UAA Institute of Social and Economic Research
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Using Administrative Data to Improve ACS Small Area Estimates

Experimental Synthetic Data for Rural Alaska Communities

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Challenge with ACS small-area estimates: Balancing data privacy vs. usability

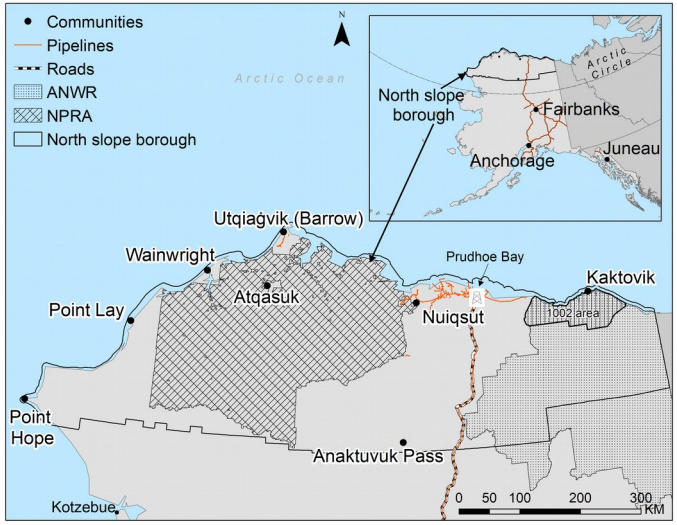
Census Bureau historical approach

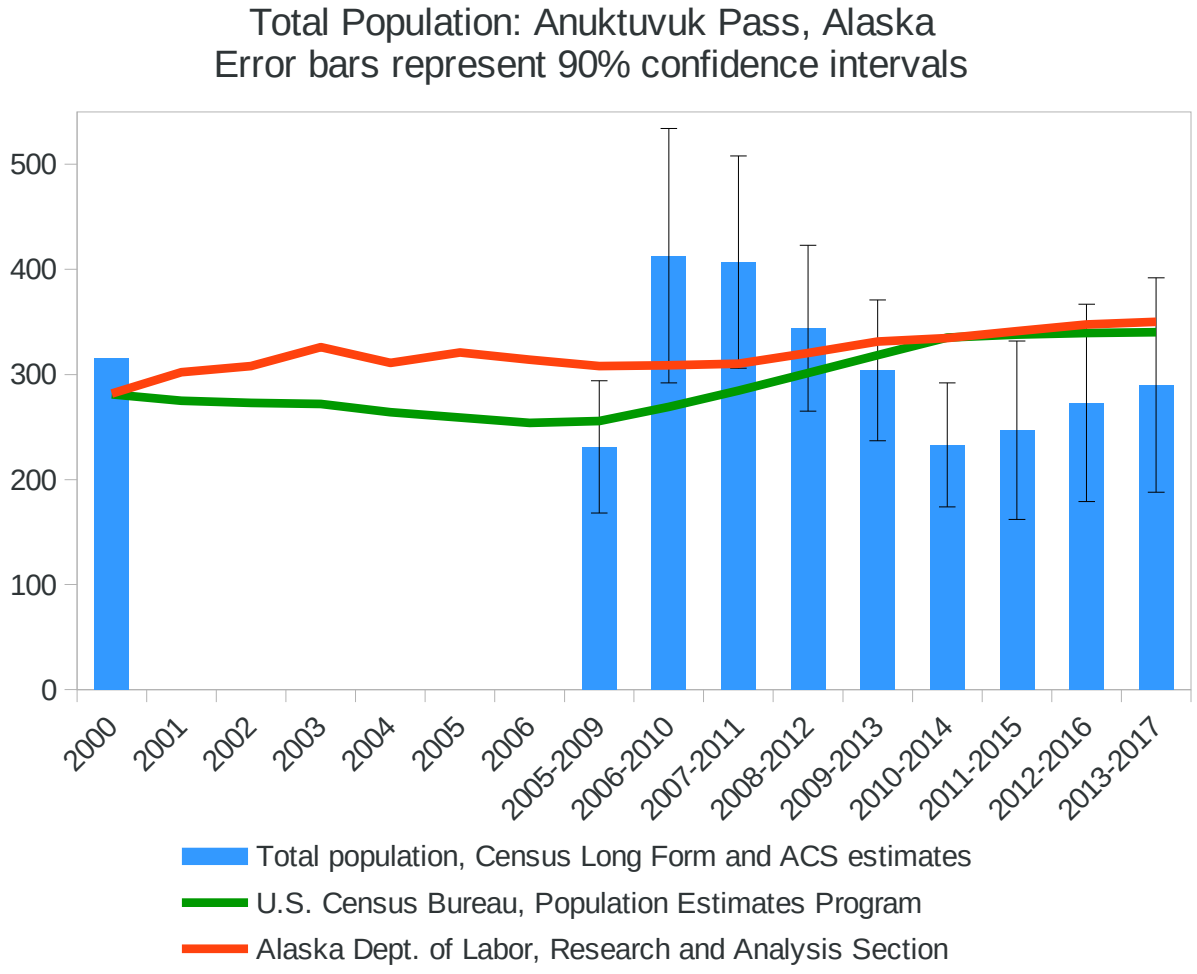
- Randomly select a small number of housing units for sampling each year
- Replace survey non-response items with data from randomly selected “similar” individuals (imputation)
- Apply additional obfuscation techniques: top and bottom coding, swapping, etc.
- Add edited survey responses to generate total counts by community
- Report 5-year moving averages

