**Title:** Effects of Measurement Error in the American Community Survey on Statistical Analysis: An Example using County and Census Tract Mortality Rates.

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**Abstract:** The American Community Survey (ACS) summary file data provide rolling 5-year estimates of demographic and socioeconomic indicator data for small geographies throughout the United States. These estimates are commonly used as indicators for regression models to measure conditions in communities. The Margins of Error (MOE) in the ACS estimates for small geographic areas can often be very large, and without taking them into account, regression analyses using them can be mis-specified, leading to bias in regression coefficients and model standard errors. This paper directly compares measurement error model specifications to naive model specifications for a mortality outcome in Texas Census tracts using Bayesian model specializations. The results show that there is bias in the naive regression model results. We urge users of the ACS summary file data to be aware of such bias as it can potentially impact interpretation of model results and hypothesis tests.

## Introduction

When the American Community Survey (ACS) first began in 2001, the program was greeted with a mixture of excitement and skepticism. Those who were excited thought of the value of (eventual) yearly or rolling averages of hundreds of different demographic, social and economic indicators the survey would provide in areas as small as block groups, without having to wait for the decennial census. The skeptics thought of the difficulties in coverage that test cases of the survey faced, and the validity of the estimates produced by the survey (Census Bureau 2012; Citro et al. 2007; Herman 2008; McLaughlin et al. 2000). Since the initial publication of the ACS 2009 5-year summary file, it has been used repeatedly in demographic research, both to portray population changes, geographic variation in socioeconomic conditions, and as predictors in various regression models of health and economic behavior both at the individual and aggregate levels of analysis. It is with the latter of these uses that this paper is concerned. The concern arises based not upon the ACS survey itself, nor necessarily with the published estimates, but in the margins of error reported alongside the published estimates. These margins of error contain valuable information as to the stability and information content of the published estimates, however these margins of error (MOEs) are rarely if ever formally incorporated into statistical analysis using the ACS. This is done, despite decades of work by statisticians on the use of measurement error model specifications that incorporate errors in measurement directly into the statistical models.

The purpose of this paper is to examine the effect of incorporating measurement errors from the ACS summary file directly in a statistical analysis, and compare the results to a naive analysis, which excludes the MOEs. To accomplish this, we use as an example recent small area estimates of mortality within the state of Texas and a variety of demographic and socioeconomic variables from the ACS summary file.

## Measurement error in the ACS

Researchers often employ ACS estimates in models as counts with no accounting for measurement (sampling and non-response) error. When using geographic areas (such as census tracts) as the unit of analysis, the size of measurement error will vary, potentially quite dramatically, from one area to the next. Thus, two estimates may appear to be substantially different, yet statistically, when we consider measurement error, we may not be able to say they are different.

The Census bureau produces numerous guides to using ACS data. These guides typically focus on the construction of demographic or economic estimates from the data. They also specify how the Margins of Error (MOEs) should be used when describing the estimates. These MOEs are a measure of how imprecise a particular estimate is. As documented in other studies (Bazuin and Fraser 2013; Jurjevich et al. 2018; Spielman et al. 2014, 2015) the errors in estimates grow in relative magnitude as the size of the geographic area under estimation decreases (i.e. state level estimates are more stable than counties, and counties are more stable than census tracts, with census block group estimates being the least stable of all estimates). This is an effect of the ACS survey sample size used to estimate the quantity of interest in the area of interest. For example, estimating the minority population in a small rural county with a small minority population would produce a higher variance estimate, because the sample size used would be smaller than a larger population area. Additionally, in areas with harder to reach populations, the ACS errors can also increase because sample sizes suffer due to non-response in the survey. With the smallest geographies present in the ACS summary file, block groups have the largest margins of error.

