American Community Survey (ACS) Resources

non-technical description of ACS data

Zimmerman, J. New Kid in Town: Understanding Data from the American Community Survey. http://www2.ca.uky.edu/snarl/KentuckyByTheNumbers/ACSpages/ACSPublications/NewKidinTownACSPub1.pdf

the bottom line

The ACS is not Census 2000 SF3 (a/k/a the long form). The three key differences between Census 2000 sample data and ACS estimates are in ***data collection*** (single survey vs. ongoing surveys); the ***time frame*** (point-in-time estimates vs. period estimates); and in ***sample size*** (1 in 6 vs. 1 in 40 or more). It's tempting to ignore error in the ACS, but it can have real ramifications to policy! If math isn't your thing, there are plenty of resources: at the Census Bureau & its affiliates, and even government.

technical help

Of course most of the information you need to know about the ACS is on the internet. Specifically, http://www.census.gov/acs/www/guidance_for_data_users/guidance_main/ is a good landing page.

The Compass Series handbooks are where it's at. I recommend the "What Researchers Need to Know" or "What Users of Data for Rural Areas Need to Know", because they focus on the needs of small-town planners. Especially valuable are the appendices at the end. Attached to this handout are Appendix 3 and Appendix 4. http://www.census.gov/acs/www/guidance_for_data_users/handbooks/

When you're comparing ACS data to a non-ACS data product, like the Decennial Census, I strongly recommend looking at the tab marked "Comparing ACS Data": http://www.census.gov/acs/www/guidance_for_data_users/comparing_data/

Census Bureau's training presentations: http://www.census.gov/acs/www/guidance_for_data_users/training_presentations/

> Particularly "Understanding Multiyear Estimates from the American Community Survey": http://www.census.gov/acs/www/Downloads/presentations/ACS_Undrstnd_Multiyr_Est.ppt

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formulae & other mathematical reminders

The coefficient of variation indicates the reliability of an estimate.

$$CV = \left(\frac{\frac{MOE}{1.645}}{X}\right)$$

Consider aggregating by geography or by subject to reduce CV and improve data quality, but always use the largest geographies available. Formulas are in Appendix 3, attached.

The National Research Council uses CV to show how reliable an estimate is. Their guidelines are:

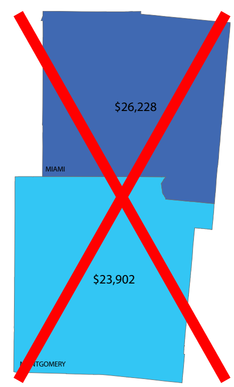
CV<12%—reliable
12%<CV<40%—use caution
CV>40%—**unreliable, *caveat emptor,* danger zone, etc.**

Testing for significance is best done in Excel. *Remember that testing for significance is not a matter of seeing whether the margins of error overlap!* Use this as your equation:

$$=ABS(EST_{GEOG1}-EST_{GEOG2})/(SQRT(MOE_{GEOG1}{}^{2}+MOE_{GEOG2}{}^{2}))>1.645$$

(Do yourself a favor: use actual numerical values for EST_{GEOG1} and MOE_{GEOG2}—don't refer to a cell. Excel quirk.) Your result will be TRUE (there is a significant difference) or FALSE (there isn't).

mapping



Don't just map the estimates. Two estimates that are not statistically significant can be put in different categories, implying that there is a difference when there isn't. Yes, the Census Bureau itself does this, but such maps are misleading.

Eathington, L. (2011). Holy MOE! Don't marginalize the error in the American Community Survey. 2011 Annual Meeting of the Southern Regional Science Association. http://www.econ.iastate.edu/sites/default/files/publications/papers/p13783-2011-03-31.pdf

support from your government

MVRPC's Census Data Center, for data, maps, tables, and charts. http://www.mvrpc.org/data-mapping/census

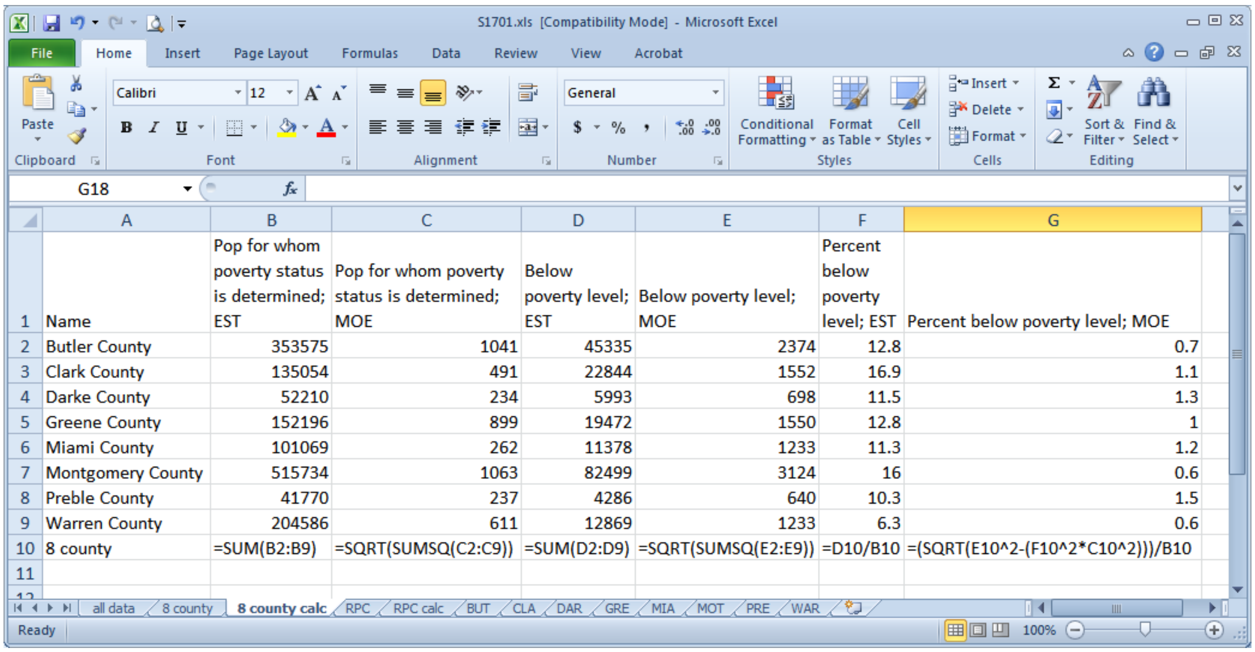
Ohio's Development Service Agency's Research page. http://development.ohio.gov/reports/reports_research.htm