Multiple Problems with the Census Bureau Approach to Small Area 5-year Moving Average Estimates

- The total population is estimated from the survey responses, generating high margins of error for smaller communities.
- ACS sample sizes are smaller than Census Long Form sample sizes: the small number of households randomly selected for interviews, even across a 5-year period, may not represent the community as a whole.
- Social and economic conditions change from year to year, adding to the margin of error in moving average estimates.
- Limited and problematic choices for imputing values for respondents who don't answer certain questions

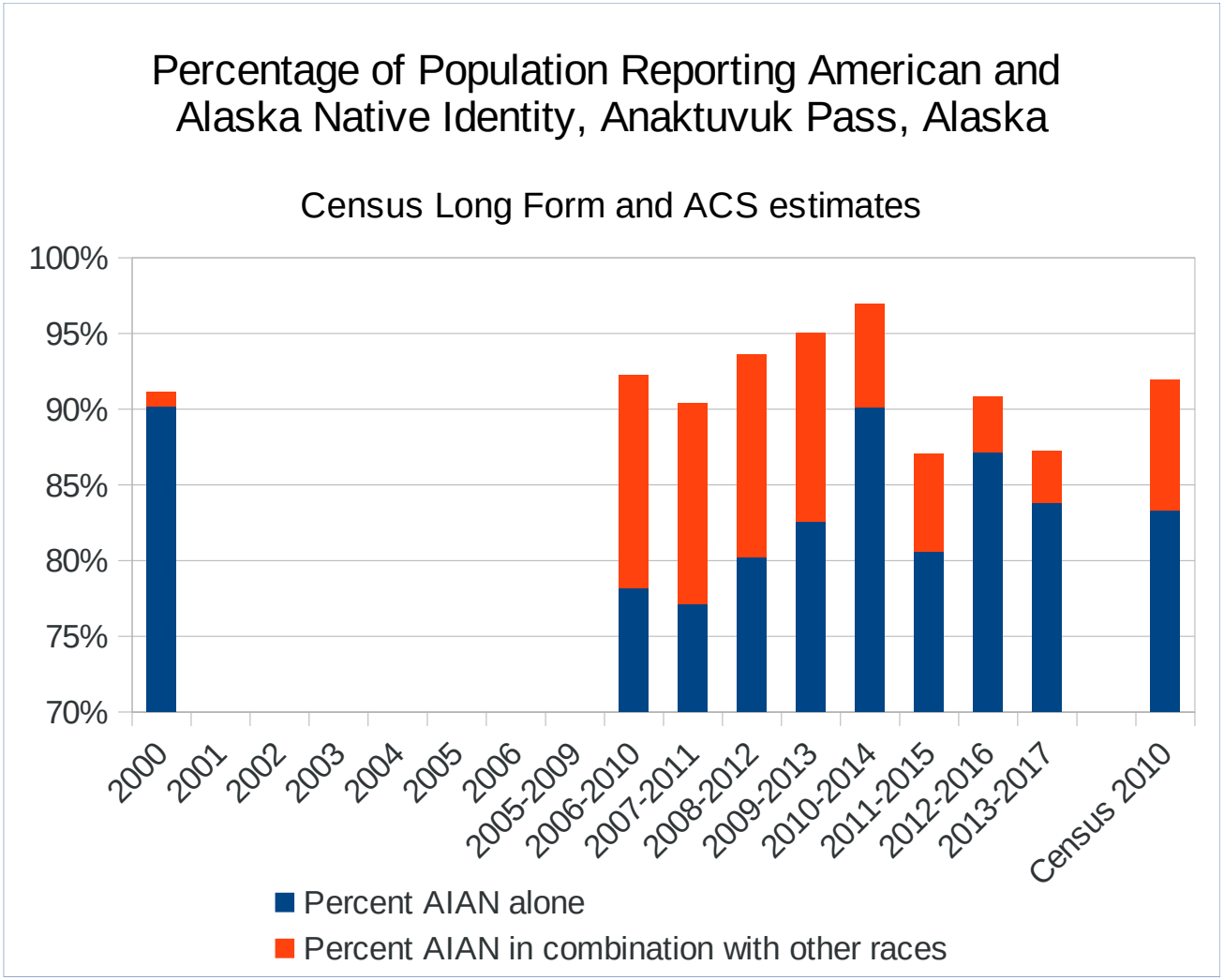
Strike 1: Population is unknown and estimated from the survey response rate





