. Individuals who have experienced some wage or salary shock are more likely to report their wages as being closer to their short-run (three year) average which may be indicative of their permanent income. Pischke (1995) noted that people tended to misreport

[9] These measures of the previous three years' average income and the income volatility measures are all computed using the administrative data from the FSM social security administration. This is an important distinction in that these measures are not themselves contaminated with measurement error.

the transitory component of their earnings in the US. I also find that years of education are on the verge of statistical significance and have a negative sign as is to be expected. The two labor market experience variables are highly significant and they retain their opposing signs as was the case when they were entered individually in the regression.

The fourth column includes a variable for whether the individual is the survey respondent. It is highly unlikely that everyone in the household was interviewed individually and responded themselves to questions on wage and salary income. In all likelihood the household head or the spouse answered for the rest of the household members. While it is not possible to determine exactly who answered the census questionnaire, it is probably not unreasonable to assume that either the head of household or their spouse answered the FSM census questions. Therefore, this variable measures the effect of being the survey respondent on the misreporting of wages. The estimated coefficient on this variable is positive and statistically significant. The positive coefficient indicates either that the person who answers the census questionnaire is more likely to over report their own wages or that the person answering is more likely to underreport other household members' wages.[10]

Finally, the fifth column of Table 6 includes a slightly longer average of wages and salaries - in this case it is a four year average. I lose about three hundred observations for the1999 sample as this requires that someone be continuously employed for at least five years; I only lose two hundred observations for the 1993 sample. I provide three simple difference terms and the mean of the four year earnings history. This is a robustness check to see if additional years may possibly affect measurement error. The results mirror those of the previous regression - in particular, a deviation in the previous year has a negative effect on misreporting of wages or salaries. There is no evidence that shocks to wages or salaries persists more than one year.

The results for 1993 are qualitatively very similar to the results found in the 1999 sample.

4 Classical and Non-Classical Measurement Error in a Bivariate Regression

In this section, I investigate the extent of the bias from using error-ridden variables in a bivariate regression and employ a bounding technique for regression coefficients. It is instructive to first identify how the various covariances and variances affect the coefficient bias in the presences of both classical and non-classical measurement error.

First, assume that the true bivariate regression is given by the following:

[10]Examining the unconditional differences in measurement error by survey respondent status indicates the opposite result - survey respondents were more likely to underreport their wages than other household members. In 1993 (1999) the measurement error was -0.13 (0.03) log points for survey respondents and -0.02 (0.08) for everyone else in the household.

(4) $Y = \beta X^* + u$

In practice, however, we observe the following:

(5) $Y = \beta X + u$

Where X is the error-ridden wage variable as defined in equation 1. In this case, the probability limit of the estimated regression coefficient is given by the following:

(6) $$\text{plim } \beta_{OLS} = \beta\left(\frac{\sigma^2_{X^*} + \sigma_{X^*,\epsilon}}{\sigma^2_{X^*} + 2\sigma_{X^*,\epsilon} + \sigma^2_\epsilon}\right)$$

Under the assumption of classical measurement error, the term $\sigma_{X^*,\epsilon}$is zero in both the numerator and denominator and the standard attenuation bias occurs. When measurement error is non-classical, all five terms in equation 6 matter. Attenuation bias occurs if $\sigma_{X^*,\epsilon} + \sigma^2_\epsilon > 0$, otherwise the estimated coefficient may be larger than the true coefficient.

A solution to measurement error is the use of instrumental variables. Estimated coefficients from an IV regression is consistent under classical measurement error. A good instrument must meet all of the standard requirements and must also be uncorrelated with the measurement error itself. We can define an instrument as follows:

(7) $Z = X^* + \eta$

The instrument Z is related directly to the true value of wages and has an error component, η, which is assumed to be independent of the true value of wages. The error term in equation 7 is must also be independent of the error in the regression equation (4) and independent of the measurement error term ϵ. Given these specifications, the probability limit of the estimated coefficient from an instrumental variables regression is the following:

(8) $$\text{plim } \beta_{IV} = \frac{\beta(\sigma^2_{X^*} + \sigma_{X^*,\eta}) + \sigma_{\eta,u}}{(\sigma^2_{X^*} + \sigma_{X^*,\eta}) + \sigma_{X^*,\epsilon} + \sigma_{\eta,\epsilon}}$$

For the IV estimate to be consistent the term $\sigma_{\eta,u}$ (covariance of the error terms from equation 7 and 4) must be zero. The term $\sigma_{X^*,\epsilon}$(covariance of the true value of wages and measurement error from equation 1) must also be zero - this is the assumption of classical measurement error. Finally, the term $\sigma_{\eta,\epsilon}$ (covariance of the error terms from equations 7 and 1) must also be zero; this ensures that there is no correlation between the error terms of the two measures of wages. If any of these covariance terms are not zero, it will not be possible in general to sign the bias. I show in the next section how these non-zero covariances in practice can attenuate or inflate regression coefficients. As suggested by Black et al (2000) I attempt to bound the estimated coefficients when the measurement error in wages is non-classical.

