IPUMS-International Working Paper:

Drawing Statistical Inferences from International Census Data

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Although census microdata used by social scientists derive from complex samples, researchers commonly apply methods designed for simple random samples. Using full count census data from 4 countries, we evaluate the impact of sample design on standard error estimates of microdata samples from the IPUMS International. We compare replicate standard error estimates from the full count data to estimates from the 10% public use samples using 3 methods: subsample replicate, Taylor series linearization, and estimates using simple random sample assumptions. We suggest that, for some types of analyses, especially those involving highly clustered or stratified variables or for analysis done on subsets of the population, researchers should consider adjusting for such influences in their estimation procedures, and we propose a pseudo-strata variable to help identify implicit geographic stratification.

Census microdata are collected by countries around the globe and contain a wealth of information useful to social science researchers. Although large machine-readable census microdata samples exist for many countries, access to these data has been limited and the documentation has often been inadequate. Even where such microdata are available for scholarly research, comparisons across countries or time periods are difficult because of inconsistencies in both data and documentation. The Integrated Public Use Microdata Series-International (IPUMS International) addresses these issues by converting census microdata for multiple countries into a consistent format, supplying comprehensive documentation, and making the data available through a web-based data dissemination system. IPUMS International provides users access to 185 census samples based on subsets of full population data from 62 countries throughout the world. Although census microdata used by social scientists, like the data in the IPUMS, derive from complex samples, researchers commonly apply methods designed for simple random samples. Using full count data from 4 countries, we evaluate the impact of sample design on standard error estimates of microdata samples from the IPUMS International. We compare standard error estimates from the full count data to estimates from the 10% public use samples using three methods: subsample replicate, Taylor series linearization, and estimates using simple random sample assumptions. We conclude by discussing strategies for obtaining unbiased and efficient estimates of statistical significance.

Like most census microdata, IPUMS samples contain individual level data, clustered by household, and often stratified and differentially weighted. Standard error estimates from clustered, stratified, and differentially weighted data can differ dramatically from those derived from simple random samples of the same size. To the extent that the characteristics of individuals are homogeneous within households, household clustering yields standard errors that

are greater than would be obtained from a simple random sample of the same size. (Graubard and Korn 1996; Mansen, Hurwitz, and Madow 1953; Kish 1992; Korn and Graubard 1995, 1999). If all members of households shared identical characteristics, the standard errors for variables would be inversely proportional to the square root of the number of households rather than the number of individuals. Variables such as race and poverty status tend to be comparatively homogeneous within household, and therefore pose a risk for underestimated standard errors if clustering is ignored. In a few cases, IPUMS samples are clustered by locality as well as by household, and this may substantially increase the risk of underestimated standard errors. The effects of differential weighting similarly increase the risk of underestimated standard errors.

Stratification in census microdata samples has the opposite effect from clustering and differential weighting: in general, failure to control for the effects of stratification leads to *overestimated* standard errors. To the extent that the characteristics of individuals or households are homogeneous within strata, the variance within the stratum is decreased. Estimates that account for the additional information about the sample have lower standard errors. In some cases, the IPUMS samples incorporate explicit stratification by such factors as household size or geographic location. More often, however, the data are implicitly geographically stratified as a result of the sample design. Most IPUMS-International samples are systematic random samples, typically drawn by selecting every tenth household in the source file after designating a random starting point. The data are usually collected through direct enumeration, a procedure by which census enumerators travel from block to block and from village to village within a specified geographic area, recording census information about persons in a roughly systematic geographic order. As a result, census data are often in sequential order within each enumeration unit. Even

where sequential sorting is not preserved, census data are often sorted according to small geographic areas so that records in resulting samples retain geographic proximity. Therefore, the systematic sample design is equivalent to low-level geographic stratification, even though no explicit stratification may have been carried out.

In recent years, it has become fairly straightforward for users if IPUMS-International data to account for the effects of clustering and differential weighting on estimates of standard errors. All the major statistical analysis software packages now include automated procedures to accommodate complex sample design through Taylor series linearization. Users need only identify a case weight and a variable identifying the clusters, and the software will automatically adjust the estimates to account for the sample design. Controlling for the effects of implicit stratification, however, is more difficult, since there is no variable in the data identifying the strata. This article proposes a solution that will allow IPUMS-International users to create more reliable estimates.