The Census Bureau has a good program to estimate annual small-area populations; so does the Alaska Dept. of Labor, using independent sources. This information is not used for ACS estimates.

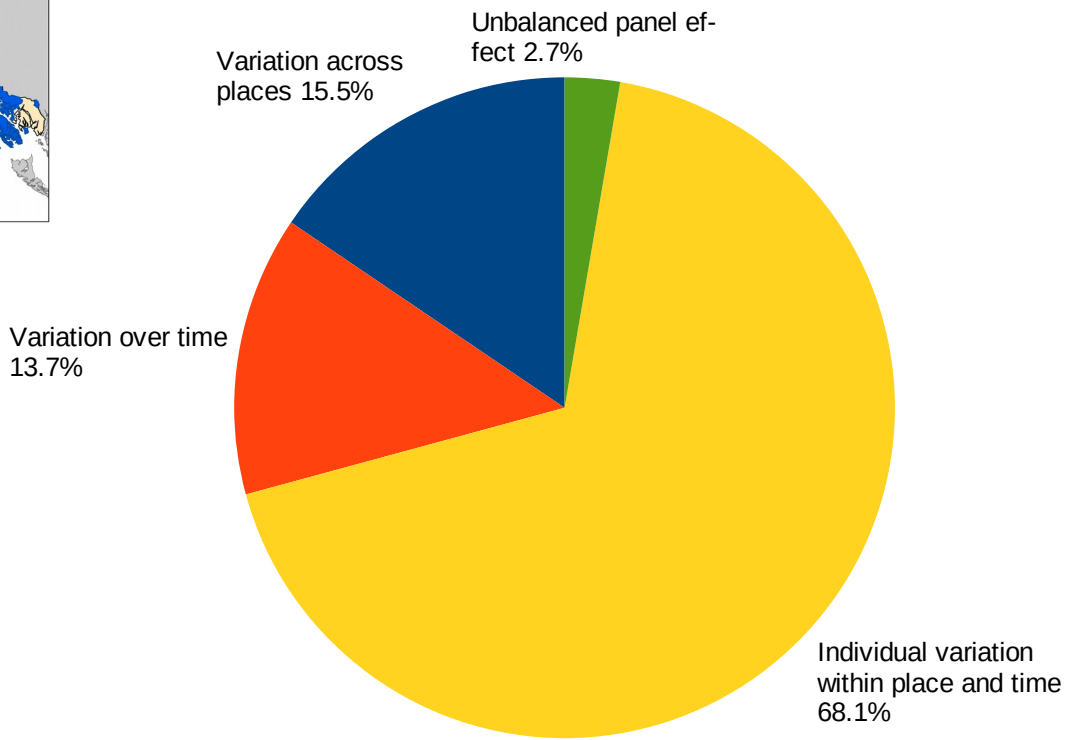
Strike 2: People interviewed each year differ in lots of ways



- Population characteristics likely change gradually over time
- Information on repeated sampling of the population not used