## Measurement error models in statistics

There is a well-documented literature on the effects of measurement error in predictors on inference in linear and generalized linear models. In short, measurement error in predictor variables lead to bias in parameter estimates and on estimated errors in these parameters (Buonaccorsi 2010). Typically, model intercepts are over-estimated, and the regression effects are under estimated in such situations. In addition, the variance covariance matrices of these models are also incorrect, which leads to incorrect standard errors for all model parameters, and ultimately to errors in the statistical tests which depend on these estimates.

One model for accounting for measurement error in covariates is the Berkson additive error model (Berkson 1950). This model states that if a predictor $x_{\text{obs}}$ is observed with error $e_x$ then a model can be specified so the random variable $X_{true}$ can be modeled as: $X_{true} = x_{\text{obs}} + e_x$, with $e_x$ having mean 0 and variance $\sigma^2_u$. Specifically, this model assumes that the true value of the variable and the error in the observed variable are independent of one another. This model is used when aggregate or group-level characteristics are assigned to individuals, in order to provide proxies for the individual-level variables that are unmeasured. For example, using the median household income in a Census tract to proxy the income of an individual residing within that tract.

The second common measurement error model is the classical measurement error model. This model, in contrast to the Berkson error model, includes error in the predictors themselves, versus the use of a group -level variable to proxy an individual-level measurement. This model assumes that the error in the measurement and the true value are independent of one another, meaning that the measurements themselves have error. When using ACS data in an aggregate analysis, the classical error model seems most appropriate, because we are not assigning group-level characteristics to individuals, we are instead using the estimates and the MOEs measured for areas. Szpiro et al (2011) describe in a very effective fashion how errors in measurement affect the inference in a regression model. If we are using a simple linear regression model, the model is originally:

$$y = \beta_0 + \beta_1 x_1 + e$$

But with measurement error in x, the model become:

$$y = \beta_0 + \beta_1 x_{err} + (e + u)$$

Which now has error from the original model, plus error from the covariate, $u$. By assuming the predictors in a model have no error, then the standard errors in a regression model are estimated as

$$\text{s.e.}(\hat{\beta}) = \widehat{\sigma^2}(X'X)^{-1}$$

which only depends on the error in the outcome, $\widehat{\sigma^2}$, implied by the model. When measurement error in the *X's* is introduced, this formula is then incorrect. The exact details of the addition of measurement error into the calculation of model standard errors can be found in texts on the subject (Buonaccorsi 2010), but can best be seen by the inclusion of the reliability ratio for the model parameter. The reliability ratio, λ, is the ratio of the variability in the true X's, over the variance in their errors.

$$\lambda = \frac{\sigma_x}{\sigma_x + \sigma_u}$$

In general, the bias in the regression coefficients themselves can be estimated as $\lambda * \beta$, the bias then attenuates the regression effects by the value $\lambda$. In terms of the errors in the model parameters, the standard errors should now be:

$$\text{s.e.}(\hat{\beta}) = \left(\widehat{\sigma_e^2} + \widehat{\sigma_u^2}\right)(X'X)^{-1}$$

if one X is measured with error, while if all X's are measured with error, the equation become more complex, with the measurement errors being a variance covariance matrix instead of a scalar.

In general, the exclusion of measurement errors will bias the hypothesis tests based on the bias introduced in the regression effects themselves, as well as the bias in the uncorrected standard errors. This will lead to incorrect tests of model parameters and incorrect interpretation of the model itself. Methods for correcting measurement error have been described by other authors in the statistical and econometric literature (Arima et al. 2016; Buonaccorsi 2010; R. J. Carroll et al. 2011; R. Carroll et al. 2006; Fuller 1987), and various methods of correction have been described including the SIMEX method (R. J. Carroll et al. 1996; Wang et al. 1998).