Methods

Where possible, IPUMS-International provides 10% samples of census data to the public. Some countries of origin provide full count census microdata to IPUMS International, others provide samples, which can vary in density from country to country or sample to sample. Further, IPUMS International receives varying levels of detail about geography from the national statistics offices of the source countries resulting in varying degrees of confidence about the true geographic stratification of a given sample. Although descriptive information about the source data and sampling techniques varies from one country to another as well as across time, in all cases, the data are sorted by relatively small geographic areas. Sampling and some swapping of records is used to preserve anonymity, but typically does not preclude the use of geographic

stratification in adjusting for standard errors. After basic record clean-up and standardized formatting, IPUMS-International creates a 10% sample from the full count census data by selecting every 10th household given a random start. This sampling strategy preserves any existing geographic ordering of the households and results in a geographically representative sample of households.

Large dwellings or households are treated differently. Prior to sampling, households over a certain size (greater than 30 persons in most countries) are split into separate single-person households and are sampled as though each person was residing in his or her own one-person household. This procedure maintains representativeness and improves the precision of estimates for the population of residents in group quarters. It increases efficiency of the sample by raising the number of independent observations, but over represents the large dwelling at the household level if the sampling procedure is not accounted for in household level analyses. In many cases, large household units are formal group quarters, consisting of institutions for education, detention, medical treatment, old-age care, etc. Often, however, they are simply large units of unrelated persons without clear demarcation about the type of residence. Occasionally, they may be large collective family units. Differences among these types of dwellings are recorded in a group quarters variable.

For our analysis in this paper, we assume the existence of low-level geographic sorting in our source data, an assumption that we can confirm for some samples, but which we make less confidently for others. If households are very heterogeneous within small level geographic units, or if records are sorted randomly within the smallest available level of geography, our procedures will do little to improve the precision of estimates. If, however, households are sorted geographically to a very low-level and are relatively homogeneous by geographic area, we can

capitalize on geographic ordering to improve the precision of estimates using geographic stratification in our estimation procedures. Access to full count census data from some countries provides a unique opportunity to test measures of standard error using the implicit geographic stratification of census data.

Pseudo Strata and Taylor Series Linearization

Taylor series linearization has been underutilized by census researchers because the method requires explicit information about strata. The data contain no geographic unit that corresponds to the geographic stratification embedded in the geographic ordering of census records. Davern et al. (2009) used information from a complete machine-readable enumeration of the 1880 U.S. census to develop and test geographic pseudostrata. They constructed these pseudostata by grouping contiguous records together to simulate small geographic areas. Due to their access to full count data, they were able to compare estimated variance from Taylor series procedures to known variance from replicate samples of the full count data.

The present paper replicates the Davern et al. (2009) approach for 4 IPUMS-International census samples. To create a proxy for implicit geographic stratification within a subset of IPUMS International samples, we used the ordering of full count data sets along with the as much low level geographic information as was available accompanying them. We created pseudostrata of 10 households, ensuring that each stratum fell entirely within an administrative unit of the country. A stratum at the end of a geographic break containing fewer than 10 households was pooled with the preceding stratum.

An alternative to Taylor series variance estimation is the subsample replicate approach (Rust 1985; Wolter 2007; Verma 1993). In this approach, the sample is divided into subsamples (or replicates) that reflect the complex design of the entire sample. Each subsample incorporates

the same stratification and clustering used to select the original sample. The subsample replicate method may not be reliable in samples that incorporate implicit geographic stratification, however. The estimates may be biased if the degree of geographic homogeneity varies greatly with geographic scale (Davern et al. 2009). For example, a typical IPUMS International sample includes one household every tenth record. If the ten percent sample is divided into subsample replicates, in which a random household is pulled from each set of 10 households, cases in the subsample may be up to 190 households apart.

Validation

As in Davern et al. (2009), to validate both the Taylor series linearization with pseudo-strata and the subsample replicate approach, we needed a "true" estimate of variance in the census samples. Since some data samples in IPUMS International were drawn from full count census data, we were able to consult full count census data for nearly perfect estimates for a test set of countries. We used recent census data from four countries for which we had access to full count data: Bolivia 2001, Ghana 2000, Mongolia 2000, and Rwanda 2002. We chose these samples as exemplar test samples because the data were well formatted and did not require special correction measures for missing cases or poorly constructed households.

These data enable us to simulate our sample design by drawing repeated samples from the full data to compare to variance estimation procedures conducted on the sample data. Using a replicate method of variance estimation, we drew 100 10% replicates from the full count data using a sampling procedure that mimics the procedure used to draw the 10% public use sample and estimated the standard error of the mean around several household and person-level variables. We considered these variance estimates the gold standard against which to measure three methods of variance estimation for the 10% public use sample: subsample replicate, Taylor

series, and simple random sample assumptions. If data are clustered by household or geographically stratified, we would expect the standard errors from the subsample replicate and Taylor series estimates to better approximate the standard errors from the "gold standard" estimates than those derived assuming a simple random sample.

