Modeling Health Insurance Coverage Estimates for Minnesota Counties

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Abstract
The percent of people without health insurance in a county provides important information for policymakers. The Minnesota Health Access Survey (MNHA) provides rich detail but its survey design does not attempt to create estimates at the county level. To provide consistent results with that survey, we estimate uninsurance using a Bayesian small area estimation (SAE) technique implementing a CAR model with auxiliary demographic and administrative data. Those results are fed into a Bayesian simultaneous equation model (SEM) which includes estimates, and uncertainty measures, from other sources, including the American Community Survey (ACS) and the Small Area Health Insurance Estimates (SAHIE) program. We develop and test the model on the 2009 MNHA data with plans to implement with the 2011 data.

Key Words: Health insurance coverage, small area estimation, simultaneous equation model, MNHA, county estimates

1. Introduction

The Minnesota Department of Health's (MDH) Health Economics Program contracted with the University of Minnesota's State Health Access Data Assistance Center (SHADAC) to develop and test methods for conducting a small area analysis of county level uninsurance rates. The state conducts a survey of Minnesota households every two years which includes detailed information about health insurance and access to insurance and health services. The Minnesota Health Access Survey (MNHA) provides state and regional estimates, including estimates for select populous counties and cities in Minnesota, but does not have a large enough sample to provide estimates for all counties.

This study uses additional sources of uninsurance estimates and auxiliary data sources as covariates to create composite county level uninsurance estimates for the entire state population using a Bayesian Hierarchical model. While many organizations, including the U.S. Census Bureau, in its Small Area Health Insurance Estimates (SAHIE) program, and several states have conducted similar analyses, this is the first to combine multiple sources of the outcome (uninsurance) in the model. The goal of the project is to develop a modeling framework that can be used to produce and publish county uninsurance estimates from the 2009 MNHA survey and subsequent MNHA surveys.

The Background section provides information from previous work on small area estimation and modeling approaches and the Overview section provides the framework for our modeling strategy. The Data section describes the data sources used in our models and the Methods section provides details about the model. We conclude with the Results section.

2. Background

Small area estimation (SAE) involves the production of estimates for geographic levels or subgroups, referred to as domains, that standard survey methods could not provide due to sample size or sampling strategy constraints. There is a rich set of tools available for producing these estimates (Rao, 2003) that typically fall into Bayesian and frequentist paradigms. The benefits of Bayesian approaches for policy decisions are summarized nicely by Gomez-Rubio et al. (2008). They note Bayesian models are particularly well suited to address problems common with small area estimation including: missing data, spatially correlated outcomes and variances, and the ability to make inference without asymptotic assumptions.

Within Bayesian methods, the two types of models used for SAE include area-level and unit-level models. Area-level models use information at the county level such as unemployment rate to predict the county uninsurance rate. Unit-level models use the characteristics of respondents in a survey such as employment status to predict the uninsurance rate. Gomez-Rubio et al. (2008) also discuss the performance of these models and their variants. According to simulations on their data, area-level and unit-level models performed similarly with slightly less bias in area-level models and slightly smaller errors in unit-level models. One major advance in SAE is the inclusion of spatially correlated errors in a conditional autoregressive (CAR) model which allow the geographic area prediction to be, in part, similar to its neighbors. Gomez-Rubio et al. (2008) show that accounting for spatial correlation decreases the error in models, particularly when direct estimates are weak.

The Census Bureau produces uninsurance estimates in its SAHIE program (Bauder and Luery, 2010). These estimates use an area-level hierarchical Bayesian model of uninsurance rates by predicting a 3-year average of Current Population Survey Annual Social and Economic Supplement (CPS ASEC) uninsurance estimates with county level covariates from administrative records and Census 2000. The SAHIE model and covariates are described further in the Data section. Small area estimates of sub-state outcomes have also been undertaken by several other states including California, Florida, and North Carolina. Most of these models use a methodology similar to the Census Bureau's SAHIE model.

The methodology for the 2009 Minnesota county uninsurance estimates uses a framework similar to the Census Bureau's SAHIE program, previous approaches by California, Florida and North Carolina, and also builds on previous work done by SHADAC for Oklahoma (SHADAC, 2009). We expand the framework to include multiple outcome estimates and spatially correlated errors.