4.1 Ordinary Least Squares with Non-Classical Measurement Error

Table 7 provides the bivariate regression coefficients of log annual household fuel costs in 1999 on log wages in 1993. This analysis is restricted to the panel data set so that there is no problem with identification of the wage coefficient in this consumption regression. In Panel A of Table 7 I present the regression coefficients (a constant term is included but not reported here) of the log of household fuel expenditures for 1999 on the administrative record of wages and salary in 1993. The second column provides the same regression with the self-reported amount of wages. The estimated coefficient from the regression with the error-ridden variable is attenuated as expected. The difference in the two coefficients is big - about 30% of the true value.

4.2 Instrumental Variables with Classical Measurement Error

Panel B provides instrumental variables regressions for a scenario where the wage variable has classical measurement error. Unfortunately, I do not have a credible instrument in my survey data, so, instead, I create an instrument using the administrative record of wages and add a white noise component. In actual survey data environments, one could ask a spouse or other individual in the household the value of the respondent's wages as a secondary measure. Ashenfelter and Krueger (1994) employed this technique for their twin study where they asked each respondent to provide their own educational attainment as well as their twin's educational attainment. Additionally, I create another wage variable using the administrative record and a white noise component so that I have an artificially-created variable which has classical measurement error. My original self-reported wage variable, as noted previously, contains non-classical measurement error and will also be used in the analysis that follows. Creating these two new variables is merely for illustration purposes; this would not, of course, be possible in a true survey environment. I intend to show that even in the best case scenario, when a true instrument exists, there are still other issues that one must contend with to ensure that regression coefficients are not biased. I will show below that applied researchers much also be concerned with the correlation between an instrument and the measurement error itself as well as whether the measurement error is classical or not.

In the first column of Panel B, I present the estimated coefficient when there is classical measurement error ($\sigma_{X^*,\epsilon} = 0$) and a well-specified instrument exists. The estimated coefficient accords exactly with that of the ordinary least squares regression coefficient from column 1 of Panel A above. By construction, the instrumental wage variable and the error-ridden wage variable will produce the OLS results as both error terms are orthogonal white noise disturbances.

In the next three columns, I relax the assumption that the instrument is uncorrelated with the error-ridden variable. For example, as noted by Bound et al (2001), if an individual misreports his wage in a given year it is highly likely that someone else in the household would also similarly misreport that person's wage in the same survey. The second person would likely have gotten her information on the other person's wage from that person - so the wage information is derived from the same, flawed source. In such a case there would be strong correlation in the measurement error in equations 1 and 7. In equation 8 this would imply that $\sigma_{\eta,\epsilon}$ is non-zero and positive. This would tend to attenuate any regression coefficients if there were non-classical measurement error. In the next three columns I present this case with three different levels of correlation between the error in the instrument and the error in self-reported wages; these three measures of wages were again calculated using the administrative record and a white noise component that I explicitly created to be correlated with the instrumental variable's white noise component. At very small covariance levels (the correlation here is 1 by construction) the additional term does not affect the estimated coefficient very much. At larger values, the estimated coefficient is smaller than that of the ordinary least squares estimates. In practice, one will never truly know the degree of covariance between the error terms of the instrument and error-ridden variables. Nonetheless, an instrumental variable that is correlated with the measurement error should be an important concern for applied researchers.

4.3 Instrumental Variables with Non-Classical Measurement Error

The third panel of Table 7 examines the same regression model under an assumption of non-classical measurement errors. As Black et al (2000) notes, the IV coefficients may serve as an upward bound of the estimated coefficient when there is non-classical measurement error.[11] When the covariance between the true value and the measurement error is negative ($\sigma_{X^*,\epsilon} < 0$), the denominator in equation 8 decreases in value and inflates the estimated coefficient away from the true value. In this case, the bound is quite large. Nevertheless, it is instructive in applied work to know the range of the true estimated coefficient. In the first column of Panel C, I present the estimated coefficient when the instrument is not correlated with any of the errors in the regression or the error-ridden variables. In this case, the bounds (the lower bound is derived from the OLS estimate in column 2 of Panel A above) would put the true coefficient in the range of 0.135 and 0.326. Black et al. (2000) suggest a method of tightening the bounds by restricting the analysis to cases where the two measures of wages agree. When the two reports of earnings (the self-reported and instrument) contain measurement error that is orthogonal to one another, a restricted sample