Results

Tables 1 through 4 compare the methods for estimating standard errors for each country. The first two columns in each table are based on the 100 10% sample replicates of the full count population. Since we could not draw more than 10 independent samples of size 10%, we approximated our sampling strategy by creating strata of 10 households and randomly drawing one household from each stratum to form 10% samples. We estimated the variance using the full count "true" mean from the population. The standard errors from the resulting 100 replicate samples are reasonably unbiased estimates of the standard error that would be expected in a 10% sample.

The last three columns in each table contain ratios of standard errors from the 10% sample to standard errors from the full count replicate estimates for each country using the three methods of calculating standard errors described above: subsample replicate, Taylor series linearization, and simple random sample assumptions. Ratios of estimates from both household-level and person-level characteristics are presented in the table.[1] For household estimates, geographic sorting is accounted for in the subsample and Taylor series estimates, but not in the

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[1] We measure household characteristics at the household-level rather than at the individual level because of the effect of household clustering. As demonstrated by Davern et al. (forthcoming), when household characteristics are written across person level records and analyzed at the individual level, standard errors based on a simple random sample assumption are severely underestimated.

simple random sample estimates. Individual level estimates account for both geographic stratification and household clustering. We expect that both our subsample and our Taylor series estimates will more closely approximate the full count replicate estimates for variables that represent characteristics that contain systematic geographic sorting or household clustering than the simple random estimates. The subsample method accounts for geographic sorting due to systematic sampling, and Taylor series allows us to specify our geographic pseudo-strata variable in the estimation. If the full count estimates are the standard by which other estimates should be measured, the ideal ratio of sample to full count estimate would be 1.0. Ratios under 1.0 indicate underestimated standard errors, and ratios over 1.0 indicate overestimated standard errors.

Due to the relatively large sample sizes (10%), all sample estimates have been corrected by the finite population correction factor. Most standard error estimations are based on the premise that the selected sample has been chosen with replacement. In reality, many are not and all are taken from populations of a finite size. A finite population correction factor is necessary to adjust the standard error of the mean or proportion for samples of more than 5% of the total population (Berenson 2007, Korn and Graubard 1999). The finite population correction factor (fpc) is expressed as $fpc = \sqrt{\frac{N-n}{N-1}}$ where n is the sample size and N is the population size.

Table 1 illustrates that, according to the 2002 Census of Rwanda, the average number of persons in a household was 4.71, with a full count census replicate standard error estimate of 0.005. The ratio of the 10% Rwanda 2002 replicate standard error estimate to the full count estimate is 0.8. The ratio for the Taylor series estimate is 0.9, and the simple random sample is 0.9. These estimates are close to one another, suggesting that the method of standard error estimation does not matter much for this variable. The same pattern applies to the standard error

ratios for the number of non-relatives in the household. This is not surprising because the characteristics of these two variables are not highly correlated within geographic strata.

We get mixed results for household characteristics that are frequently used to represent wealth or economic development. In all cases, the subsample replicate estimates and Taylor series estimates using geographic pseudo-strata are close to 1.0 and close to each other. Further, there is little difference between such estimates and simple random estimates for some variables such as radio ownership, floor material and the presence of a flush toilet. Again, the method of standard error estimation does not matter much for these variables in the 2002 sample from Rwanda. For other variables, including electricity and home ownership, the simple random assumption overestimates standard errors. Simple random estimates are 1.3 times larger than the full count estimates for electricity and home ownership. Failure to account for the geographic sorting of the data can lead to inflated standard errors for some household characteristics.

The opposite effect is present for select person level characteristics largely due to household clustering. Again, for many characteristics, subsample replicate, Taylor series, and simple random sample methods of estimating standard errors are all comparable and closely approximate those of the full count replicate method. For characteristics that we expect to cluster by household, like race or religion, we see evidence of clustering in reduced standard error estimates from the simple random sample. In Rwanda 2002, religion clusters in this way.

Table 2 presents results of the same method for the full count and sample data from the 2000 census of Mongolia. The same pattern of overestimation of standard errors for variables representing dwelling characteristics exists in Mongolia. Replicate and Taylor series estimates approximate the full count replicate estimates, while the simple random estimates grossly overestimate standard errors for electricity, flush toilet, separate household kitchen and

bathroom. Household clustering again influences standard errors for the relition variables at the individual level.