3. Overview

The small area model developed for this study implemented existing methodologies and a robust framework for incorporating multiple sources of uninsurance estimates. We use data from the following sources:

- Minnesota Health Access Survey (MNHA)
- U.S. Census Bureau's American Community Survey (ACS)

- U.S. Census Bureau's Small Area Health Insurance Estimates Program (SAHIE)
- Additional data sources including administrative records

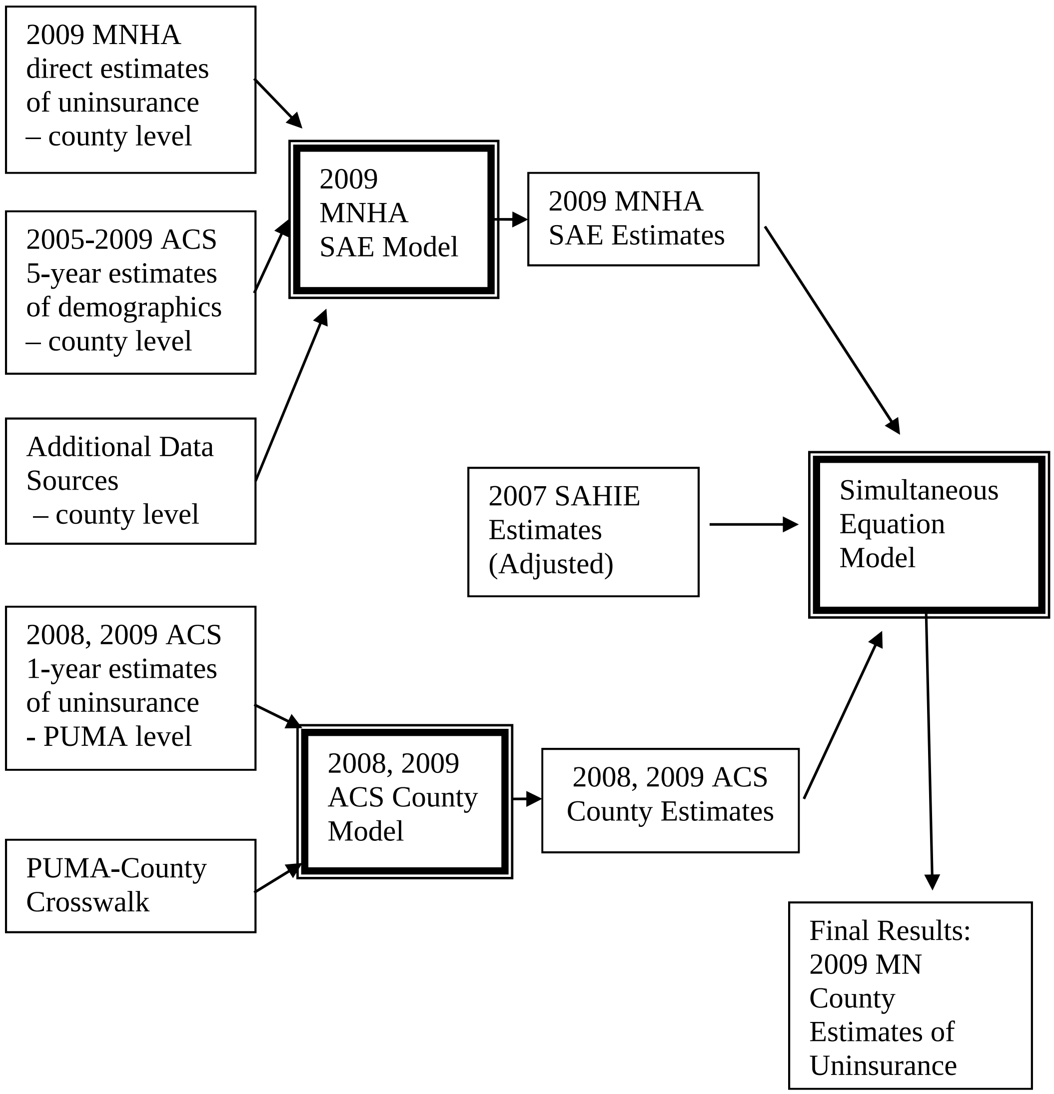
Figure 1 shows a conceptual overview of the small area methodology; a brief description of the methodology follows. Details of the data and each model step are provided in the Data and Methods sections.