Strike 3: Conditions change systematically annually

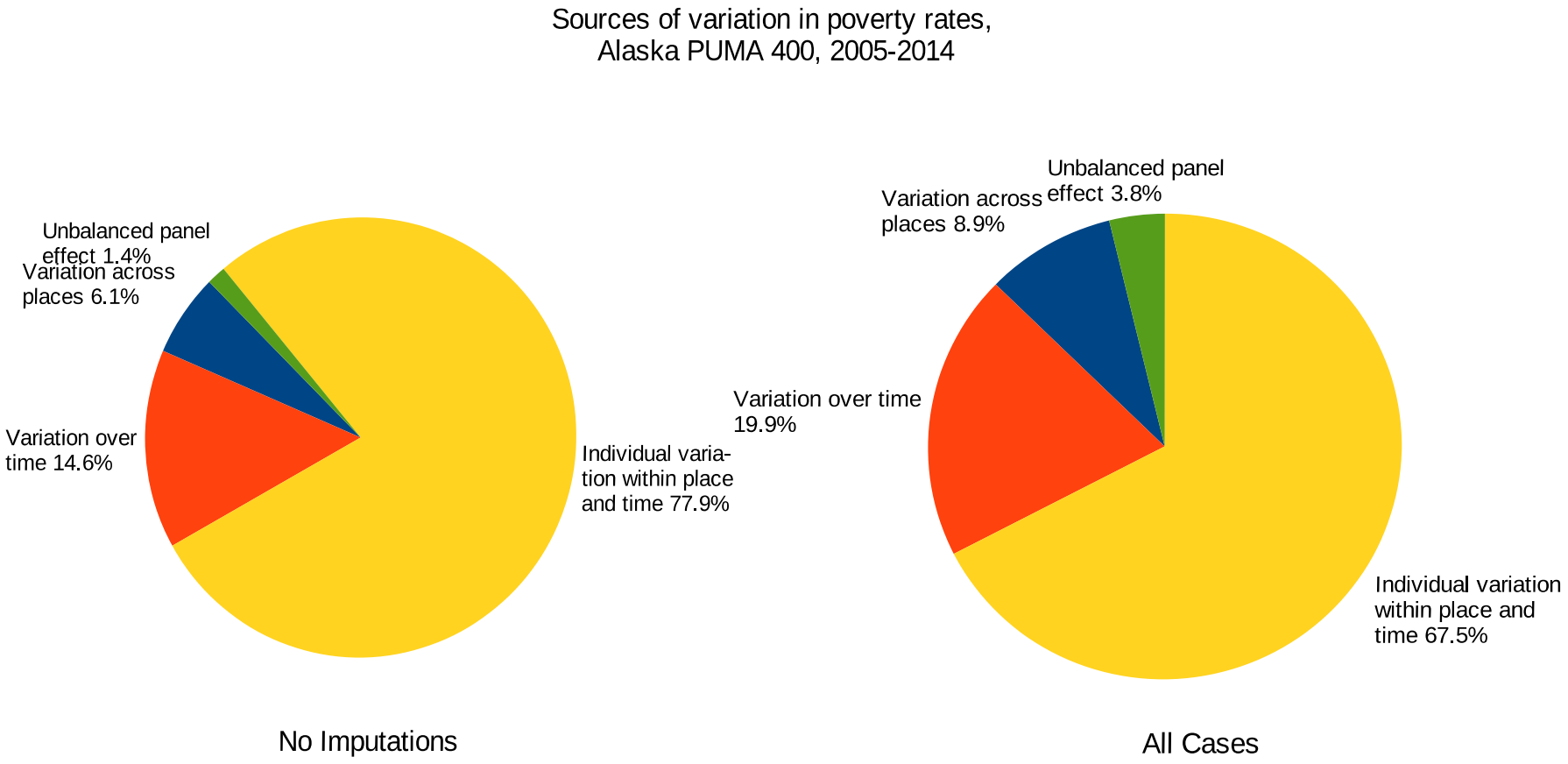
Sources of variation in household income,
Alaska PUMA 400, 2005-2014



- National and regional economic fluctuations: information ignored
- changing state budgets affecting social outcomes: information ignored

Strike 4: Imputation adds error

Higher time variation relative to place variation in imputed values

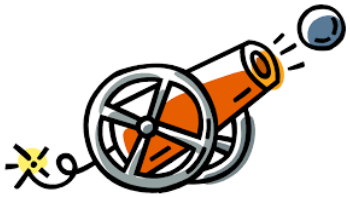


- Assumptions about whose answer to use are poorly documented
- Small sample means that many imputed values have to be drawn from households in other communities
- Information about community differences relevant to imputation not known

The data privacy challenge in the era of Big Data

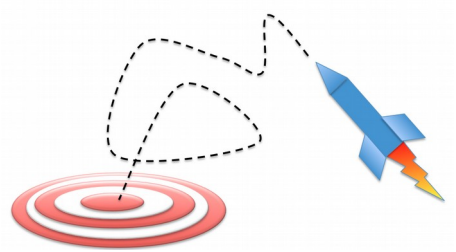
- The Census Bureau has figured out that a sophisticated statistician with a fast computer and lots of time can possibly identify individual responses from the 5-year moving average estimates.

- CB approach to data privacy: add random noise to further obfuscate the data



- Noise infusion is a crude weapon against an adversary that exists only in theory at this point
  - Data usability is already severely compromised, and will degrade further
  - Individual responses will still be identifiable in the published results; however, now they will be incorrect.