~~misery loves company~~ support from your peers

ACS Data Users Group: http://www.acsdatausers.org/

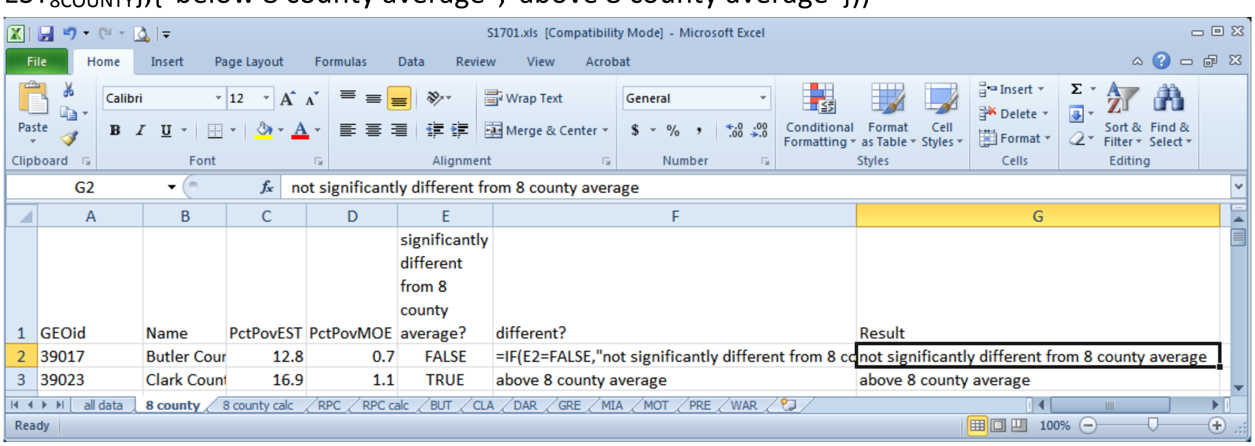
ACS procedure for mapping the 8 county region

1. Download data (e.g., poverty) for all 8 counties.
2. Save as xls(x). Delete unneeded data fields.
3. Calculate the 8-county average for your data, using the formulas provided by the census to aggregate margins of error. Use these EST & MOE figures in the 8-county tab.



	A	B	C	D	E	F	G
1	Name	Pop for whom poverty status is determined; EST	Pop for whom poverty status is determined; MOE	Below poverty level; EST	Below poverty level; MOE	Percent below poverty level; EST	Percent below poverty level; MOE
2	Butler County	353575	1041	45335	2374	12.8	0.7
3	Clark County	135054	491	22844	1552	16.9	1.1
4	Darke County	52210	234	5993	698	11.5	1.3
5	Greene County	152196	899	19472	1550	12.8	1
6	Miami County	101069	262	11378	1233	11.3	1.2
7	Montgomery County	515734	1063	82499	3124	16	0.6
8	Preble County	41770	237	4286	640	10.3	1.5
9	Warren County	204586	611	12869	1233	6.3	0.6
10	8 county	=SUM(B2:B9)	=SQRT(SUMSQ(C2:C9))	=SUM(D2:D9)	=SQRT(SUMSQ(E2:E9))	=D10/B10	=(SQRT(E10^2-(F10^2*C10^2)))/B10
11							

4. Determine whether each given county is significantly different from the 8-county average. Create a column dedicated to this called "SIGDIF", using the following formula: =ABS($EST_{8COUNTY}$-EST_{TRACT})/(SQRT($MOE_{8COUNTY}^2$+MOE_{TRACT}^2))>1.645
   Use actual numerical values for $EST_{8COUNTY}$ and $MOE_{8COUNTY}$; don't refer to a cell.
5. Determine how/whether each county differs from the 8-county average: =IF([SIGDIF]=FALSE,"not significantly different from 8 county average",LOOKUP(C2,{0, $EST_{8COUNTY}$},{"below 8 county average","above 8 county average"}))



	A	B	C	D	E	F	G
1	GEOid	Name	PctPovEST	PctPovMOE	significantly different from 8 county average?	different?	Result
2	39017	Butler Cour	12.8	0.7	FALSE	=IF(E2=FALSE,"not significantly different from 8 c	not significantly different from 8 county average
3	39023	Clark Count	16.9	1.1	TRUE	above 8 county average	above 8 county average

Appendix 3.
Measures of Sampling Error

All survey and census estimates include some amount of error. Estimates generated from sample survey data have uncertainty associated with them due to their being based on a sample of the population rather than the full population. This uncertainty, referred to as sampling error, means that the estimates derived from a sample survey will likely differ from the values that would have been obtained if the entire population had been included in the survey, as well as from values that would have been obtained had a different set of sample units been selected. All other forms of error are called nonsampling error and are discussed in greater detail in Appendix 6.

Sampling error can be expressed quantitatively in various ways, four of which are presented in this appendix—standard error, margin of error, confidence interval, and coefficient of variation. As the ACS estimates are based on a sample survey of the U.S. population, information about the sampling error associated with the estimates must be taken into account when analyzing individual estimates or comparing pairs of estimates across areas, population subgroups, or time periods. The information in this appendix describes each of these sampling error measures, explaining how they differ and how each should be used. It is intended to assist the user with analysis and interpretation of ACS estimates. Also included are instructions on how to compute margins of error for user-derived estimates.