- Step 1: 2009 MNHA SAE Model
    - Model: MNHA direct estimates of county level uninsurance = county level demographic estimates from the 5-year ACS + county level additional data sources + error
- Step 2: 2008, 2009 ACS County Model
    - ACS Public Use Microdata Area (PUMA) estimates of uninsurance cross-walked to counties for 2008 and 2009 to create 2008 and 2009 ACS county estimates of uninsurance
- Step 3: Simultaneous Equation Model (SEM) to combine the 2009 MNHA SAE Estimates (Step 1) with the 2008 and 2009 ACS County Estimates (Step 2) and 2007 SAHIE estimates (adjusted) to get 2009 estimates of uninsurance for all Minnesota counties.

A Simultaneous Equation Model (SEM) framework represents the core of the small area methodology we employed. The model's use of a Bayesian Hierarchical methodology allows the incorporation of multiple estimates of the outcome measure, uninsurance, weighted by their relative standard errors. The predictions from the model take into account the accuracy of an input source by weighting the prediction by the inverse of the estimate's standard error. A larger standard error equates to a lower weight. With comparable estimates from multiple sources, the predictions exhibit "shrinkage" whereby the resulting prediction is the weighted average of each of the input estimates. The model is run using OpenBUGS software with the posterior, or prediction, generated with the Gibbs sampler.[1]

[1] OpenBUGS is a software package for performing Bayesian modeling. It is freeware available at http://www.openbugs.info/w/FrontPage. The Gibbs sampler is a type of Markov Chain Monte Carlo (MCMC) algorithm used for Bayesian analysis (Gilks et al. 1996). These algorithms are fed into the model to create the distribution of parameter values reported.

Figure 1: Overview of Small Area Methodology



4. Data

4.1 Minnesota Health Access Survey (MNHA)

The Minnesota Health Access Survey (MNHA) is a large-scale telephone survey designed to study trends in health insurance coverage at the state and economic development region (EDR) levels. Conducted every two years, this is a rich dataset with important measures of family and individual access to health insurance and care. The survey primarily collects data on one randomly selected member of the household, but certain information, such as health insurance coverage and race/ethnicity is collected for all members of the household and employment characteristics and education is collected for all adult members of the household. This analysis makes use of direct estimates from the complete file of all household members (for 2009, n=31,802). The reason why the complete file is used here is that after statistically adjusting for the correlation of data within households the larger sample sizes for counties ensures that the estimates will be made with greater precision. We use 2009 MNHA direct estimates of uninsurance at the county level in step 1 of our models.

4.2 American Community Survey (ACS)

The American Community Survey (ACS), conducted by the Census Bureau, is an ongoing general household survey of the entire population (including persons living in group quarters). It is primarily a mail survey with telephone and in-person interviews used for non-response follow-up. The ACS samples about three million addresses annually, with about two million interviews completed. This survey provides annual estimates of economic, social, demographic, and housing information for the nation, states, and sub-state geographies. The ACS releases 1-year estimates for areas with populations of 65,000 or more, 3-year estimates for areas with populations of 20,000 or more, and 5-year estimates for all legal and administrative entities including census tracts and blocks.

A question on health insurance coverage was added in 2008, so currently only 1-year estimates are available. In fall 2011, 3-year estimates of health insurance coverage will be available and 5-year estimates in 2013.

The ACS data is released as summary tabulations, with margins of error, through the Census Bureau's American FactFinder (AFF).[2] For all three releases (1-year, 3-year, and 5-year) a subset of the full file is available as public use microdata. The lowest level of geography available in these files is the Public Use Microdata Area (PUMA), representing about 100,000 people. PUMAs may be aggregations of counties/county pieces or subsets of counties.