[11] Frisch (1934) describes another potential upper bound derived from the inverse coefficient from the reverse regression. Essentially one inverts the coefficient of a regression of the independent variable on the dependent variable. In my example, this provides an upper bound for the coefficient of 4.76. Bound et al (2001) and Black et al (2000) note that the reverse regression bounds depend on the explanatory power of the true regression. In my example, the R^2 value is low at 0.05. In these cases when the overall power of the model is low the reverse regression tends to produce large upper bound estimates.

where the two reports agree is a random sample with little or no measurement error. For instance, Black et al (2000) replicated the Ashenfelter and Krueger (1994) research using the cases in which the two siblings exactly agreed upon the differences in their years of education. An ordinary least squares regression was run on this subsample and a new upper bound is produced. Column 2 in panel C provides this estimate for the FSM data. In this case I take the central 50% of the distribution when ranked according to differences between the individual reported wages and the value from the instrument. A further restriction of the data to even more accurate matches only slightly improves the estimated coefficient. The bound is lower at 0.30, but it is still far away from the true value of 0.19.

In column 3 of Panel C, I explore how instrumental variables fare when there is not only non-classical measurement error but the instrument is also correlated with the error-ridden variable as well. The estimated coefficient is 0.145 which is smaller than the true value of the coefficient, 0.19. This attenuation bias, however, is not a general result. The positive value of $\sigma_{\eta,\epsilon}$ (0.744) in this case offset the negative value of $\sigma_{X^*,\epsilon}$ (-0.395) and led to the attenuation bias. Perfect correlation between the instrumental variable and the original self-report of wages will result in the OLS coefficient from panel A column 2. In another situation, this would not necessarily hold and the estimated coefficient could either be larger or smaller than the true value. In a world where the instrument has some correlation with the self-report of wages, the coefficients from IV regression will not function very well as upper bounds for the true coefficients. Column 4 of Panel C indicates that the bound technique suggested by Black et al (2000) once again provides an accurate upper bound even when there is non-classical measurement error as well as a correlated instrument.

5 Conclusion

In this research I described the measurement errors in self-reported earnings for the wage sector in a small, developing country. I matched individuals contained in two of the Federated States of Micronesia's censuses to the FSM Social Security Administration's records on wages. Additionally, I created a panel data set from a subset of these two cross-section data sets. I find that the measurement error is centered on zero, but has a larger variance than findings for the US. Also, I find that the reliability of the wage variable varies substantially over the two years, ranging from 0.42 to 0.67. Finally, first-differencing of the data actually exacerbates the problem; an important determinant of measurement error is time variant and is not removed by first-differencing the data. The reliability ratio for the first-differenced data is only 0.20.

I also seek to explain some of the determinants of measurement error. I find that tenure with current employer tends to reduce the reporting error in wages. I also find that the survey respondent tends to over report their own wages. Using past wage information, I find that previous deviations from a short-run mean of wages (determined using the administrative data on wages) has a large effect on reporting errors in the current period. Deviations that were two and three years prior appear to have little or no effect on reporting errors in the current period. In research which uses wages as an independent variable, it will be useful, as a robustness check, to restrict the analysis to observations where there were no shocks in the immediately previous period.[12] Of course, research that examines the effect of income shocks explicitly will be unable to conduct such robustness checks.

For those cases, the researcher will have to be satisfied with bounding their coefficient estimates. In this work, I have shown how one may use bounding techniques when instruments are available in the data to produce upper bounds even in the presence of non-classical measurement errors.

References

[1] Abowd, John M. and David Card. 1989. "On the Covariance Structure of Earnings and Hours Changes." Econometrica, 57(2) : 411-445.

[2] Abowd, John M. and Martha H. Stinson. 2004. "Estimating Measurement Error in SIPP Annual Job Earnings: A Comparison of Census Survey and SSA Administrative Data." Econometric Society North American Winter Meetings, no. 123.

[3] Angrist, J. and A. Krueger. 1999. "Empirical Strategies in Labor Economics." in Handbook of Labor Economics. O. Ashenfelter and D. Card, eds. Amsterdam: North-Holland. V. 3A, 1277-1366.

[4] Antman, Francisca and David J. McKenzie. 2007. "Earnings Mobility and Measurement Error: A Pseudo-Panel Approach." Economic Development and Cultural Change, 56(October): 125-161.