Sampling Error Measures and Their Derivations

Standard Errors

A standard error (SE) measures the variability of an estimate due to sampling. Estimates derived from a sample (such as estimates from the ACS or the decennial census long form) will generally not equal the population value, as not all members of the population were measured in the survey. The SE provides a quantitative measure of the extent to which an estimate derived from the sample survey can be expected to deviate from this population value. It is the foundational measure from which other sampling error measures are derived. The SE is also used when comparing estimates to determine whether the differences between the estimates can be said to be statistically significant.

A very basic example of the standard error is a population of three units, with values of 1, 2, and 3. The average value for this population is 2. If a simple random sample of size two were selected from this population, the estimates of the average value would be 1.5 (units with values of 1 and 2 selected), 2 (units with values of 1 and 3 selected), or 2.5 (units with values of 2 and 3 selected). In this simple example, two of the three samples yield estimates that do not equal the population value (although the average of the estimates across all possible samples do equal the population value). The standard error would provide an indication of the extent of this variation.

The SE for an estimate depends upon the underlying variability in the population for the characteristic and the sample size used for the survey. In general, the larger the sample size, the smaller the standard error of the estimates produced from the sample. This relationship between sample size and SE is the reason ACS estimates for less populous areas are only published using multiple years of data: to take advantage of the larger sample size that results from aggregating data from more than one year.

Margins of Error

A margin of error (MOE) describes the precision of the estimate at a given level of confidence. The confidence level associated with the MOE indicates the likelihood that the sample estimate is within a certain distance (the MOE) from the population value. Confidence levels of 90 percent, 95 percent, and 99 percent are commonly used in practice to lessen the risk associated with an incorrect inference. The MOE provides a concise measure of the precision of the sample estimate in a table and is easily used to construct confidence intervals and test for statistical significance.

The Census Bureau statistical standard for published data is to use a 90-percent confidence level. Thus, the MOEs published with the ACS estimates correspond to a 90-percent confidence level. However, users may want to use other confidence levels, such as 95 percent or 99 percent. The choice of confidence level is usually a matter of preference, balancing risk for the specific application, as a 90-percent confidence level implies a 10 percent chance of an incorrect inference, in contrast with a 1 percent chance if using a 99-percent confidence level. Thus, if the impact of an incorrect conclusion is substantial, the user should consider increasing the confidence level.

One commonly experienced situation where use of a 95 percent or 99 percent MOE would be preferred is when conducting a number of tests to find differences between sample estimates. For example, if one were conducting comparisons between male and female incomes for each of 100 counties in a state, using a 90-percent confidence level would imply that 10 of the comparisons would be expected to be found significant even if no differences actually existed. Using a 99-percent confidence level would reduce the likelihood of this kind of false inference.

Calculating Margins of Error for Alternative Confidence Levels

If you want to use an MOE corresponding to a confidence level other than 90 percent, the published MOE can easily be converted by multiplying the published MOE by an adjustment factor. If the desired confidence level is 95 percent, then the factor is equal to 1.960/1.645.[1] If the desired confidence level is 99 percent, then the factor is equal to 2.576/1.645.

Conversion of the published ACS MOE to the MOE for a different confidence level can be expressed as

$$MOE_{95} = \frac{1.960}{1.645} MOE_{ACS}$$

$$MOE_{99} = \frac{2.576}{1.645} MOE_{ACS}$$

where MOE_{ACS} is the ACS published 90 percent MOE for the estimate.

Factors Associated With Margins of Error for Commonly Used Confidence Levels
90 Percent: 1.645 95 Percent: 1.960 99 Percent: 2.576
Census Bureau standard for published MOE is 90 percent.

For example, the ACS published MOE for the 2006 ACS estimated number of civilian veterans in the state of Virginia is ±12,357. The MOE corresponding to a 95-percent confidence level would be derived as follows:

$$MOE_{95} = \frac{1.960}{1.645}(\pm 12{,}357) = \pm 14{,}723$$

Deriving the Standard Error From the MOE

When conducting exact tests of significance (as discussed in Appendix 4) or calculating the CV for an estimate, the SEs of the estimates are needed. To derive the SE, simply divide the positive value of the published MOE by 1.645.[2]

Derivation of SEs can thus be expressed as

$$SE = \frac{MOE_{ACS}}{1.645}$$

where MOE_{ACS} is the positive value of the ACS published MOE for the estimate.

For example, the ACS published MOE for estimated number of civilian veterans in the state of Virginia from the 2006 ACS is ±12,357. The SE for the estimate would be derived as

$$SE = \frac{12{,}357}{1.645} = 7{,}512$$

Confidence Intervals

A confidence interval (CI) is a range that is expected to contain the average value of the characteristic that would result over all possible samples with a known probability. This probability is called the "level of confidence" or "confidence level." CIs are useful when graphing estimates to display their sampling variabilites. The sample estimate and its MOE are used to construct the CI.

Constructing a Confidence Interval From a Margin of Error

To construct a CI at the 90-percent confidence level, the published MOE is used. The CI boundaries are determined by adding to and subtracting from a sample estimate, the estimate's MOE.

For example, if an estimate of 20,000 had an MOE at the 90-percent confidence level of ±1,645, the CI would range from 18,355 (20,000 – 1,645) to 21,645 (20,000 + 1,645).

For CIs at the 95-percent or 99-percent confidence level, the appropriate MOE must first be derived as explained previously.

Construction of the lower and upper bounds for the CI can be expressed as

$$L_{CL} = \hat{X} - MOE_{CL}$$

$$U_{CL} = \hat{X} + MOE_{CL}$$

where $\hat{X}$ is the ACS estimate and

MOE_{CL} is the positive value of the MOE for the estimate at the desired confidence level.

The CI can thus be expressed as the range

$$CI_{CL} = (L_{CL}, U_{CL}).$$ [3]

[1] The value 1.65 must be used for ACS single-year estimates for 2005 or earlier, as that was the value used to derive the published margin of error from the standard error in those years.

[2] If working with ACS 1-year estimates for 2005 or earlier, use the value 1.65 rather than 1.645 in the adjustment factor.

[3] Users are cautioned to consider logical boundaries when creating confidence intervals from the margins of error. For example, a small population estimate may have a calculated lower bound less than zero. A negative number of persons doesn't make sense, so the lower bound should be set to zero instead.