In order to get information for all counties, we use pooled ACS 5-year (2005-2009) demographic estimates from AFF in step 1 of our model. As mentioned, currently only 1-year estimates of health insurance coverage are available so we do not have this information for all counties. We use 2008 and 2009 ACS PUMA estimates of uninsurance from AFF in step 2 of our model. These estimates are restricted to the civilian non-institutionalized population. Due to the increased precision of the ACS estimates, two years of ACS data are used in the model.

4.3 Small Area Health Insurance Estimates (SAHIE)

The Census Bureau's Small Area Health Insurance Estimates (SAHIE) program produces model-based estimates of health insurance coverage for states and all counties. Currently, the SAHIE program is the only source of health insurance coverage data for all counties in the United States. The ACS will publish estimates of health insurance coverage for all counties when 5-year estimates are available in 2013. From the SAHIE program, state estimates are available by age, sex, race and Hispanic origin, and income categories. County estimates are available by age, sex, and income categories. For more information on research conducted during the development of the SAHIE program see Fisher and Campbell, 2002; Fisher and Turner, 2003; Fisher and Turner, 2004; and O'Hara et al., 2006.

The SAHIE program uses area-level statistical models that combine survey data with administrative records and Census 2000 data. The SAHIE program models use health insurance coverage estimates from the CPS ASEC, demographic population estimates from the Census Bureau's Population Estimates Program, County Business Patterns data, federal tax returns, Supplemental Nutrition Assistance Program (SNAP) participation,

[2] Available at http://factfinder.census.gov.

Medicaid and Children's Health Insurance Program participation, and Census 2000 data. The most current year of available estimates is 2007. The SAHIE program plans to use the ACS instead of the CPS ASEC in future models and plans to release estimates for 2008 and 2009 in fall 2011.

The SAHIE estimates are only available for the under 65 population. To incorporate this data source into our SEM model for all ages (step 3), these estimates were modified using the proportion of the county population over age 65 from the ACS 5-year file and their statewide uninsurance rate from the 2008 (calendar year 2007) CPS ASEC. Equation (1) was used to approximate the uninsurance rate from the SAHIE for the whole population.

$$Unin_{All}^{SAHIE} = Unin_{under65}^{SAHIE} - Prop65over^{ACS5year} * Unin_{under65}^{SAHIE} + Prop65over^{ACS5year} * Unin_{65over}^{CPS} \quad (1)$$

4.4 Additional Data Sources including Administrative Records

The MDH explored the availability of various other state specific data sources and assessed their possible relevance. The study team was interested in current data that was available at the county level for all Minnesota counties. The MDH provided SHADAC with a data file containing many variables that might aid in estimating health insurance coverage in step 1 of our model.

5. Methods

5.1 MNHA SAE Model (Step 1)

To create model-based estimates that make use of direct estimates of the uninsurance rate, we constructed an area-level spatial conditional autoregressive (CAR) model. The area-level model fits the survey's direct estimate of the uninsurance rate with covariates from other sources with larger sample sizes to provide a more reliable prediction of the uninsurance in each county. The spatial correlation allows for borrowing of strength by using an average uninsurance rate of adjacent counties, for each county, to increase the precision of the predicted county estimates.[3] The Hierarchical Bayes methodology provides posterior, or predicted, estimates and variances of the multivariate Fay-Herriot model (1979) with spatially correlated errors as described by Rao (2003). The performance of area-level models has been tested in several simulations (Gomez-Rubio et al. 2008) and provides distinct improvements over using direct estimates. Alternative models using individual data, discussed above as unit-level models, have some advantages but are less feasible given the size of the MNHA survey. Next, these predicted probabilities were averaged over all the people in the county in the survey to generate the uninsurance estimates.

Covariates for the small area model come from the pooled ACS 5-year data and additional data sources including administrative records. While there are hundreds of variables available from the ACS 5-year file, the majority are provided only as counts with their margin of error in counts. The small area model is based on proportions and therefore these variables require significant data manipulation to be converted into percentages and standard errors. Fortunately, the Census Bureau produces approximately

[3] While none of the counties in the MNHA had direct estimates of 0 percent, 19 counties had less than 5 observed uninsured observations.

50 variables in their Geographic Comparison Tables that have been converted into the correct metric.