[5] Ashenfelter, O. and Krueger, A. 1994. "Estimates of the Economic Return to Schooling from a New Sample of Twins." American Economic Review, 84: 1157-1173.

[6] Black, D. and M. Berger and F. Scott. 2000. "Bounding Parameter Estimates with Nonclassical Measurement Error." Journal of the American Statistical Association, 95(451):739-748.

[7] Black, D. and S. Sanders and L. Taylor. 2003. "Measurement of Higher Education in the Census and Current Population Survey." Journal of the American Statistical Association, 98(463):545-554.

[12] Increasingly survey data in developing countries are asking respondents directly about prior shocks to the household, which include shocks to employment as well as agricultural productivity shocks. See the World Bank Living Standards Measurement Surveys for instance.

[8] Bound, John and Alan B. Krueger. 1991. "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?" Journal of Labor Economics, 9(1): 1-24.

[9] Bound, J. and Charles Brown, Greg J. Duncan and Willard L. Rodgers. 1994. "Evidence on the Validity of Cross-sectional and Longitudinal Labor Market Data." Journal of Labor Economics, 12(3): 345-368.

[10] Bound, J. and Charles Brown and Nancy Mathiowetz. 2001. "Measurement Error in Survey Data." In The Handbook of Econometrics, Volume 5. eds. James J. Heckman and Edward Leamer, 3705-3843. New York : Elsevier Science.

[11] Cappellari, Lorenzo. 1999. "Minimum Distance Estimation of Covariance Structures." Fifth UK Meeting of STATA Users, Royal Statistical Society, London, UK.

[12] Chamberlain, Gary. 1984. "Panel Data." In The Handbook of Econometrics, Volume 2, eds. Zvi Griliches and Michael Intrilligator. New York : North Holland.

[13] Deaton, Angus. 1997. The Analysis of Household Surveys. Baltimore, Maryland : Johns Hopkins Press.

[14] De Mel, Suresh and David McKenzie and Christopher Woodruff. 2007. "Measuring Microenterprise Profits: Must we ask how the sausage is made?" Journal of Development Economics, doi: 10.1016/j.jdeveco.2008.01.007.

[15] Duncan, Greg J. and Daniel H. Hill. 1985. "An Investigation of the Extent and Consequences of Measurement Error in Labor-economic Survey Data." Journal of Labor Economics, 3,(4) : 508-532.

[16] Frisch, R. 1934. Statistical Confluence Analysis by Means of Complete Regression Systems. Oslo, Norway: University Economics Institute.

[17] Gibson, John and Bonggeun Kim. 2008. "The effect of reporting errors on the cross-country relationship between inequality and crime." Journal of Development Economics, doi:10.1016/j.jdeveco.2007.12.001.

[18] Gottschalk, Peter and Minh Huynh. 2006. "Are Earnings Inequality and Mobility Overstated? The Impact of Non-Classical Measurement Error." IZA Discussion Paper No. 2327.

[19] Hu, Yingyao and Susanne M. Schennach. 2008. "Instrumental Variable Treatment of NonClassical Measurement Error Models." Econometrica, 76(1): 195-216.

[20] Kapteyn, Arie and Jelmer Y. Ypma. 2007. "Measurement Error and Misclassification: A Comparison of Survey and Administrative Data." Journal of Labor Economics, 25(3), 513-551.

[21] Lee, Lung-Fei and Jungsywan H. Sepanski. 1995. "Estimation of Linear and Nonlinear Errors-in Variables Models Using Validation Data." Journal of the American Statistical Association, 90(429) : 130-140.

[22] Moffit, Robert and Peter Gottschalk. 2002. "Trends in the Transitory Variance of Earnings in the United States." The Economic Journal. 112(March) : 68-73.

[23] Pischke, Jorn-Steffen. 1995. "Measurement Error and Earnings Dynamics: Some Estimates from the PSID Validation Study." Journal of Business and Economic Statistics. 13(3) : 305-314.

Table 1 Data Set Creation

Panel A: Creation of Cross-Section Matched Samples

	Number of Observations for 1993 Sample	Number of Observations for 1999 Sample
1. Report Wage Income in current year in Social Security Data	19525	19676
2. Successful Matches with Census Data	12165	12308
3. Non Duplicates	6396	6537
4. Not Self-Employed	4227	4268
5. Reported Wage is not zero	3801	4073
6. Education variable is not missing	3684	4073
7. Other Covariates are not missing	2854	3142

Panel B: Creation of Panel Data Sample

	Number of Observations
1. Total 1993 Observations where other covariates may be missing	3684
2. Total 1999 Observations where other covariates may be missing	4073
3. Merged between the 1993 and 1999 by social security identification numbers	1357