Despite the availability of various models for measurement error, little has been done on how the errors in ACS estimates influence findings in social science settings, a recent publication by Orndahl and Wheeler (2018) have noted how the errors influence the substantive interpretation of model results. In their article, Orndahl and Wheeler describe that by ignoring the errors in the ACS variables included at the county level, there were areas that appeared to cluster spatially in their analysis of suicide mortality. After taking account of the errors in measurement, several of these areas were no longer spatial clusters. While this finding is significant from an epidemiological standpoint, it does not address the larger concerns that using predictor variables with errors incorporates into any modeling strategy that uses the ACS. Another study by Napierala and Denton (2017) shows how the index of dissimilarity used in segregation studies can be sensitive to the errors in ACS estimates used to compute it. They describe that in areas with smaller populations, or in areas with smaller populations of minorities, the index of dissimilarity shows marked variation from its point estimate, and the confidence intervals for the index are very wide in such places.

**Purpose**

The purpose of this paper is to illustrate the effects of ignoring ACS measurement error on the interpretation of regression coefficients. This paper fills a gap in the literature, where no attention has been paid to the repercussions of using ACS estimates within models and ignoring the measurement error in the estimates. Based on research from the measurement error literature, we propose a relatively simple model that incorporates the errors in all ACS estimates included in a model and show how the results of the measurement error model compares to that of a naïve analysis, which ignores the errors in measurement. The strategy for this analysis uses Bayesian modeling specifications, which can accommodate measurement errors very directly (Orndahl and Wheeler 2018). We use a model that does not incorporate measurement error (naïve) and a second that incorporates measurement errors directly into the model. Through the Bayesian modeling strategy, we can compare model parameter point estimates, standard errors and coverage intervals for all parameters between the two approaches. This will allow us to measure the relative bias in the naïve model. To illustrate these ideas, data on age and sex specific mortality in Texas census tracts and counties are used, along with several ACS estimates as predictor variables in the analysis. Two different levels of geography are used in order to ascertain the relative bias in using small versus larger geographic areas, which have been described elsewhere (Spielman et al. 2014; Sun and Wong 2010) as being a natural source of larger errors in ACS estimates.

Two different levels of analysis are used in order to determine how much bias is introduced by the errors in the ACS variables at small and larger geographic areas. Spielman et. al. (2014) describe how census tracts in the ACS have much smaller sample sizes on average than the 2000 Census summary file 3 samples, and this would also be true for counties, but since counties are larger areas, the sample sizes will be larger as a result. Thus, the errors in measurement at the tract level are expected to be greater in the analysis of tracts than in the analysis of counties, but since both levels of analysis are common in the health literature (Gant et al. 2014; Mode et al. 2016; Yang et al. 2015; Yang and Jensen 2015), the authors believe that it is worthwhile to describe the bias introduced at both levels of analysis.

## Data

To illustrate the effects of measurement error on regression results, we use the 2015 5-year ACS summary file measured at the census tract and county level for the state of Texas. Following protocols for small area mortality rate estimation, we limit the tracts in the analysis to those with at least 5,000 residents, and with non-zero populations at risk at each age group. The outcome considered in this analysis is age and sex specific all-cause mortality. Data on individual death certificates were obtained from the Texas Department of State Health Services (DSHS) from the years 2011 to 2015. These data are geocoded to 2010 census tracts and aggregated over the 5-year period by 10-year age intervals and sex of the deceased. This generates a total of 20 rates for each tract and a total of 70,871 rates for the state for the tract-level analysis and 4568 rates for the 254 counties in the state. For each respective level of the analysis, the observation unit is either the tract-specific age and sex count of deaths, or for the county-level analysis, each observation is the county-specific age and sex count of deaths.

This paper is not trying to test a theoretical perspective, per se, so predictor variables are chosen to be representative of other ecological analyses of mortality in the United States (Dwyer-Lindgren et al. 2016; Sparks et al. 2009; Sparks and Sparks 2010; Yang and Jensen 2015). We use data from the 2015 ACS summary file demographic profile tables, which overlaps the period when the mortality data are observed. The demographic profile tables combine information from multiple ACS detailed tables and provide pre-calculated percentages and rates with associated margins of error. For predictors in the regression models, we use the home vacancy rate, the proportion of the population over age 25 with a college degree, the proportion of the population that is non-Hispanic black, the proportion of households below the poverty line and the proportion of the population that is insured. All variables are expressed as proportions with the margins of error expressed as 90% margins of error for each proportion.