Model selection was conducted in two steps. First variables pre-selected from the ACS 5-year geographic comparison table and other sources that were plausibly linked to uninsurance were compiled. Next, a stepwise regression with a 10 percent removal significance threshold was performed using Stata 11. We start with all relevant variables and use backward elimination (removing one variable at a time). This procedure only keeps variables that have coefficients significantly different from zero at the 10 percent level.

Below is the list of variables predicting the direct estimate of uninsurance in the MNHA survey:

- Percent moved into state, 2005-2009; ACS 5-year
- Percent White, 2005-2009; ACS 5-year
- Percent households (HHLDS) 65 and over, 2005-2009; ACS 5-year
- Percent of population growth over 2000-2009 due to immigrants from outside county; Atlas of Rural and Small-Town America
- Percent land in farms, 2007; Atlas of Rural and Small-Town America
- Percent employed working in retail, 2009; Department of Employment and Economic Development (DEED)
- Average unemployment rate, 2009; Department of Employment and Economic Development (DEED)
- Weekly wage, 2009; Department of Employment and Economic Development (DEED)

As shown in equation (2) the direct estimate uninsurance rates ($y_c^{MNHA-direct}$) is assumed to come from a normal distribution (N) with mean ($\overline{y_c}$) and variance of the inverse of the precision (τ). In equation (3) the mean is modeled as a linear function of a constant (α), the covariates (X) listed above and a CAR specification for the error term (v_c) specified in equation (4) as described in Besag et al. (1991). The error term for any county (c), conditional on other county error terms (-c) and the variance of the error term (σ_v^2), comes from a normal distribution (N) with mean equal to average error of adjacent counties (δ_c) and variance equal to the variance of the error term of adjacent counties ($\frac{\sigma_v^2}{|\delta_c|}$) defined as the inverse of the precision (v_c). County adjacency matrices used in this specification were created using the internal mapping capabilities of GeoBUGS.[4]

$$y_c^{MNHA-direct} \sim N\left(\overline{y_c}, \frac{1}{\tau}\right) \tag{2}$$

$$\overline{y_c} = \alpha + \beta X + v_c \tag{3}$$

[4] GeoBUGS is an add-on to OpenBUGS to fit spatial models and to produce maps. More information is available at http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/geobugs.shtml.

$$v_c | v_{-c}, \sigma_v^2 \sim N\left(\sum_{j\in\delta_c} \frac{v_j}{|\delta_c|}, \frac{\sigma_v^2}{|\delta_c|}\right) \quad (4)$$

The model was run in OpenBUGS with 5,000 iterations of burn-in and 10,000 production cycles. The burn-in period is the amount of time dedicated for the algorithm to converge on a range of values. Once this is established through examination of the convergence plots a production cycle is chosen that produces relatively smooth parameter densities. The Deviance Information Criteria (DIC) was 541.9 and the effective number of parameters (Pd) was 7.78. The DIC is a tool for Bayesian model selection. A smaller DIC equals a better fitting model. The actual value of the DIC is not instructive, but the increase or decrease is used to select between multiple models and structures. The effective number of parameters is analogous to the degrees of freedom in a frequentist model. Due to the shrinkage factors used in Bayesian methods, the effective number of parameters can be less than the declared number of parameters. Listed in Table 1 are the priors and posterior medians of the model parameters.

Table 1: MNHA SAE Model Parameter Priors and Posterior Medians

Parameters	Prior	Median	SE
Percent Moved into State, 2005-2009	$N(0, 1/1 \times 10^6)$	1.501	0.6422
Percent White, 2005-2009	$N(0, 1/1 \times 10^6)$	-0.3024	0.1143
Percent HHLDS 65 and Over, 2005-2009	$N(0, 1/1 \times 10^6)$	0.2638	0.1089
Percent of Population Growth, 2000-2009	$N(0, 1/1 \times 10^6)$	-2.643	0.9837
Percent Land in Farms, 2007	$N(0, 1/1 \times 10^6)$	0.05293	0.02414
Percent Employed Working in Retail, 2009	$N(0, 1/1 \times 10^6)$	0.5771	0.244
Average Unemployment Rate, 2009	$N(0, 1/1 \times 10^6)$	2.102	0.3965
Weekly Wage, 2009	$N(0, 1/1 \times 10^6)$	0.02775	0.007752
Constant	$N(0, 1/1 \times 10^6)$	-16.63	13.36
Precision v	$\Gamma(0.001,0.001)$	2.262	94.55
Precision τ	$\Gamma(0.001,0.001)$	0.03686	0.006257
DIC		541.9	
Pd		7.788	