Table 2
Differences in Sample and Population Means for Selected Characteristics

	1993 Sample			1993 Population			T-test
Variables	Obs	Mean	Std. Dev	Obs	Mean	Std. Dev	
Years of Education	2854	12.57	4.09	13178	11.69	4.40	-10.32
Age	2854	40.16	9.98	13178	37.08	11.05	-14.66
Marital Status	2854	0.84	0.36	13178	0.77	0.42	-9.49
Sex	2854	0.69	0.46	13178	0.68	0.47	-0.76
English Language Usage	2854	0.71	0.45	13178	0.66	0.47	-5.18
Yap State Residence	2854	0.20	0.40	13178	0.15	0.36	-5.68
Chuuk State Residence	2854	0.24	0.43	13178	0.37	0.48	14.44
Pohnpei State Residence	2854	0.36	0.48	13178	0.38	0.49	1.77
Kosrae State Residence	2854	0.20	0.40	13178	0.10	0.30	-12.76
Reported Income	2854	7288.19	6610.62	13178	5834.92	6964.81	-10.55

	1999 Sample			1999 Population			T-test
Variables	Obs	Mean	Std. Dev	Obs	Mean	Std. Dev	
Years of Education	3142	13.01	3.54	13662	12.06	3.94	-13.35
Age	3142	40.49	9.84	13662	38.16	11.61	-11.54
Marital Status	3142	0.84	0.37	13662	0.76	0.43	-10.38
Sex	3142	0.68	0.47	13662	0.68	0.47	0.05
English Language Usage	3142	0.72	0.45	13662	0.66	0.47	-7.53
Yap State Residence	3142	0.23	0.42	13662	0.17	0.37	-8.18
Chuuk State Residence	3142	0.21	0.40	13662	0.32	0.47	14.35
Pohnpei State Residence	3142	0.37	0.48	13662	0.40	0.49	3.08
Kosrae State Residence	3142	0.19	0.40	13662	0.11	0.32	-10.73
Reported Income	3142	7958.44	16864.50	13662	6911.46	64752.04	-1.66

Table 3
Means and Standard Deviations

	1993 Sample		1999 Sample	
	Mean	St. Dev.	Mean	St. Dev.
Earnings Variables				
Administrative Annual Earnings Data	7524.00	6081.57	7452.74	6215.49
Self-Reported Annual Earnings Data	7288.19	6610.62	7958.44	16864.50
Log Administrative Annual Earnings Data	8.58	0.95	8.58	0.94
Log Self-Reported Annual Earnings Data	8.48	1.10	8.62	0.83
Simple Difference Between Log Admin and Log Self-Reported Earnings Data	-0.11	1.05	0.04	0.80
Earnings Volatility Variables				
Simple Difference (One Year Prior)	562.87	1430.83	395.45	1455.85
Simple Difference (Two Years Prior)	38.13	1170.54	233.26	1207.62
Mean (Three Year Earnings History)	6454.01	5405.40	7097.61	6024.19
Earnings Volatility Variables - 4 Year Average				
Simple Difference (One Year Prior)	846.20	1637.74	521.51	1720.74
Simple Difference (Two Years Prior)	321.46	1410.56	107.20	1335.74
Simple Difference (Three Years Prior)	-367.55	1390.49	62.54	1413.26
Mean (Four Year Earnings History)	6170.68	5140.01	6971.55	5924.72
Basic Demographic Variables				
Age	40.16	9.98	40.49	9.84
Years of Education	12.57	4.09	13.01	3.54
Sex	0.69	0.46	0.68	0.47
Currently Married	0.84	0.36	0.84	0.37
Total Number in Household	7.85	4.17	7.30	3.98
Survey Respondent	0.77	0.42	0.75	0.43
Employment Experience Variables				
Current Tenure with Employer	6.69	3.55	11.51	6.01
Total Labor Market Experience Net of Current Employer	20.90	10.33	15.97	10.15
Geographic Location Variables				
Yap State	0.20	0.40	0.23	0.42
Chuuk State	0.24	0.43	0.21	0.40
Pohnpei State	0.36	0.48	0.37	0.48
Kosrae State	0.20	0.40	0.19	0.40
Household Consumption Variable				
Log Kerosene, Fuel and Electricity Annual Use in Dollars	3.66	1.02	3.83	0.81

Note: Sample size is 2854 observations in 1993 except for the Earnings Volatility Variables - 4 Year Averages where there are only 2557 observations

Note: Sample size is 3142 observations in 1999 except for the Earnings Volatility Variables - 4 Year Averages where there are only 2859 observations