Synthetic data: A better approach for producing ACS small-area estimates



- Utilize the wealth of information available from multiple administrative sources to supplement and interpret ACS survey results
- Regression-based estimates of community conditions
- Potential outcomes:
  - More information about contemporary conditions in small areas
  - Better data privacy and improved data usability

Synthetic data approach

- **Use administrative data to estimate community populations**, not ACS sample data
  - Use Census Bureau population estimates program to estimate annual small-area population
  - Use information from decadal census counts to provide benchmark housing, occupancy, and household demographic information
- **Estimate rates, not counts**, from ACS surveys
  - Use co-varying characteristics of ACS sample households to estimate rates independent of population size
  - Multiply estimated rates by estimated population in step 1 if counts are desired
  - Assume rates change systematically, not randomly over time, in response to demographic, economic, and social processes revealed by the sample data
- **Use local area administrative data** to separate systematic changes (to be reported) from random variation (sampling error to be ignored)
  - State and local employment data, BEA LAPI, tax returns, provide economic data
  - School enrollments, social program enrollments, provide social data
- **Apply statistical methods to impute non-response** rather than random substitution

Synthetic data approach: technical details

- Model: indicator y_{ijt} for individual, household, or family *i* in community *j* in year *t* is assumed to be a function of individual and household demographic characteristics (measurable in the decennial census), *x*, community indicators, *z,* a community-specific error term, *u,* and random sampling error, *ε*:

$$y_{ijt} = f\left(x_{ijt}, z_{jt}, t\right) + u_{jt} + \varepsilon_{ijt} \qquad u_{jt} \sim N\left(0, \sigma_u^2\right) \qquad \varepsilon_{ijt} \sim N\left(0, \sigma_\varepsilon^2\right)$$

- Using the ACS survey observations for *x* and *y*, and publicly available administrative data for z, estimate the relationship *f* (estimated function *g*) and estimated community-specific random effect *v*, and use the predicted values to generate synthetic annual community-level indicators *s* with a variance estimate σ_ε^2 , which can be considered as a Bayesian prior for y_{jt}:
-

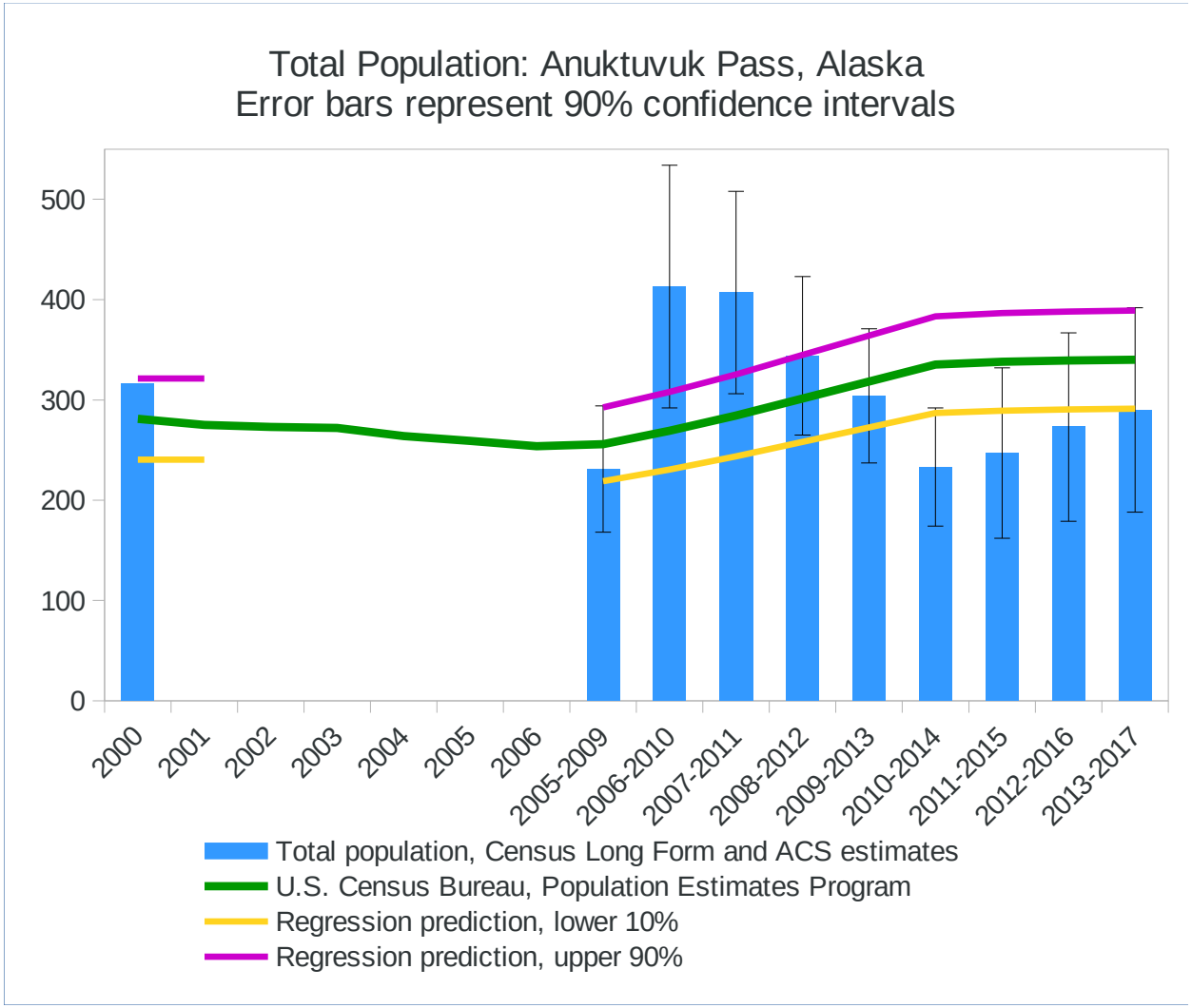
$$s_{jt} = \sum_{i=1}^{n_t} g\left(x_{ijt}, z_{jt}, t\right)/n_t + v_{jt}$$