For example, to construct a CI at the 95-percent confidence level for the number of civilian veterans in the state of Virginia in 2006, one would use the 2006 estimate (771,782) and the corresponding MOE at the 95-percent confidence level derived above (±14,723).

$$L_{95} = 771{,}782 - 14{,}723 = 757{,}059$$
$$U_{95} = 771{,}782 + 14{,}723 = 786{,}505$$

The 95-percent CI can thus be expressed as the range 757,059 to 786,505.

The CI is also useful when graphing estimates, to show the extent of sampling error present in the estimates, and for visually comparing estimates. For example, given the MOE at the 90-percent confidence level used in constructing the CI above, the user could be 90 percent certain that the value for the population was between 18,355 and 21,645. This CI can be represented visually as

Coefficients of Variation

A coefficient of variation (CV) provides a measure of the relative amount of sampling error that is associated with a sample estimate. The CV is calculated as the ratio of the SE for an estimate to the estimate itself and is usually expressed as a percent. It is a useful barometer of the stability, and thus the usability of a sample estimate. It can also help a user decide whether a single-year or multiyear estimate should be used for analysis. The method for obtaining the SE for an estimate was described earlier.

The CV is a function of the overall sample size and the size of the population of interest. In general, as the estimation period increases, the sample size increases and therefore the size of the CV decreases. A small CV indicates that the sampling error is small relative to the estimate, and thus the user can be more confident that the estimate is close to the population value. In some applications a small CV for an estimate is desirable and use of a multiyear estimate will therefore be preferable to the use of a 1-year estimate that doesn't meet this desired level of precision.

For example, if an estimate of 20,000 had an SE of 1,000, then the CV for the estimate would be 5 percent ([1,000 /20,000] x 100). In terms of usability, the estimate is very reliable. If the CV was noticeably larger, the usability of the estimate could be greatly diminished.

While it is true that estimates with high CVs have important limitations, they can still be valuable as building blocks to develop estimates for higher levels of aggregation. Combining estimates across geographic areas or collapsing characteristic detail can improve the reliability of those estimates as evidenced by reductions in the CVs.

Calculating Coefficients of Variation From Standard Errors

The CV can be expressed as

$$CV = \frac{SE}{\hat{X}} \times 100$$

where $\hat{X}$ is the ACS estimate and SE is the derived SE for the ACS estimate.

For example, to determine the CV for the estimated number of civilian veterans in the state of Virginia in 2006, one would use the 2006 estimate (771,782), and the SE derived previously (7,512).

$$CV = \frac{7{,}512}{771{,}782} \times 100 = 0.1\%$$

This means that the amount of sampling error present in the estimate is only one-tenth of 1 percent the size of the estimate.

The text box below summarizes the formulas used when deriving alternative sampling error measures from the margin or error published with ACS estimates.

Deriving Sampling Error Measures From Published MOE

Margin Error (MOE) for Alternate Confidence Levels

$$MOE_{95} = \frac{1.960}{1.645} MOE_{ACS}$$

$$MOE_{99} = \frac{2.576}{1.645} MOE_{ACS}$$

Standard Error (SE)

$$SE = \frac{MOE_{ACS}}{1.645}$$

Confidence Interval (CI)

$$CI_{CL} = \left(\hat{X} - MOE_{CL}, \hat{X} + MOE_{CL}\right)$$

Coefficient of Variation (CV)

$$CV = \frac{SE}{\hat{X}} \times 100$$

Calculating Margins of Error for Derived Estimates

One of the benefits of being familiar with ACS data is the ability to develop unique estimates called derived estimates. These derived estimates are usually based on aggregating estimates across geographic areas or population subgroups for which combined estimates are not published in American FactFinder (AFF) tables (e.g., aggregate estimates for a three-county area or for four age groups not collapsed).

ACS tabulations provided through AFF contain the associated confidence intervals (pre-2005) or margins of error (MOEs) (2005 and later) at the 90-percent confidence level. However, when derived estimates are generated (e.g., aggregated estimates, proportions, or ratios not available in AFF), the user must calculate the MOE for these derived estimates. The MOE helps protect against misinterpreting small or nonexistent differences as meaningful.

MOEs calculated based on information provided in AFF for the components of the derived estimates will be at the 90-percent confidence level. If an MOE with a confidence level other than 90 percent is desired, the user should first calculate the MOE as instructed below and then convert the results to an MOE for the desired confidence level as described earlier in this appendix.

Calculating MOEs for Aggregated Count Data

To calculate the MOE for aggregated count data:

1) Obtain the MOE of each component estimate.
2) Square the MOE of each component estimate.
3) Sum the squared MOEs.
4) Take the square root of the sum of the squared MOEs.

The result is the MOE for the aggregated count. Algebraically, the MOE for the aggregated count is calculated as:

$$MOE_{agg} = \pm\sqrt{\sum_c MOE_c^2}$$

where MOE_c is the MOE of the c^{th} component estimate.

The example below shows how to calculate the MOE for the estimated total number of females living alone in the three Virginia counties/independent cities that border Washington, DC (Fairfax and Arlington counties, Alexandria city) from the 2006 ACS.

Table 1. **Data for Example 1**

Characteristic	Estimate	MOE
Females living alone in Fairfax County (Component 1)	52,354	±3,303
Females living alone in Arlington County (Component 2)	19,464	±2,011
Females living alone in Alexandria city (Component 3)	17,190	±1,854

The aggregate estimate is:

$$\hat{X} = \hat{X}_{Fairfax} + \hat{X}_{Arlington} + \hat{X}_{Alexandria} =$$
$$52{,}354 + 19{,}464 + 17{,}190 = 89{,}008$$

Obtain MOEs of the component estimates:

$$MOE_{Fairfax} = \pm 3{,}303\,,$$
$$MOE_{Arlington} = \pm 2{,}011\,,$$
$$MOE_{Alexandria} = \pm 1{,}854$$

Calculate the MOE for the aggregate estimated as the square root of the sum of the squared MOEs.

$$MOE_{agg} = \pm\sqrt{(3{,}303)^2 + (2{,}011)^2 + (1{,}854)^2} =$$
$$\pm\sqrt{18{,}391{,}246} = \pm 4{,}289$$

Thus, the derived estimate of the number of females living alone in the three Virginia counties/independent cities that border Washington, DC, is 89,008, and the MOE for the estimate is ±4,289.