Table 4
Simple Correlations and Reliability Ratios for Administrative, Reported Earnings Data and Reporting Errors

A. Correlation Coefficients	Year	All	Women	Government Sector
Correlation (Log Administrative Wage, Log Self-Reported Wage)	1993	0.48	0.44	0.48
	1999	0.60	0.63	0.59
Correlation (Log Administrative Wage, Measurement Error)	1993	-0.4	-0.44	-0.33
	1999	-0.55	-0.49	-0.44
Correlation (Log Self-Reported Wage, Measurement Error)	1993	0.61	0.62	0.67
	1999	0.34	0.35	0.45

B. Reliability Ratios for the Cross Section Data

Reliability Ratio for Classical Measurement Error
Reliability Ratio = True Measure Variance / (Error Variance + True Measure Variance)

	Year	All	Women	Government Sector
Reliability Ratio =	1993	0.45	0.43	0.42
Reliability Ratio =	1999	0.58	0.60	0.55

Reliability Ratio for Non-Classical Measurement Error
Reliability Ratio = Covariance(lnadmin, lnreport) / Variance (lnreport)

	Year	All	Women	Government Sector
Reliability Ratio =	1993	0.42	0.38	0.38
Reliability Ratio =	1999	0.67	0.69	0.59

C. Reliability Ratios for the Panel Data Set

Reliability Ratio for Classical Measurement Error

	Year	All	Women	Government Sector
First Difference	1993-1999	0.36	0.30	0.34

Reliability Ratio for Non-Classical Measurement Error

	Year	All	Women	Government Sector
First Difference	1993-1999	0.20	0.18	0.19

Table 5
Variance - Covariance Matrix for 1993-1999 Panel Data

All	True 1993	True 1999	Error 1993	Error 1999
True 1993	0.937	***0.612***	***-0.449***	***-0.182***
True 1999	0.562	0.9	***-0.179***	***-0.596***
Error 1993	-0.395	-0.154	0.827	***0.114***
Error 1999	-0.134	-0.429	0.079	0.576

Note: Computed for the 1357 observations in the matched 1993-1999 panel
Note: Correlations are given above the diagonal line

Women	True 1993	True 1999	Error 1993	Error 1999
True 1993	0.746	***0.707***	***-0.37***	***-0.225***
True 1999	0.489	0.641	***-0.184***	***-0.456***
Error 1993	-0.267	-0.123	0.699	***0.159***
Error 1999	-0.128	-0.241	0.088	0.438

Note: Computed for the 431 observations in the matched 1993-1999 panel
Note: Correlations are given above the diagonal line

Government Sector	True 1993	True 1999	Error 1993	Error 1999
True 1993	0.742	***0.597***	***-0.353***	***-0.098***
True 1999	0.444	0.747	***-0.119***	***-0.515***
Error 1993	-0.261	-0.088	0.734	***0.086***
Error 1999	-0.06	-0.319	0.053	0.513

Note: Computed for the 971 observations in the matched 1993-1999 panel
Note: Correlations are given above the diagonal line

Table 6. Effect of Previous Earnings History on Error in Current Reported Earnings with Simple Deviation Term in 1999

	Error in Reported Earnings									
	(1)		**(2)**		**(3)**		**(4)**		**(5)**	
Variable	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**
Human Capital and Characteristics										
Years of Education	0.005	0.020	-0.018	0.018	-0.036*	0.019	-0.038*	0.019	-0.028	0.020
Years of Education Squared	0.000	0.001	0.001	0.001	0.004***	0.001	0.004***	0.001	0.003***	0.001
Currently Married	-0.130***	0.043	-0.049	0.043	-0.052	0.043	-0.089*	0.048	-0.052	0.050
Sex	0.017	0.030	0.014	0.029	0.055*	0.029	0.056*	0.029	0.028	0.030
Years Labor Market Experience Net of Current Employer	0.005***	0.002			0.008***	0.002	0.007***	0.002	0.007***	0.002
Years with Current Employer			-0.026***	0.003	-0.015***	0.003	-0.016***	0.003	-0.012***	0.003
Deviation Terms										
Simple Difference (One Year Prior Earnings)					-0.039***	0.013	-0.040***	0.013	-0.046***	0.013
Simple Difference (Two Years Prior Earnings)					0.011	0.012	0.011	0.012	-0.001	0.0118
Simple Difference (Three Years Prior Earnings)									-0.014	0.0144
Mean of Earnings History					-0.035***	0.004	-0.035***	0.004	-0.029***	0.004
Survey Respondent							0.083	0.041	0.066	0.042
Observations	3142		3142		3142		3142		2859	
Relevant F-Test	4.74		14.92		16.83		15.82		10.44	
R - squared	0.014		0.045		0.098		0.099		0.076	

Note: The coefficients and standard errors for the Means and Deviation Variables are multiplied by 10-e3.