- Using the sample mean, $\bar{y}_{jt} = \sum_{i=1}^{n_t} y_{ijt}/n_t$ with its sampling variance estimate σ_{jt}^2 adjust s_{jt} to generate the Bayesian posterior distribution,

$$\bar{s}_{jt} = g\left(\bar{x}_{jt}, z_{jt}, t\right) + v_{jt} + \mu_{jt} \quad \text{where} \quad \mu_{jt} = \frac{\sigma_{jt}^2 s_{jt} + \sigma_\varepsilon^2 \bar{y}_{jt}}{\sigma_{jt}^2 + \sigma_\varepsilon^2}$$

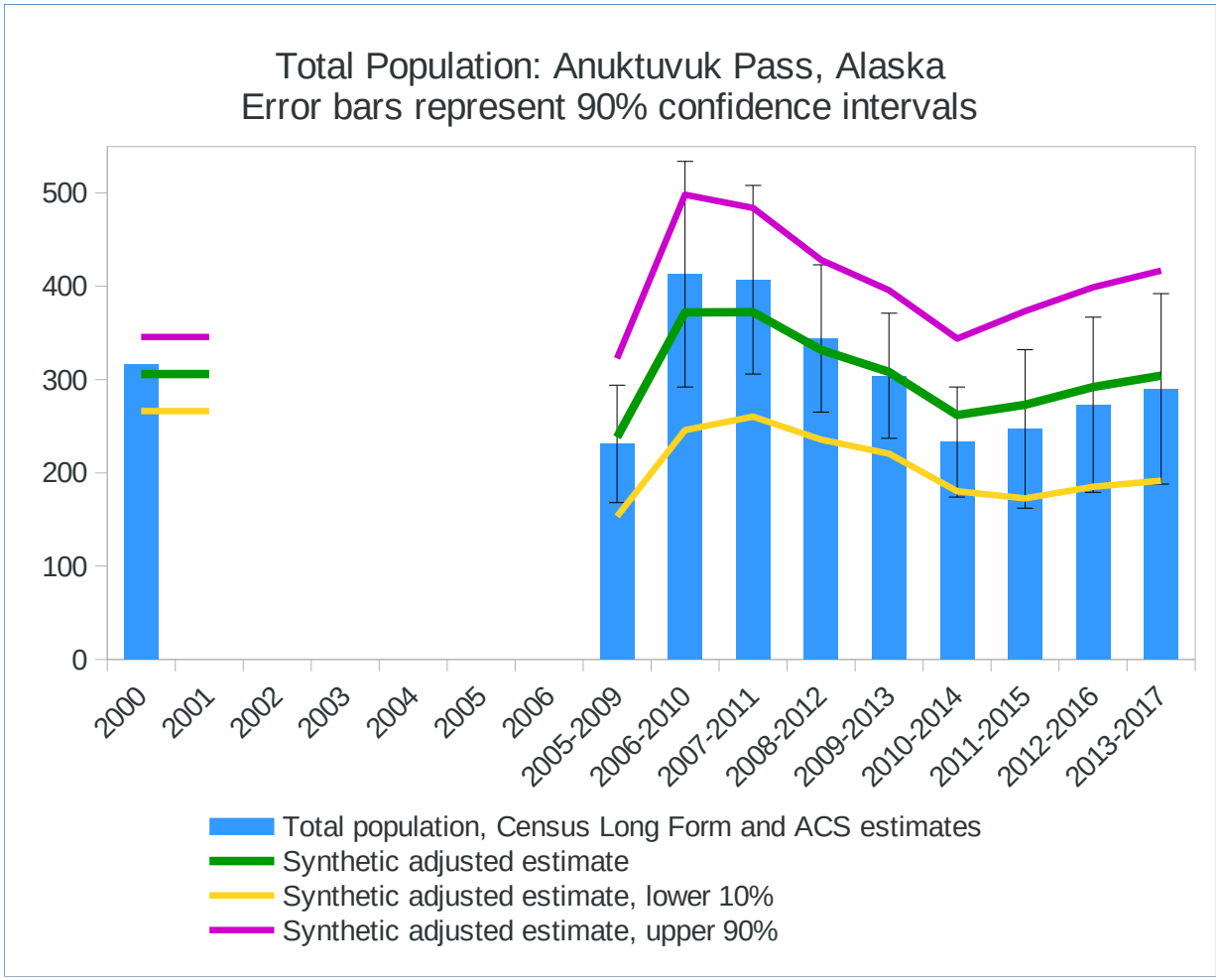
Illustrate method with a simple example, population of Anaktuvuk Pass