Calculating MOEs for Derived Proportions

The numerator of a proportion is a subset of the denominator (e.g., the proportion of single person households that are female). To calculate the MOE for derived proportions, do the following:

1) Obtain the MOE for the numerator and the MOE for the denominator of the proportion.
2) Square the derived proportion.
3) Square the MOE of the numerator.
4) Square the MOE of the denominator.
5) Multiply the squared MOE of the denominator by the squared proportion.
6) Subtract the result of (5) from the squared MOE of the numerator.
7) Take the square root of the result of (6).
8) Divide the result of (7) by the denominator of the proportion.

The result is the MOE for the derived proportion. Algebraically, the MOE for the derived proportion is calculated as:

$$MOE_p = \frac{\pm\sqrt{MOE_{num}^2 - (\hat{p}^2 * MOE_{den}^2)}}{\hat{X}_{den}}$$

where MOE_{num} is the MOE of the numerator.

MOE_{den} is the MOE of the denominator.

$\hat{p} = \frac{\hat{X}_{num}}{\hat{X}_{den}}$ is the derived proportion.

$\hat{X}_{num}$ is the estimate used as the numerator of the derived proportion.

$\hat{X}_{den}$ is the estimate used as the denominator of the derived proportion.

There are rare instances where this formula will fail—the value under the square root will be negative. If that happens, use the formula for derived ratios in the next section which will provide a conservative estimate of the MOE.

The example below shows how to derive the MOE for the estimated proportion of Black females 25 years of age and older in Fairfax County, Virginia, with a graduate degree based on the 2006 ACS.

Table 2. **Data for Example 2**

Characteristic	Estimate	MOE
Black females 25 years and older with a graduate degree (numerator)	4,634	±989
Black females 25 years and older (denominator)	31,713	±601

The estimated proportion is:

$$\hat{p} = \frac{\hat{X}_{gradBF}}{\hat{X}_{BF}} = \frac{4,634}{31,713} = 0.1461$$

where $\hat{X}_{gradBF}$ is the ACS estimate of Black females 25 years of age and older in Fairfax County with a graduate degree and $\hat{X}_{BF}$ is the ACS estimate of Black females 25 years of age and older in Fairfax County.

Obtain MOEs of the numerator (number of Black females 25 years of age and older in Fairfax County with a graduate degree) and denominator (number of Black females 25 years of age and older in Fairfax County).

$$MOE_{num} = \pm 989, \; MOE_{den} = \pm 601$$

Multiply the squared MOE of the denominator by the squared proportion and subtract the result from the squared MOE of the numerator.

$$MOE_{num}^2 - (\hat{p}^2 * MOE_{den}^2) =$$
$$(989)^2 - [(0.1461)^2 * (601)^2] =$$
$$978,121 - 7,712.3 = 970,408.7$$

Calculate the MOE by dividing the square root of the prior result by the denominator.

$$MOE_p = \frac{\pm\sqrt{970,408.7}}{31,373} = \frac{\pm 985.1}{31,373} = \pm 0.0311$$

Thus, the derived estimate of the proportion of Black females 25 years of age and older with a graduate degree in Fairfax County, Virginia, is 0.1461, and the MOE for the estimate is ±0.0311.

Calculating MOEs for Derived Ratios

The numerator of a ratio is not a subset (e.g., the ratio of females living alone to males living alone). To calculate the MOE for derived ratios:

1) Obtain the MOE for the numerator and the MOE for the denominator of the ratio.
2) Square the derived ratio.
3) Square the MOE of the numerator.
4) Square the MOE of the denominator.
5) Multiply the squared MOE of the denominator by the squared ratio.
6) Add the result of (5) to the squared MOE of the numerator.
7) Take the square root of the result of (6).
8) Divide the result of (7) by the denominator of the ratio.

The result is the MOE for the derived ratio. Algebraically, the MOE for the derived ratio is calculated as:

$$MOE_R = \frac{\pm\sqrt{MOE_{num}^2 + (\hat{R}^2 * MOE_{den}^2)}}{\hat{X}_{den}}$$

where MOE_{num} is the MOE of the numerator.

MOE_{den} is the MOE of the denominator.

$\hat{R} = \frac{\hat{X}_{num}}{\hat{X}_{den}}$ is the derived ratio.

$\hat{X}_{num}$ is the estimate used as the numerator of the derived ratio.

$\hat{X}_{den}$ is the estimate used as the denominator of the derived ratio.

The example below shows how to derive the MOE for the estimated ratio of Black females 25 years of age and older in Fairfax County, Virginia, with a graduate degree to Black males 25 years and older in Fairfax County with a graduate degree, based on the 2006 ACS.

Table 3. **Data for Example 3**		
Characteristic	Estimate	MOE
Black females 25 years and older with a graduate degree (numerator)	4,634	±989
Black males 25 years and older with a graduate degree (denominator)	6,440	±1,328

The estimated ratio is:

$$\hat{R} = \frac{\hat{X}_{gradBF}}{\hat{X}_{gradBM}} = \frac{4,634}{6,440} = 0.7200$$

Obtain MOEs of the numerator (number of Black females 25 years of age and older with a graduate degree in Fairfax County) and denominator (number of Black males 25 years of age and older in Fairfax County with a graduate degree).

$$MOE_{num} = \pm 989, \ MOE_{den} = \pm 1,328$$

Multiply the squared MOE of the denominator by the squared proportion and add the result to the squared MOE of the numerator.

$$MOE_{num}^2 + (\hat{R}^2 * MOE_{den}^2) =$$

$$(989)^2 + [(0.7200)^2 * (1,328)^2] =$$

$$978,121 + 913,318.1 = 1,891,259.1$$

Calculate the MOE by dividing the square root of the prior result by the denominator.

$$MOE_R = \frac{\pm\sqrt{1,891,259.1}}{6,440} = \frac{\pm 1,375.2}{6,440} = \pm 0.2135$$

Thus, the derived estimate of the ratio of the number of Black females 25 years of age and older in Fairfax County, Virginia, with a graduate degree to the number of Black males 25 years of age and older in Fairfax County, Virginia, with a graduate degree is 0.7200, and the MOE for the estimate is ±0.2135.