All regressions include state of residence controls and a constant term.

Note: *** indicates statistical significance at the 99% confidence level, ** at the 95% confidence level, * at the 90% confidence level.

Table 6 cont. Effect of Previous Earnings History on Error in Current Reported Earnings with Simple Deviation Term in 1993

	Error in Reported Earnings									
	(1)		**(2)**		**(3)**		**(4)**		**(5)**	
Variable	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**
Human Capital and Characteristics										
Years of Education	0.002	0.021	0.000	0.020	-0.021	0.020	-0.023	0.020	-0.017	0.020
Years of Education Squared	0.000	0.001	0.001	0.001	0.003***	0.001	0.003***	0.001	0.002**	0.001
Currently Married	-0.092*	0.052	-0.027	0.050	-0.007	0.050	-0.048	0.058	-0.055	0.063
Sex	-0.039	0.044	-0.045	0.043	0.008	0.042	0.011	0.042	-0.005	0.045
Years Labor Market Experience Net of Current Employer	-0.003	0.002			0.003	0.003	0.001	0.003	0.003	0.003
Years with Current Employer			-0.052***	0.006	-0.038***	0.006	-0.040***	0.006	-0.035***	0.006
Deviation Terms										
Simple Difference (One Year Prior Earnings)					-0.057***	0.022	-0.057***	0.022	-0.045***	0.019
Simple Difference (Two Years Prior Earnings)					-0.033	0.025	-0.033	0.025	-0.028	0.020
Simple Difference (Three Years Prior Earnings)									0.001	0.026
Mean of Earnings History					-0.036*	0.005	-0.036***	0.005	-0.031***	0.005
Head of Household or Spouse							0.091*	0.057	0.080	0.060
Observations	2854		2854		2854		2854		2557	
Relevant F-Test	12.05		21.35		19.10		18.18		13.31	
R - squared	0.048		0.077		0.106		0.106		0.099	

Note: The coefficients and standard errors for the Means and Deviation Variables are multiplied by 10-e3.
All regressions include state of residence controls and a constant term.

Table 7: Ordinary Least Squares and Instrumental Variables Regressions with Measurement Error in Wages

Panel A Ordinary Least Squares

	Log Annual Household Utilities in 1999			
	Ordinary Least Squares		**Ordinary Least Squares and Non-Classical ME**	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Log Wages in 1993 - Admin	0.190	0.021		
Log Wages in 1993 - Self-Reported			0.135	0.021

Note: All regressions include a constant term. Total observations are 1353

Panel B Instrumental Variables with Classical Measurement Error

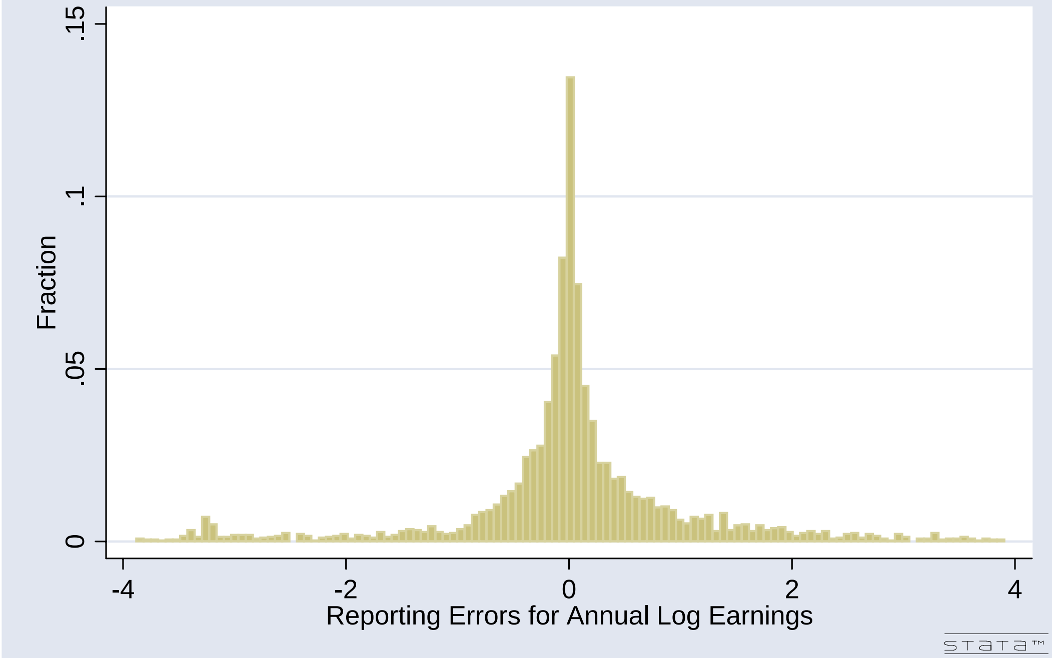
	Log Annual Household Utilities in 1999							
	IV with Random Instrument and Classical ME		**IV with Correlated Instrument and Classical ME**		**IV with Correlated Instrument and Classical ME**		**IV with Correlated Instrument and Classical ME**	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Log Wages in 1993 - Self-Reported	0.190	0.021	0.189	0.021	0.180	0.023	0.121	0.058
Note: All regressions include a constant term. Total observations are 1353								
Covariance(Error in Instrument, Error in Wages)			0.003		0.019		0.120	