SE: Standard Error

5.2 ACS County Model (Step 2)

We use ACS PUMA level uninsurance estimates to approximate county level estimates. There are 37 PUMAs in Minnesota. The principle reason the ACS estimates are used despite being at the PUMA and not county level is because the sample size of the ACS allows for much greater precision than possible from the MNHA. For 2009, the ACS full file available from AFF has an unweighted sample count of 126,686 observations in Minnesota while the MNHA has 31,802 in the file of all household members.

Due to differences in the geographic alignment of counties and PUMAs, the model for creating county level uninsurance estimates from the PUMA data uses the following two approaches. First, in the 12 counties where the Census Bureau releases a county estimate, the estimate and its standard error were used. Second, for the 75 counties within a PUMA, the counties were assigned given an adjusted estimate from the encompassing PUMA.

The estimate from the PUMA was adjusted by first modeling the impact of PUMA level poverty on PUMA level uninsurance as shown in equation (5). Then, the difference between the county level poverty and the PUMA level poverty were calculated in equation (6). Next, in equation (7) the uninsurance rate for the county was calculated by multiplying the coefficient on the poverty rate times the difference and adding to the PUMA estimate of uninsurance.

$$Unin_c^{puma} = \beta_0 + \beta_1 Pov_c^{puma}; c = 1,2,\ldots,87 \tag{5}$$

$$Pov\_diff_c^{puma} = Pov_c^{County} - Pov_c^{puma} \tag{6}$$

$$unin_c^{county} = Unin_c^{puma} + \beta_1 Pov\_diff_c^{puma} \tag{7}$$

Because the standard error is not yet available at the county level in the 5-year ACS estimates, it was approximated using the ratio of the county's poverty rate standard error to the corresponding PUMA's poverty rate standard errors shown in equation (8). The poverty rate was used as a proxy due to its similar scale (15 percent of population) and overall correlation with uninsurance.

$$unin\_se_c^{county} = unin\_se_c^{puma} \sqrt{\left(\frac{pov\_se_c^{county}}{pov\_se_c^{puma}}\right)} \tag{8}$$

The adjusted uninsurance estimate and standard error were used in the SEM model that follows.

5.3 Simultaneous Equation Model (SEM) (Step 3)

The SEM model takes posterior estimates from the MNHA SAE model and combines with the ACS county models and the existing SAHIE county level estimates (adjusted). The models were fit using the free downloadable OpenBUGS software. The following model was used to create the county estimates. Input data from the four surveys (s) for each county (c) is assumed to be normally distributed around an unknown mean (u_{sc}). The precision of the mean (τ_{sc}^{u}) is assumed to have a multiplicative structure of a survey specific precision term (τ_s) times the county-survey precision term (τ_{sc}^{τ}). The precision (τ_{sc}^{τ}) for each survey and county is defined as the inverse of the variance of the county survey estimate (σ_{sc}^2).

$$y_{sc} \sim N(u_{sc}, \tau_{sc}^{u}); c = 1,2,\ldots,87; s = MNHA\_SAE\_2009, ACS\_2009, ACS\_2008, SAHIE\_2007 \tag{9}$$

$$\tau_{sc}^{u} = \tau_s * \tau_{sc}^{\tau} \quad (10)$$

$$\tau_{sc}^{\tau} = \frac{1}{\sigma_{sc}^2} \quad (11)$$

Each equation is fitted below with a survey specific term α_{1-4} and a county specific term β_c. The resulting predictions are created by averaging the survey effects.

$$u_c^{MNHA\_SAE\_2009} = \alpha_1 + \beta_c County_c \quad (12)$$

$$u_c^{ACS\_2009} = \alpha_2 + \beta_c County_c \quad (13)$$

$$u_c^{ACS\_2008} = \alpha_3 + \beta_c County_c \quad (14)$$

$$u_c^{SAHIE\_2007} = \alpha_4 + \beta_c County_c \quad (15)$$

The outcomes were predicted as:

$$y_c^{SEM} = (\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4)/4 + \beta_c County_c \quad (16)$$

The model included a single Markov Chain Monte Carlo (MCMC) chain with a 20,000 iteration production period after 1,000 burn-in iterations. The priors for each of the parameters are listed in Table 2. The priors represent any previous knowledge about the outcome. For this application, uninformative priors were used so as to let the data determine the results.