**Methods**

We estimate two types of regression models to document the effects of incorporating measurement error on the regression results. All models are specified as a Negative Binomial regression model for the age and sex specific mortality rates, with a population offset (n), as:

$$y_{ij} \sim \mathrm{NB}(\eta)$$

$$log(\eta) = log(n) + \beta_0 + \psi * Sex_i + \gamma * Age_j + \sum_k \beta_k \, x_{ki}$$

We first consider a naïve regression model, where no measurement error is incorporated. This naïve approach represents the standard/traditional approach most researchers would apply when using the ACS - derived estimates as predictors in a regression model, where no uncertainty in the estimates is incorporated into the analysis. The second model is a Classical measurement error model implementation, with measurement errors in all the ACS - derived predictors are included directly in the model. This model uses a Bayesian measurement error specification of the additive Classical error model. This strategy assumes the true value of the ACS estimates can be modeled using a latent variable from a Normal distribution, with a mean equal to the observed point estimate and a standard deviation equal to the estimated standard error of the ACS point estimate (s.e.(ACS estimate) = MOE/1.645)).

$$y_{ij} \sim \mathrm{NB}(\eta)$$

$$log(\eta) = log(n) + \beta_0 + \psi * Sex_i + \gamma * Age_j + \sum_k \beta_k \, x_{k\,\mathrm{true}}$$

$$x_{k\,\mathrm{true}} \sim \mathrm{Normal}(x_{obs}, \sigma_{obs})$$

Models are estimated using Bayesian model specifications using the brms package (Bürkner 2017) and the Stan modeling language (Carpenter et al. 2017; Gelman et al. 2015) for R 3.5.2 (R Core Team and R Development Core Team 2018).

Since a Bayesian modeling strategy is used, all model parameters are given prior distributions according to recommended best practices (Burkner, 2017; Gelman 2004; Gelman et al., 2015; Gelman et al., 2017). Flat priors are assigned to all the population level parameters ($\beta, \gamma, \psi$ ). Two independent Markov chains were used, and models were burned in for 3.000 iterations, followed by another 3,000 iterations for sampling of the parameters. Models showed signs of convergence with all model parameters having Rhat values of 1 (Gelman and Rubin, 1992). Models are summarized in terms of the posterior means of the parameters and 95% Bayesian credible intervals.

**Results**

Table 1 shows the descriptive statistics for the outcome variable, and the ACS predictors, and their associated standard errors for both the county and tract levels of analysis. As expected, the level of error in the county-level estimates is much lower than that of the tract-level analysis. The average number of deaths is much higher for counties than tracts, with only 2 deaths on average in each tract during the period. There are also noticeable differences in the means of several of the estimates between the two levels of analysis, with the % Non-Hispanic black, the % with a college education and the poverty rate all being lower in the county-level data, and the vacancy rate being higher on average in counties.

Table 1. Descriptive statistics

**Descriptive Statistics for County-Level Analysis**

| Statistic | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| Deaths | 37.081 | 173.924 | 0 | 4,931 |
| Population Size | 8,881.414 | 51,804.640 | 2 | 2,203,545 |
| Male (1) | 0.500 | 0.500 | 0 | 1 |
| %NH Black | 6.262 | 6.613 | 0.000 | 33.300 |
| %NH Black Error | 0.863 | 1.942 | 0.100 | 26.900 |
| % Vacant housing units | 21.364 | 10.244 | 4.600 | 56.400 |
| % Vacant housing units Error | 3.041 | 1.777 | 0.200 | 11.800 |
| %Age 25+ w/College Edu | 18.105 | 7.343 | 1.900 | 49.800 |
| %Age 25+ w/College Edu Error | 2.526 | 1.610 | 0.200 | 8.700 |
| Poverty Rate | 13.065 | 5.540 | 0.000 | 37.200 |
| Poverty Rate Error | 3.570 | 4.492 | 0.200 | 75.100 |
| % Insured | 79.594 | 4.857 | 62.400 | 94.500 |
| % Insured Error | 3.084 | 2.146 | 0.200 | 15.900 |