Results from the estimation for Bolivia 2001 are presented in Table 3. Standard errors for utility and dwelling characteristics at the household level are more precisely estimated using replicate or Taylor series methods than using typical estimation under simple random sampling assumptions. In particular, standard errors are greatly overestimated for electricity, earth flooring and availability of a flush toilet under simple random sampling assumptions. Estimates for person level characteristics are relatively similar across all variables, even the ethnicity variables, which we assumed would be more severely underestimated for the ethnicity variables. Both Taylor series and subsample replicate estimates compare most closely with the full count replicate estimates.

Finally, Table 4 presents results from the 2000 Ghana census data. Standard error estimates for the utilities and dwelling characteristics are overestimated by all three techniques relative to estimates from the full count replicate data, though the subsample and Taylor series estimates fare better than the simple random results for the presence of electricity and flush toilet. The person level clustering results are as expected, with underestimated standard errors for ethnicity under simple random assumptions. It is possible that the grouping of household characteristics in Ghana is not well represented by the sampling method, but further investigation is required to determine whether this occurs as a result of scale differences from full count to subsample or some other type of stratification of these household features.

Taylor series linearization methods allow us to make separate adjustments for the effects of clustering and stratification, both of which influence the individual level estimates. Results from these separate analyses are presented for the Bolivia sample in Table 5. Again, we present

the ratio of the standard error from the 10% sample to the replicate standard error from the full count data. Column 3 presents the Taylor series standard error estimates from the 10% sample accounting for both clustering and implicit geographic stratification (as presented in Table 3). Column 4 displays the standard error ratio after adjusting for stratification only, and illustrating the effect of clustering on standard errors. Column 5 reports the standard error ration adjusting for clustering only, illustrating the effect of stratification on standard errors. Ethnic group membership is both highly clustered by household and geographically clustered, effects which nearly cancel one another as indicated by the 0.8 ratio of sample standard error to full count standard error reported in column 6. This is the intent of stratification, that it will provide representative samples and yield precise estimates, but as illustrated in the samples reported here, household cluster effects often overwhelm the opposite effect of geographic stratification.

Discussion

The sample methodology of IPUMS-International samples has the potential to significantly affect the precision of sample estimates. Individuals are sampled as parts of households because many important topics of analysis, such as fertility, household composition, and nuptiality, require information about multiple individuals within the same household. Clustering violates the assumption of independent observations and can produce exaggerated estimates of statistical significance. In addition, all of the IPUMS International are implicitly or explicitly stratified. Stratification has the opposite effect of clustering; it increases the precision of sample estimates both for characteristics that are explicitly stratified and characteristics that are correlated with them. In some cases, the positive effects of stratification outweigh the adverse effects of clustering, but researchers should not rely exclusively on these opposing effects.

The IPUMS samples are large, and for the great majority of studies there is little risk of drawing invalid inferences because of underestimated variance. Geographic clustering can lead to overestimated standard errors for a set of variables describing household characteristics, but analysis based on these estimates will be conservative at worst. For studies of weak relationships or small population subgroups, however, there can be risk of misleading estimates of statistical significance. The effects of clustering are of greater concern because underestimated standard errors have the potential to lead to erroneous findings of statistical significance. However, most census research has minimal household clustering because it focuses on particular subpopulations that rarely cluster in households. For example, studies of fertility focus on women of childbearing age, and households typically only have one such woman. The clustering concern can arise with studies of children, since households often include multiple children. When doing analyses of children and other groups likely to appear multiple times in the same household, researchers can adopt strategies to eliminate the redundant cases. Instead of assessing the characteristics of all children, for example, one can look at eldest children, or youngest children, or children of a particular age, or a randomly selected child from each household.

An alternative, thanks to improvements in the analytical power of modern statistical software, is to incorporate information about sample design into estimation procedures. All major statistical software programs, including SAS, Stata, SPSS, and R, now allow researchers to specify basic elements of complex sample design. These programs make use of Taylor Series linearization to adjust variance estimates and tests of statistical significance. IPUMS users can specify the household identifier as the cluster variable (or primary sampling unit) for any analysis that might be influenced by household clustering, and can also specify the weight variable (WTPER) to account for the effects of heterogeneous sample weights. The IPUMS staff

is developing a new cluster variable that will offer the potential for more refined variance estimates. The new variable will identify geographic clustering as well as household clustering.