Calculating MOEs for the Product of Two Estimates

To calculate the MOE for the product of two estimates, do the following:

1) Obtain the MOEs for the two estimates being multiplied together.
2) Square the estimates and their MOEs.
3) Multiply the first squared estimate by the second estimate's squared MOE.
4) Multiply the second squared estimate by the first estimate's squared MOE.
5) Add the results from (3) and (4).
6) Take the square root of (5).

The result is the MOE for the product. Algebraically, the MOE for the product is calculated as:

$$MOE_{A \times B} = \pm\sqrt{A^2 \times MOE_B^2 + B^2 \times MOE_A^2}$$

where *A* and *B* are the first and second estimates, respectively.

MOE_A is the MOE of the first estimate.

MOE_B is the MOE of the second estimate.

The example below shows how to derive the MOE for the estimated number of Black workers 16 years and over in Fairfax County, Virginia, who used public transportation to commute to work, based on the 2006 ACS.

Table 4. **Data for Example 4**		
Characteristic	Estimate	MOE
Black workers 16 years and over (first estimate)	50,624	±2,423
Percent of Black workers 16 years and over who commute by public transportation (second estimate)	13.4%	±2.7%

To apply the method, the proportion (0.134) needs to be used instead of the percent (13.4). The estimated product is 50,624 × 0.134 = 6,784. The MOE is calculated by:

$$MOE_{A \times B} = \pm\sqrt{50,624^2 \times 0.027^2 + 0.134^2 \times 2,423^2}$$

$$= \pm 1,405$$

Thus, the derived estimate of Black workers 16 years and over who commute by public transportation is 6,784, and the MOE of the estimate is ±1,405.

Calculating MOEs for Estimates of "Percent Change" or "Percent Difference"

The "percent change" or "percent difference" between two estimates (for example, the same estimates in two different years) is commonly calculated as

$$Percent\ Change = 100\% * \frac{\hat{X}_2 - \hat{X}_1}{\hat{X}_1}$$

Because $\hat{X}_2$ is not a subset of $\hat{X}_1$, the procedure to calculate the MOE of a ratio discussed previously should be used here to obtain the MOE of the percent change.

The example below shows how to calculate the margin of error of the percent change using the 2006 and 2005 estimates of the number of persons in Maryland who lived in a different house in the U.S. 1 year ago.

Table 5. **Data for Example 5**

Characteristic	Estimate	MOE
Persons who lived in a different house in the U.S. 1 year ago, 2006	802,210	±22,866
Persons who lived in a different house in the U.S. 1 year ago, 2005	762,475	±22,666

The percent change is:

$$Percent\ Change = 100\% * \frac{\hat{X}_2 - \hat{X}_1}{\hat{X}_1} =$$

$$100\% * \left(\frac{802{,}210 - 762{,}475}{762{,}475}\right) = 5.21\%$$

For use in the ratio formula, the ratio of the two estimates is:

$$\hat{R} = \frac{\hat{X}_2}{\hat{X}_1} = \frac{802{,}210}{762{,}475} = 1.0521$$

The MOEs for the numerator ($\hat{X}_2$) and denominator ($\hat{X}_1$) are:

$$MOE_2 = +/-22{,}866,\ MOE_1 = +/-22{,}666$$

Add the squared MOE of the numerator (MOE_2) to the product of the squared ratio and the squared MOE of the denominator (MOE_1):

$$MOE_2^2 + (\hat{R}^2 * MOE_1^2) =$$

$$(22{,}866)^2 + [(1.0521)^2 * (22{,}666)^2] =$$

$$1{,}091{,}528{,}529$$

Calculate the MOE by dividing the square root of the prior result by the denominator ($\hat{X}_1$).

$$MOE_R = \frac{\pm\sqrt{1{,}091{,}528{,}529}}{762{,}475} = \frac{\pm 33{,}038.3}{762{,}475} = \pm 0.0433$$

Finally, the MOE of the percent change is the MOE of the ratio, multiplied by 100 percent, or 4.33 percent.

The text box below summarizes the formulas used to calculate the margin of error for several derived estimates.

Calculating Margins of Error for Derived Estimates

Aggregated Count Data

$$MOE_{agg} = \pm\sqrt{\sum_c MOE_c^2}$$

Derived Proportions

$$MOE_p = \frac{\pm\sqrt{MOE_{num}^2 - (\hat{p}^2 * MOE_{den}^2)}}{\hat{X}_{den}}$$

Derived Ratios

$$MOE_R = \frac{\pm\sqrt{MOE_{num}^2 + (\hat{R}^2 * MOE_{den}^2)}}{\hat{X}_{den}}$$

Appendix 4.
Making Comparisons

One of the most important uses of the ACS estimates is to make comparisons between estimates. Several key types of comparisons are of general interest to users: 1) comparisons of estimates from different geographic areas within the same time period (e.g., comparing the proportion of people below the poverty level in two counties); 2) comparisons of estimates for the same geographic area across time periods (e.g., comparing the proportion of people below the poverty level in a county for 2006 and 2007); and 3) comparisons of ACS estimates with the corresponding estimates from past decennial census samples (e.g., comparing the proportion of people below the poverty level in a county for 2006 and 2000).

A number of conditions must be met when comparing survey estimates. Of primary importance is that the comparison takes into account the sampling error associated with each estimate, thus determining whether the observed differences between estimates are statistically significant. Statistical significance means that there is statistical evidence that a true difference exists within the full population, and that the observed difference is unlikely to have occurred by chance due to sampling. A method for determining statistical significance when making comparisons is presented in the next section. Considerations associated with the various types of comparisons that could be made are also discussed.