Panel C Instrumental Variables with Non-Classical Measurement Error

	Log Annual Household Utilities in 1999							
	IV with Random Instrument and Non-Classical ME		**Ordinary Least Squares and Non-Classical ME on Restricted Range**		**IV with Correlated Instrument and Non-Classical ME**		**Ordinary Least Squares and Non-Classical ME on Restricted Range**	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Log Wages in 1993 - Self-Reported	0.326	0.039	0.306	0.043	0.145	0.021	0.314	0.043
Observations	1353		684		1353		689	

Note: All regressions include a constant term.

Figure 1: Distribution of Errors in Annual Log Earnings
for the FSM in 1993



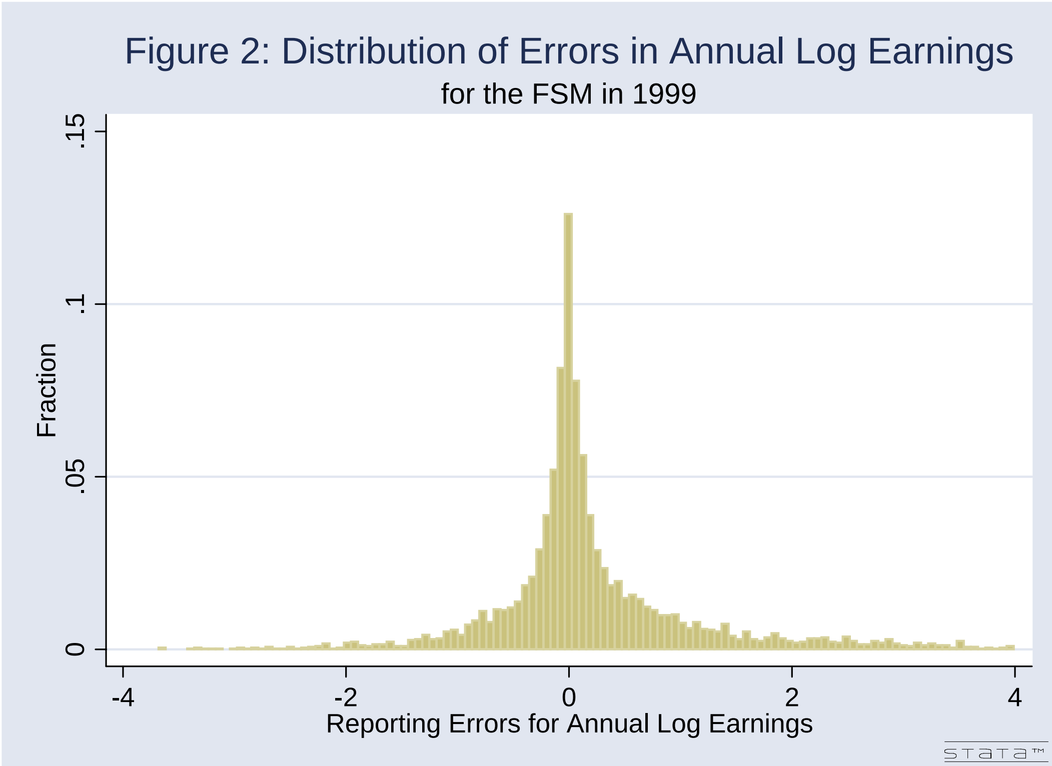


Figure 2: Distribution of Errors in Annual Log Earnings
for the FSM in 1999
Fraction
0
.05
.1
.15
-4
-2
0
2
4
Reporting Errors for Annual Log Earnings