Population, $y_t = f(x,z,t) = z_t$, using Census population estimate for z_t:



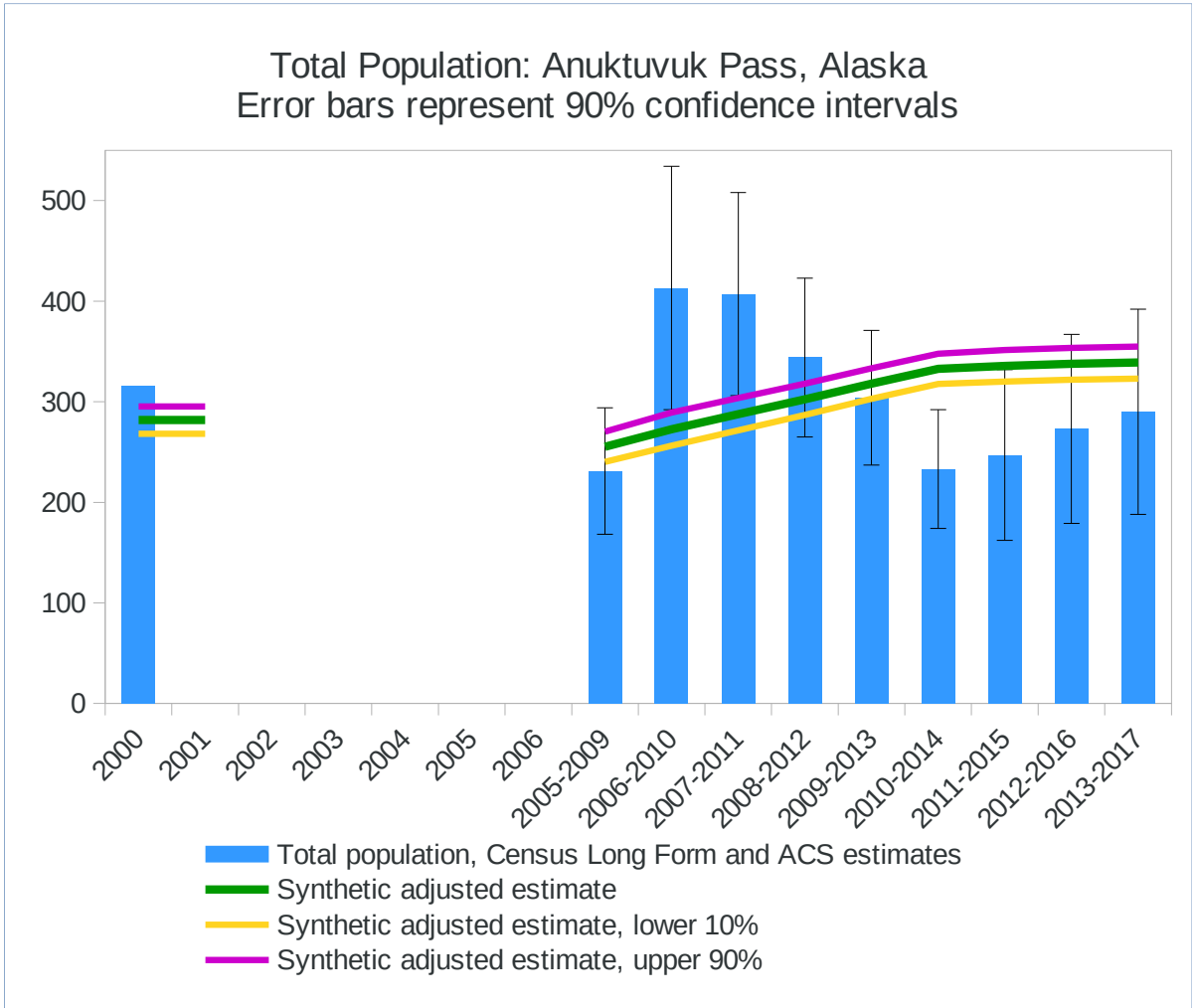
Illustrate method with a simple example, population of Anaktuvuk Pass