Determining Statistical Significance

When comparing two estimates, one should use the test for significance described below. This approach will allow the user to ascertain whether the observed difference is likely due to chance (and thus is not statistically significant) or likely represents a true difference that exists in the population as a whole (and thus is statistically significant).

The test for significance can be carried out by making several computations using the estimates and their corresponding standard errors (SEs). When working with ACS data, these computations are simple given the data provided in tables in the American FactFinder.

1) Determine the SE for each estimate (for ACS data, SE is defined by the positive value of the margin of error (MOE) divided by 1.645).[4]
2) Square the resulting SE for each estimate.
3) Sum the squared SEs.
4) Calculate the square root of the sum of the squared SEs.
5) Calculate the difference between the two estimates.
6) Divide (5) by (4).
7) Compare the absolute value of the result of (6) with the critical value for the desired level of confidence (1.645 for 90 percent, 1.960 for 95 percent, 2.576 for 99 percent).
8) If the absolute value of the result of (6) is greater than the critical value, then the difference between the two estimates can be considered statistically significant at the level of confidence corresponding to the critical value used in (7).

[4] NOTE: If working with ACS single-year estimates for 2005 or earlier, use the value 1.65 rather than 1.645.

Algebraically, the significance test can be expressed as follows:

If $\left|\dfrac{\hat{X}_1 - \hat{X}_2}{\sqrt{SE_1^2 + SE_2^2}}\right| > Z_{CL}$, then the difference

between estimates $\hat{X}_1$ and $\hat{X}_2$ is statistically significant at the specified confidence level, CL

where $\hat{X}_i$ is estimate *i* (=1,2)

SE_i is the SE for the estimate *i* (=1,2)

Z_{CL} is the critical value for the desired confidence level (=1.645 for 90 percent, 1.960 for 95 percent, 2.576 for 99 percent).

The example below shows how to determine if the difference in the estimated percentage of households in 2006 with one or more people of age 65 and older between State A (estimated percentage =22.0, SE=0.12) and State B (estimated percentage =21.5, SE=0.12) is statistically significant. Using the formula above:

$$\left|\frac{\hat{X}_1 - \hat{X}_2}{\sqrt{SE_1^2 + SE_2^2}}\right| = \left|\frac{22.0 - 21.5}{\sqrt{(0.12)^2 + (0.12)^2}}\right| =$$

$$\left|\frac{0.5}{\sqrt{0.015 + 0.015}}\right| = \left|\frac{0.5}{\sqrt{0.03}}\right| = \left|\frac{0.5}{0.173}\right| = 2.90$$

Since the test value (2.90) is greater than the critical value for a confidence level of 99 percent (2.576), the difference in the percentages is statistically significant at a 99-percent confidence level. This is also referred to as statistically significant at the alpha = 0.01 level. A rough interpretation of the result is that the user can be 99 percent certain that a difference exists between the percentages of households with one or more people aged 65 and older between State A and State B.

By contrast, if the corresponding estimates for State C and State D were 22.1 and 22.5, respectively, with standard errors of 0.20 and 0.25, respectively, the formula would yield

$$\left|\frac{\hat{X}_1 - \hat{X}_2}{\sqrt{SE_1^2 + SE_2^2}}\right| = \left|\frac{22.5 - 22.1}{\sqrt{(0.20)^2 + (0.25)^2}}\right| =$$

$$\left|\frac{0.4}{\sqrt{0.04 + 0.0625}}\right| = \left|\frac{0.4}{\sqrt{0.1025}}\right| = \left|\frac{0.4}{0.320}\right| = 1.25$$

Since the test value (1.25) is less than the critical value for a confidence level of 90 percent (1.645), the difference in percentages is not statistically significant. A rough interpretation of the result is that the user cannot be certain to any sufficient degree that the observed difference in the estimates was not due to chance.

Comparisons Within the Same Time Period

Comparisons involving two estimates from the same time period (e.g., from the same year or the same 3-year period) are straightforward and can be carried out as described in the previous section. There is, however, one statistical aspect related to the test for statistical significance that users should be aware of. When comparing estimates within the same time period, the areas or groups will generally be nonoverlapping (e.g., comparing estimates for two different counties). In this case, the two estimates are independent, and the formula for testing differences is statistically correct.

In some cases, the comparison may involve a large area or group and a subset of the area or group (e.g., comparing an estimate for a state with the corresponding estimate for a county within the state or comparing an estimate for all females with the corresponding estimate for Black females). In these cases, the two estimates are not independent. The estimate for the large area is partially dependent on the estimate for the subset and, strictly speaking, the formula for testing differences should account for this partial dependence. However, unless the user has reason to believe that the two estimates are strongly correlated, it is acceptable to ignore the partial dependence and use the formula for testing differences as provided in the previous section. However, if the two estimates are positively correlated, a finding of statistical significance will still be correct, but a finding of a lack of statistical significance based on the formula may be incorrect. If it is important to obtain a more exact test of significance, the user should consult with a statistician about approaches for accounting for the correlation in performing the statistical test of significance.

Comparisons Across Time Periods

Comparisons of estimates from different time periods may involve different single-year periods or different multiyear periods of the same length within the same area. Comparisons across time periods should be made only with comparable time period estimates. Users are advised against comparing single-year estimates with multiyear estimates (e.g., comparing 2006 with 2007–2009) and against comparing multiyear estimates of differing lengths (e.g., comparing 2006–2008 with 2009–2014), as they are measuring the characteristics of the population in two different ways, so differences between such estimates are difficult to interpret. When carrying out any of these types of comparisons, users should take several other issues into consideration.

When comparing estimates from two different single-year periods, one prior to 2006 and the other 2006 or later (e.g., comparing estimates from 2005 and 2007), the user should recognize that from 2006 on the ACS sample includes the population living in group quarters (GQ) as well as the population living in housing units. Many types of GQ populations have demographic, social, or economic characteristics that are very different from the household population. As a result, comparisons between 2005 and 2006 and later ACS estimates could be affected. This is particularly true for areas with a substantial GQ population. For most population characteristics, the Census Bureau suggests users make comparisons across these time periods only if the geographic area of interest does not include a substantial GQ population. For housing characteristics or characteristics published only for the household population, this is obviously not an issue.