Table 2: SEM Model Parameter Priors and Posterior Medians

Parameters	Prior	Median	SE
$\alpha_{MNHA\_SAE\_2009}$	$N(0, 1/1 \times 10^6)$	36.92	9.968
α_{ACS_2009}	$N(0, 1/1 \times 10^6)$	36.2	9.962
α_{ACS_2008}	$N(0, 1/1 \times 10^6)$	35.75	9.965
α_{SAHIE_2007}	$N(0, 1/1 \times 10^6)$	36.35	9.966
β_{1-87}	$N(0, 1/1 \times 10^6)$	-30.9--22.55	9.965-10.02
$\tau_{MNHA\_SAE\_2009}$	$\Gamma(0.001, 0.001)$	0.2394	0.03831
τ_{ACS_2009}	$\Gamma(0.001, 0.001)$	3.152	146.7
τ_{ACS_2008}	$\Gamma(0.001, 0.001)$	0.5801	0.112
τ_{SAHIE_2007}	$\Gamma(0.001, 0.001)$	0.8728	0.1777
DIC		1449	
Pd		71.24	

SE: Standard Error

6. Results

County uninsurance rates are provided in Figure 2 to demonstrate geographic patterns. The estimates and standard errors are provided in Table 3. For comparison purposes the estimates along with the results from each of the components to the SEM model are also provided in Table 3. There is quite a bit of variation with each of the components which is smoothed out when combined in the SEM model.

In general, the average county uninsurance rate (over county estimates, not population) for the MNHA is 9.9%, the 2008 ACS is 9.2%, the 2009 ACS is 9.2%, and the 2007 SAHIE is 9.3%. These compare closely with the 9.2% predicted from the SEM model. The variance of the estimates between counties for the SEM model (2.1) is greater than the 2008 ACS (1.8) but less than the MNHA SAE (17.0), the 2009 ACS (6.4) and the 2007 SAHIE (2.4).

Some of the extreme input estimates from the MNHA SAE model are moderated. One example is the very high predicted uninsurance rate of 22.4% in Faribault County from the MNHA SAE model that becomes 10.1% after considering the much lower rates in the 2008 and 2009 ACS (9.5 and 8.6% respectively) and the 9.2% from the 2007 SAHIE. Alternatively, the particularly low uninsurance rate (1.8%) for Cook county from the MNHA SAE becomes 8.9% after the model considers the 9.3% and 12.3% and 14.7% in the 2008 and 2009 ACS and 2007 SAHIE.

A common statistic to use as a threshold for releasing small area results is the coefficient of variation (CV) or the ratio of the standard deviation to the estimate value.

$$CV = \frac{SD}{EST}$$

Each county had a CV of less than 30 percent, which meets the Census Bureau and National Center for Health Statistic (NCHS) criterion for releasing data.[5] Figure 3 shows the CVs for each county.

[5] See the Census Bureau's Statistical Quality Standard F1: Releasing Information Products available at: http://www.census.gov/quality/standards/standardf1.html and discussion of the coefficient of variation in the "Health People 2010 Criteria for Data Suppression" NCHS document available at: http://www.cdc.gov/nchs/data/statnt/statnt24.pdf