Population estimate = $s_t + \mu_t$. Note that this is not very accurate: only 10 observations for the synthetic estimates yields a high margin of error.



Illustrate method with a simple example, population of Anaktuvuk Pass

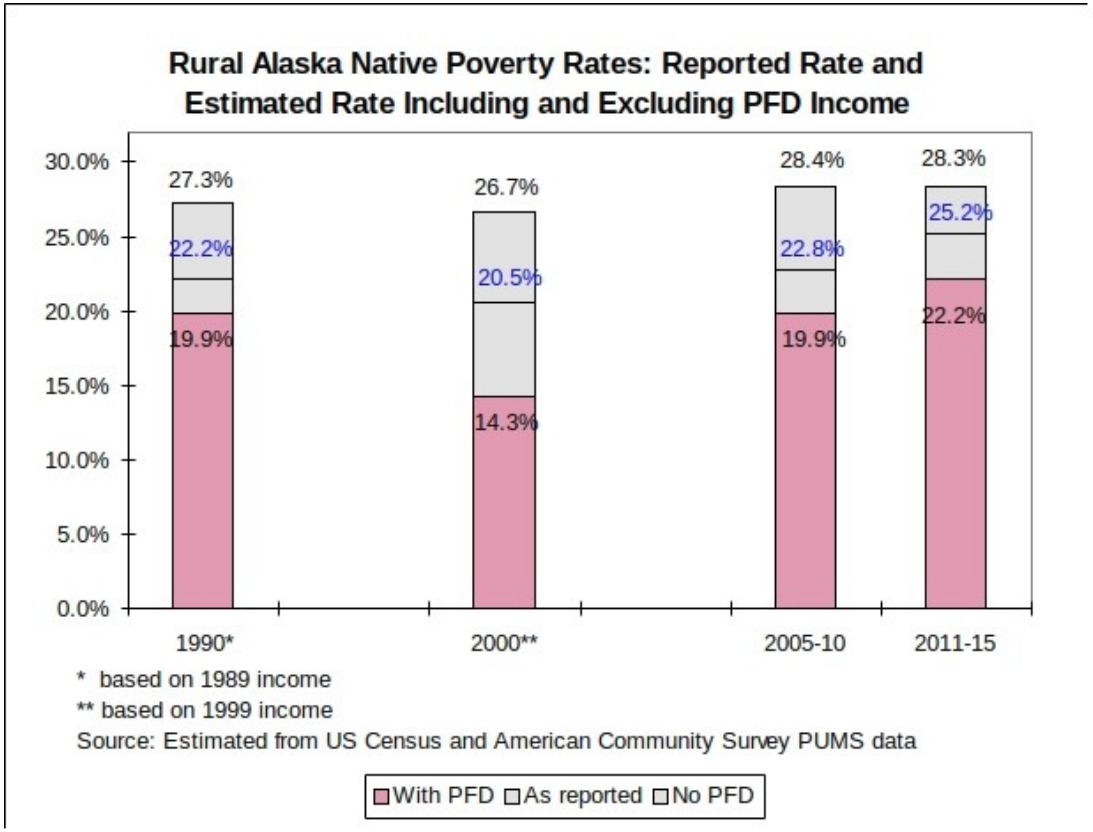
Population estimate = $s_t + \mu_t$. If we had 100 communities (which we do in PUMA 400, MOE for synthetic estimates would decline by 90%, which would yield:



Final note: we have only discussed sampling error. Administrative data can reduce non-sampling error, too.

Two examples using Alaska Permanent Fund Dividend applications:

- ACS estimates of out-migration from Alaska overestimated by 100 percent – helped Census Bureau find and fix a coding error
- Income of children not counted, resulting in large overestimate of poverty in all Alaska, especially among children



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