Comparisons Based on Overlapping Periods

When comparing estimates from two multiyear periods, ideally comparisons should be based on nonoverlapping periods (e.g., comparing estimates from 2006–2008 with estimates from 2009–2011). The comparison of two estimates for different, but overlapping periods is challenging since the difference is driven by the nonoverlapping years. For example, when comparing the 2005–2007 ACS with the 2006–2008 ACS, data for 2006 and 2007 are included in both estimates. Their contribution is subtracted out when the estimate of differences is calculated. While the interpretation of this difference is difficult, these comparisons can be made with caution. Under most circumstances, the estimate of difference should not be interpreted as a reflection of change between the last 2 years.

The use of MOEs for assessing the reliability of change over time is complicated when change is being evaluated using multiyear estimates. From a technical standpoint, change over time is best evaluated with multiyear estimates that do not overlap. At the same time, many areas whose only source of data will be 5-year estimates will not want to wait until 2015 to evaluate change (i.e., comparing 2005–2009 with 2010–2014).

When comparing two 3-year estimates or two 5-year estimates of the same geography that overlap in sample years one must account for this sample overlap. Thus to calculate the standard error of this difference use the following approximation to the standard error:

$$SE(\hat{X}_1 - \hat{X}_2) \cong \sqrt{(1-C)}\sqrt{SE_1^{\,2} + SE_2^{\,2}}$$

where C is the fraction of overlapping years. For example, the periods 2005–2009 and 2007–2011 overlap for 3 out of 5 years, so C=3/5=0.6. If the periods do not overlap, such as 2005–2007 and 2008–2010, then C=0.

With this SE one can test for the statistical significance of the difference between the two estimates using the method outlined in the previous section with one modification; substitute $\sqrt{(1-C)}\sqrt{SE_1^{\,2} + SE_2^{\,2}}$ for $\sqrt{SE_1^{\,2} + SE_2^{\,2}}$ in the denominator of the formula for the significance test.

Comparisons With Census 2000 Data

In Appendix 2, major differences between ACS data and decennial census sample data are discussed. Factors such as differences in residence rules, universes, and reference periods, while not discussed in detail in this appendix, should be considered when comparing ACS estimates with decennial census estimates. For example, given the reference period differences, seasonality may affect comparisons between decennial census and ACS estimates when looking at data for areas such as college towns and resort areas.

The Census Bureau subject matter specialists have reviewed the factors that could affect differences between ACS and decennial census estimates and they have determined that ACS estimates are similar to those obtained from past decennial census sample data for most areas and characteristics. The user should consider whether a particular analysis involves an area or characteristic that might be affected by these differences.[5]

When comparing ACS and decennial census sample estimates, the user must remember that the decennial census sample estimates have sampling error associated with them and that the standard errors for both ACS and census estimates must be incorporated when performing tests of statistical significance. Appendix 3 provides the calculations necessary for determining statistical significance of a difference between two estimates. To derive the SEs of census sample estimates, use the method described in Chapter 8 of either the Census 2000 Summary File 3 Technical Documentation <http://www.census.gov/prod/cen2000/doc/sf3.pdf> or the Census 2000 Summary File 4 Technical Documentation <http://www.census.gov/prod/cen2000/doc/sf4.pdf>.

A conservative approach to testing for statistical significance when comparing ACS and Census 2000 estimates that avoids deriving the SE for the Census 2000 estimate would be to assume the SE for the Census 2000 estimate is the same as that determined for the ACS estimate. The result of this approach would be that a finding of statistical significance can be assumed to be accurate (as the SE for the Census 2000 estimate would be expected to be less than that for the ACS estimate), but a finding of no statistical significance could be incorrect. In this case the user should calculate the census long-form standard error and follow the steps to conduct the statistical test.

Comparisons With 2010 Census Data

Looking ahead to the 2010 decennial census, data users need to remember that the socioeconomic data previously collected on the long form during the census will not be available for comparison with ACS estimates. The only common variables for the ACS and 2010 Census are sex, age, race, ethnicity, household relationship, housing tenure, and vacancy status.

The critical factor that must be considered when comparing ACS estimates encompassing 2010 with the 2010 Census is the potential impact of housing and population controls used for the ACS. As the housing and population controls used for 2010 ACS data will be based on the Population Estimates Program where the estimates are benchmarked on the Census 2000 counts, they will not agree with the 2010 Census population counts for that year. The 2010 population estimates may differ from the 2010 Census counts for two major reasons—the true change from 2000 to 2010 is not accurately captured by the estimates and the completeness of coverage in the 2010 Census is different than coverage of Census 2000. The impact of this difference will likely affect most areas and states, and be most notable for smaller geographic areas where the potential for large differences between the population controls and the 2010 Census population counts is greater.

Comparisons With Other Surveys

Comparisons of ACS estimates with estimates from other national surveys, such as the Current Population Survey, may be of interest to some users. A major consideration in making such comparisons will be that ACS

[5] Further information concerning areas and characteristics that do not fit the general pattern of comparability can be found on the ACS Web site at <http://www.census.gov/acs/www/UseData/compACS.htm>.

estimates include data for populations in both institutional and noninstitutional group quarters, and estimates from most national surveys do not include institutional populations. Another potential for large effects when comparing data from the ACS with data from other national surveys is the use of different questions for measuring the same or similar information.

Sampling error and its impact on the estimates from the other survey should be considered if comparisons and statements of statistical difference are to be made, as described in Appendix 3. The standard errors on estimates from other surveys should be derived according to technical documentation provided for those individual surveys.

Finally, the user wishing to compare ACS estimates with estimates from other national surveys should consider the potential impact of other factors, such as target population, sample design and size, survey period, reference period, residence rules, and interview modes on estimates from the two sources.