Table 1. Descriptive Statistics (Cont'd)

**Descriptive Statistics for Tract-Level Analysis**

| Statistic | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| Deaths | 2.043 | 3.105 | 0 | 58 |
| Population Size | 506.251 | 738.567 | 11 | 27,366 |
| Male (1) | 0.501 | 0.500 | 0 | 1 |
| %NH Black | 11.214 | 14.757 | 0.000 | 92.100 |
| %NH Black Error | 3.505 | 2.422 | 0.100 | 17.500 |
| % Vacant housing units | 10.168 | 7.267 | 0.000 | 58.600 |
| % Vacant housing units Error | 4.841 | 1.716 | 0.300 | 47.500 |
| %Age 25+ w/College Edu | 26.419 | 18.969 | 0.300 | 93.500 |
| %Age 25+ w/College Edu Error | 5.173 | 1.762 | 1 | 20 |
| Poverty Rate | 14.522 | 11.668 | 0.000 | 73.500 |
| Poverty Rate Error | 6.467 | 3.174 | 0.400 | 48.600 |
| % Insured | 79.195 | 10.561 | 36 | 100 |
| % Insured Error | 5.572 | 1.803 | 0 | 30 |

Turning to the county-level regression analysis, Table 2 presents the results from the Bayesian analysis. Results are summarized in terms of their posterior means, posterior standard errors and 95% Bayesian credible intervals for all regression model parameter estimates. Also presented are the between group variances for the age groups and the Negative Binomial dispersion parameters.

Table 2. Bayesian regression models for Naïve and Classical Measurement Error Models – County Level Analysis.

| | Naive Model | | | | ME Model | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Est.Error | l-95% CI | u-95% CI | Estimate | Est.Error | l-95% CI | u-95% CI |
| Intercept | -7.29 | 0.04 | -7.37 | -7.2 | -7.2989 | 0.0445 | -7.38621 | -7.21115 |
| Sex – Male (Ref= Female) | -0.0094 | 0.0217 | -0.0525 | 0.0339 | -0.00861 | 0.02169 | -0.05124 | 0.0339 |
| Age_grp10_19 | -0.6113 | 0.0675 | -0.7447 | -0.4774 | -0.6104 | 0.06738 | -0.74185 | -0.47992 |
| Age_grp20_29 | 0.1992 | 0.0577 | 0.0906 | 0.3164 | 0.19922 | 0.05799 | 0.08735 | 0.31193 |
| Age_grp30_39 | 0.6618 | 0.0558 | 0.5535 | 0.7692 | 0.66206 | 0.05583 | 0.55472 | 0.77108 |
| Age_grp40_49 | 1.3558 | 0.0532 | 1.2521 | 1.4638 | 1.35676 | 0.05313 | 1.25181 | 1.46178 |
| Age_grp50_59 | 2.4129 | 0.0498 | 2.3184 | 2.513 | 2.41365 | 0.04996 | 2.31613 | 2.51107 |
| Age_grp60_69 | 2.8563 | 0.0489 | 2.7609 | 2.9532 | 2.85549 | 0.04921 | 2.75903 | 2.95094 |
| Age_grp70_79 | 3.8383 | 0.0484 | 3.744 | 3.9336 | 3.83796 | 0.04876 | 3.74215 | 3.9322 |
| Age_grp80plus | 2.7838 | 0.0491 | 2.6886 | 2.8815 | 2.7788 | 0.04869 | 2.68269 | 2.87479 |
| %NH Black | 0.0054 | 0.0016 | 0.0024 | 0.0085 | 0.00553 | 0.00171 | 0.00223 | 0.00886 |
| % Vacant housing units | -0.005 | 0.0013 | -0.0075 | -0.0025 | -0.00623 | 0.00154 | -0.00922 | -0.00326 |
| %Age 25+ w/College Edu | -0.0133 | 0.0016 | -0.0165 | -0.0101 | -0.01462 | 0.0019 | -0.01836 | -0.01093 |
| Poverty Rate | 0.003 | 0.0027 | -0.0022 | 0.0084 | 0.00711 | 0.00869 | -0.00987 | 0.02406 |
| % Insured | 0.0134 | 0.0033 | 0.007 | 0.0198 | 0.01906 | 0.01014 | -0.00087 | 0.03876 |