We are also developing a new variable that will help users account for the effects of stratification on sample variance. As discussed above, stratification improves the precision of samples, and findings of statistical significance without adjustments for stratification will be conservative. Accordingly, adjusting for stratification effects is of less concern than adjusting for clustering. The new stratification variable will include information of explicit strata whenever such information is available, and will also include geographic pseudo-strata for the systematic samples following the procedure described in Davern et al. (2009).

For most analyses using IPUMS data, there is little risk of drawing invalid conclusions due to underestimated variance. When examining relationships on the margin of statistical significance, however, it may be wise to adjust for household clustering and weighting as outlined above. These procedures will yield conservative estimates of statistical significance for all IPUMS samples except the few that incorporate geographic clustering. Until the new clustering and stratification variables are available, marginally significant results from those samples should be viewed with caution.

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Table 1.   Rwanda 2002: Standard Error Computations Comparing Replicate Estimates From the Complete Count Census With Estimates Derived From Sample Data Using Alternative Methods

Selected Characteristics	Parameter Estimate From the Entire Rwanda 2002 Census	Replicate Standard Error Estimates Drawn From the Entire Rwanda 2002 Census	Ratio of (SE) Estimates Using the Rwanda 2002 10% Sample to Replicate Estimates From the Entire Rwanda 2002 Census		
			Subsample Replicate Method	Taylor Series Linearization With Pseudo-Strata	Simple Random Sample
Household					
HH Size (mean)	4.71	0.005	0.8	0.9	0.9
Electric Light (%)	4.18	0.034	0.9	0.9	1.3
Toilet (%)	0.38	0.013	0.9	0.9	1.0
Radio (%)	43.11	0.103	0.9	1.0	1.0
Earth Floor (%)	85.28	0.073	0.8	0.9	1.0
Home Ownership (%)	86.41	0.056	1.1	1.1	1.3
Non-relatives (mean)	0.30	0.002	1.1	1.0	1.1
Person			Subsample Replicate	Pseudostrata and HH Cluster	Simple Random Sample
Age (mean)	20.77	0.015	0.9	1.0	1.1
Sex (%)	46.81	0.045	0.9	1.0	1.1
Religion Catholic (%)	46.69	0.100	1.0	1.0	0.5
Protestant (%)	26.16	0.077	1.1	1.1	0.6
Married (%)	17.64	0.039	0.9	1.0	1.0
Literate (%)	39.75	0.060	0.9	0.9	0.8
Employed (%)	40.94	0.048	0.9	0.9	1.0

Table 2. **Mongolia 2000: Standard Error Computations Comparing Replicate Estimates From the Complete Count Census With Estimates Derived From Sample Data Using Alternative Methods**

Selected Characteristics	Parameter Estimate From the Entire Mongolia 2000 Census	Replicate Standard Error Estimates Drawn From the Entire Mongolia 2000 Census	Ratio of (SE) Estimates Using the Mongolia 2000 10% Sample to Replicate Estimates From the Entire Mongolia 2000 Census		
			Subsample Replicate Method	Taylor Series Linearization With Pseudo-Strata	Simple Random Sample
Household					
HH Size (mean)	4.45	0.008	0.9	0.9	1.0
Electric Light (%)	67.53	0.098	1.1	1.0	1.8
Toilet (%)	62.46	0.135	1.1	1.2	1.4
Kitchen as separate room (%)	39.08	0.145	1.0	1.0	1.3
Bathroom (%)	21.74	0.096	1.0	1.1	1.5
Phone (%)	17.01	0.136	1.0	1.0	1.1
Non-relatives (mean)	0.11	0.002	0.9	1.0	1.0
Person			Subsample Replicate	Pseudo-Strata and HH Cluster	Simple Random Sample
Age (mean)	24.57	0.034	1.0	1.0	1.0
Sex (%)	49.47	0.078	0.9	1.0	1.2
Ethnicity					
Khalkh (%)	81.59	0.111	0.9	1.0	0.6
Kazak (%)	4.28	0.047	1.0	1.1	0.8
Married (%)	32.33	0.081	0.9	1.0	1.1
Literate (%)	81.56	0.071	1.1	1.0	1.0
Employed (%)	32.47	0.095	0.9	0.9	0.9

Table 3. **Bolivia 2001: Standard Error Computations Comparing Replicate Estimates From the Complete Count Census With Estimates Derived From Sample Data Using Alternative Methods**