The results of the analysis are summarized again in Figure 1, which presents the posterior marginal distributions for each of the regression parameters in the analysis. The visual interpretation of the model results is perhaps easier to discuss. The effects of the various regressors are presented for both the naïve and the measurement error models. The red, solid lines represent the marginal for the measurement error model parameters, and the solid, green lines represent the marginal for the naïve model. In most case, the marginals are similar, but some parameters indicate some degree of bias in the naïve models. Bias is typically thought to decrease the effect size for a predictor, but bias can also inflate the effect sizes (Loken and Gelman 2017).

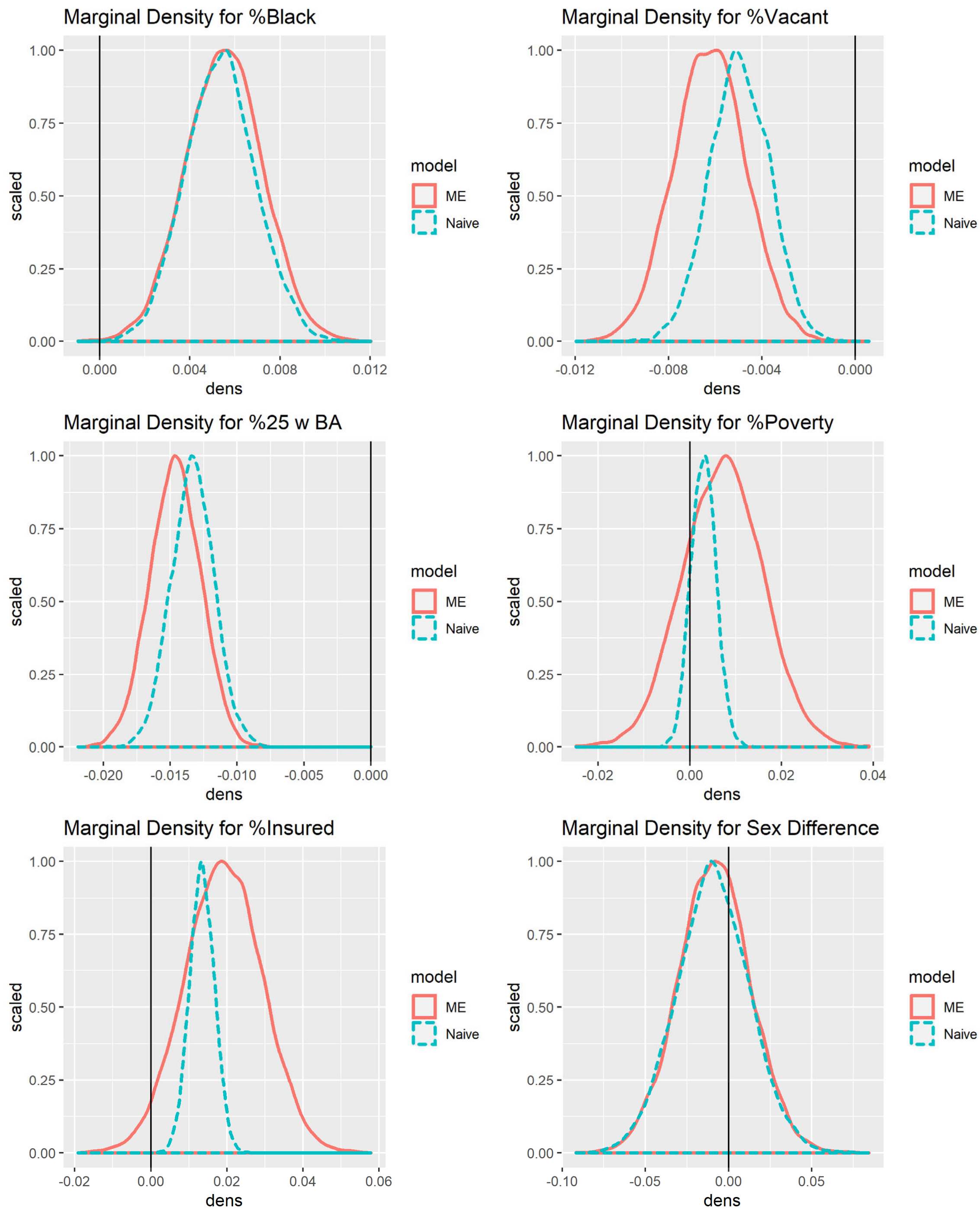


Figure 1. Posterior marginal distributions of the Naïve and Measurement Error model parameter estimates from the county-level analysis.

The credible intervals for each parameter, from Table 1 and the marginals from Figure 1, combine to show the differences between the two models. The %Non-Hispanic black parameter is significant in both models, and the marginals are nearly identical. In the measurement error model the point estimate for the parameter is larger 2.35% larger and the standard error of the estimate is 6.435 larger. The effect of the vacancy rate is 19% larger in the ME model than in the naïve model and the error is nearly 16% larger, while both suggest the effect is negative and significant. The education variable shows strong similarity between both models, with the ME model having a point estimate that is 9% larger and a standard error that is 15.8% larger than the naïve model. The effect of the poverty rate in the both models model suggests there is no significant relationships between poverty and mortality, while the ME model's point estimate is 58% larger than the naïve model, and the standard error is 68.9% larger. The effect of the rate of insurance coverage is positive and significant in the naïve model, while the ME model is not significant at the 95% level, also the parameter estimate is 29% larger in the ME model than the naïve model and the standard error is 67% larger in the ME model. Finally, the "fixed" effect of the difference between males and females is not significant in either model, and the ME model has a 9% lower estimate than the naïve model, with very little difference in the standard errors. While not plotted, the marginals for the age pattern of mortality are very consistent across the two models, in both the point estimates and the errors in the parameter estimates. Overall, the results from the models including measurement error show higher variation in the parameter estimates, larger effect sizes and a tendency towards bias in the naïve model estimates, which agrees with the measurement error model literature.

**<Tract level analysis still in progress>**

## Discussion

Results from the analysis presented here show two main effects. First, when using ACS data as point estimates only, the naïve model underestimates the standard errors of the regression parameters, leading to significant effects for some predictors considered in these models. This confirms what is suggested in the measurement error model literature, where the standard errors and ultimately point-estimate based hypothesis tests for the regression effects are biased in such models. This presents a dangerous situation, as inference from these models would be incorrect. The third result indicates that the model including measurement error properly produces consistent effects for the covariates in the model, while directly incorporating measurement error as recommended by the statistical literature on the subject. In this analysis, the results from the naïve model, in terms of the significance of the model effects is preserved in the measurement error model for all but one parameter (% insured), even though the measurement error model produced larger standard errors for all parameters.

In conclusion, based on this analysis, we would recommend that those using the ACS point estimates in a regression model setting seriously consider incorporating measurement error into their analysis, because the estimates of the parameters tend to be downwardly biased and the standard errors of the estimates too small, which could conflate point-estimate based hypothesis tests.

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