Selected Characteristics	Parameter Estimate From the Entire Bolivia 2001 Census	Replicate Standard Error Estimates Drawn From the Entire Bolivia 2001 Census	Ratio of (SE) Estimates Using the Bolivia 2001 10% Sample to Replicate Estimates From the Entire Bolivia 2001 Census		
			Subsample Replicate Method	Taylor Series Linearization With Pseudo-Strata	Simple Random Sample
Household					
HH Size (mean)	3.93	0.0046	1.0	1.0	1.1
Electric Light (%)	60.51	0.0536	1.1	1.2	1.9
Toilet (%)	59.48	0.0649	1.0	1.1	1.6
Kitchen as separate room (%)	70.62	0.0882	0.9	1.0	1.1
Phone (%)	21.33	0.0605	1.3	1.1	1.4
Radio (%)	71.17	0.0819	0.9	1.0	1.1
Earth Floor (%)	35.66	0.0519	1.2	1.3	1.9
Home Ownership (%)	62.81	0.0877	1.0	1.0	1.1
Non-relatives (mean)	0.19	0.0012	1.0	1.0	1.1
Person			Subsample Replicate	Pseudo-Strata and HH Cluster	Simple Random Sample
Age (mean)	24.70	0.0004	1.0	1.1	1.0
Sex (%)	49.84	0.0024	0.9	0.9	1.1
Ethnicity Quechua (%)	30.69	0.0053	1.0	1.0	0.8
Aymara (%)	25.19	0.0047	0.8	0.9	0.8
Married (%)	26.09	0.0023	0.9	1.0	1.0
Literate (%)	74.99	0.0025	0.9	0.9	0.9
Worked (%)	34.37	0.0022	1.1	1.1	1.0

Table 4. Ghana 2000: Standard Error Computations Comparing Replicate Estimates from the Complete Count Census with Estimates Derived from Sample Data Using Alternative Methods

Selected Characteristics	Parameter Estimate From the Entire Ghana 2000 Census	Replicate Standard Error Estimates Drawn From the Entire Ghana 2000 Census	Ratio of (SE) Estimates Using the Ghana 2000 10% Sample to Replicate Estimates From the Entire Ghana 2000 Census		
			Subsample Replicate Method	Taylor Series Linearization With Pseudo-Strata	Simple Random Sample
Household					
HH Size (mean)	4.99	0.005	1.1	1.0	1.0
Electric Light (%)	43.54	0.042	1.5	1.5	1.8
Toilet (%)	8.49	0.026	1.2	1.5	1.7
Kitchen as separate room (%)	46.17	0.062	1.2	1.2	1.2
Bathroom (%)	23.47	0.046	1.5	1.4	1.4
Non-relatives (mean)	0.14	0.001	0.9	1.0	1.0
Person			Subsample Replicate	Pseudo-Strata and HH Cluster	Simple Random Sample
Age (mean)	23.90	0.013	1.0	1.1	1.0
Sex (%)	49.48	0.035	1.0	1.0	1.0
Ethnicity					
Akan (%)	45.28	0.066	0.9	1.0	0.5
Mole-dagbani (%)	15.25	0.051	1.0	1.0	0.5
Married (%)	29.28	0.029	1.2	1.2	1.1
Literate (%)	34.00	0.038	1.0	1.1	0.9
Worked (%)	42.44	0.038	1.3	1.1	0.9

Table 5.   **Bolivia 2001: Decomposition of Clustering and Stratification Effects on Taylor Series Standard Error Estimates from the 10% Sample**

Person	Mean	SE (Full Count Replicate)	Taylor Series Linearization				SRS
			Accounting for Clustering and Implicit Stratification	**Effect of Clustering** (Adjusting for Strata Only)	**Effect of Stratification** (Adjusting for Cluster Only)	Combined Effect of Clustering and Stratification
Age (mean)	24.7	0.0004	1.1	1.0	1.1	1.0
Sex (%)	49.8	0.0024	0.9	1.1	0.9	1.1
Ethnicity						
Quechua (%)	**30.7**	**0.0053**	**1.0**	**0.6**	**1.4**	**0.8**
Aymara (%)	**25.2**	**0.0047**	**0.9**	**0.5**	**1.4**	**0.8**
Married (%)	26.1	0.0023	1.0	1.0	1.0	1.0
Literate (%)	75.0	0.0025	0.9	0.9	1.0	0.9
Worked (%)	34.4	0.0022	1.1	1.0	1.2	1.0

(Reporting Ratios of Standard Error Estimates from the 10% Sample to Full Count Replicate Estimates Adjusting for Complex Sample Design Characteristics Independently and Combined)