Figure 2: Modeled Minnesota County Uninsurance Rate Estimates for 2009

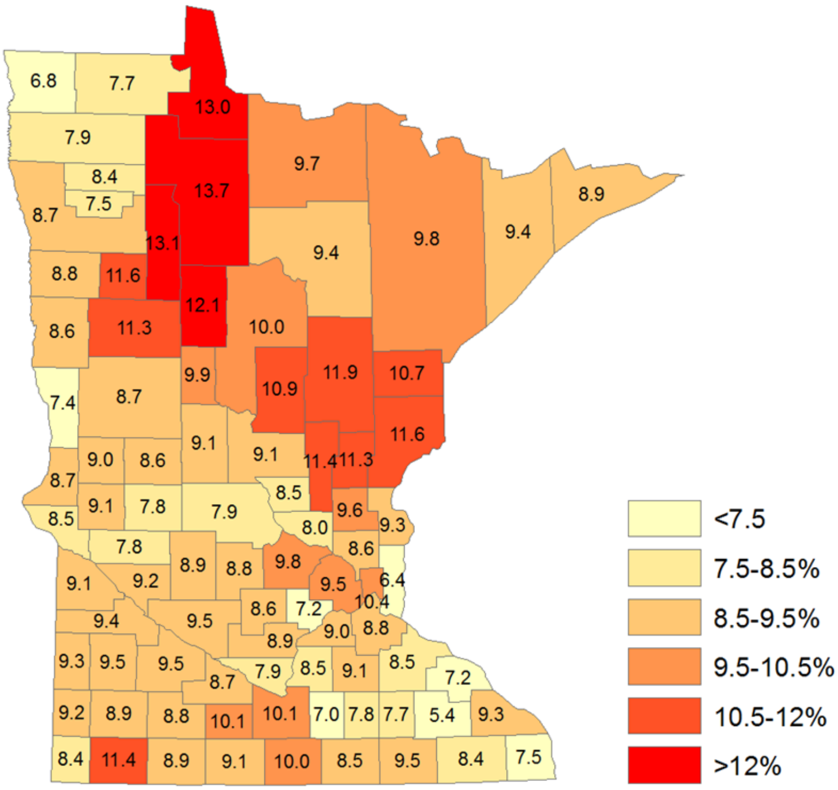


Figure 3: Coefficient of Variation by Minnesota County

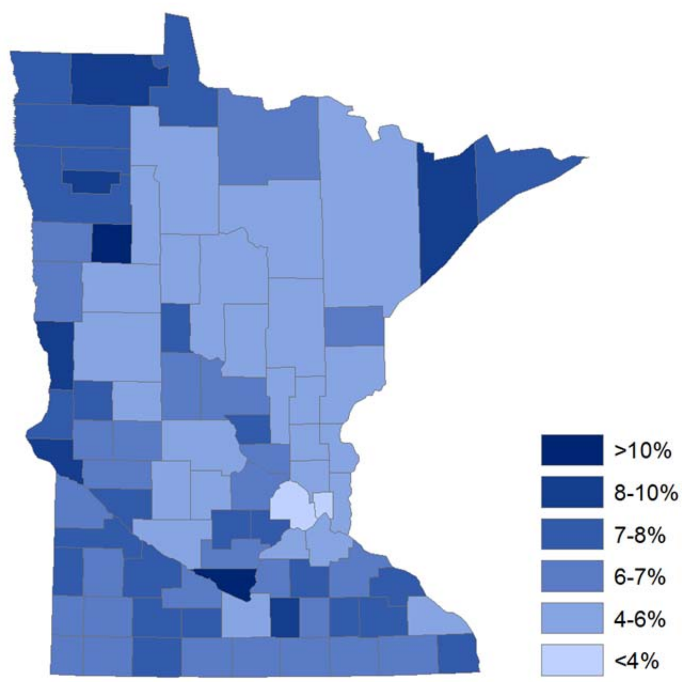


Table 3: Comparison of Modeled Minnesota County Uninsurance Estimates with Inputs to the SEM

	Final SEM Results		**2009 MNHA (SAE)**		**2009 ACS (County)**		**2008 ACS (County)**		**2007 SAHIE (Adjusted)**	
County	**Rate**	**SE**	**Rate**	**SE**	**Rate**	**SE**	**Rate**	**SE**	**Rate**	**SE**
Aitkin	11.9	0.6	14.1	2.0	11.9	1.3	11.6	1.3	10.6	2.3
Anoka	8.6	0.4	10.1	1.7	**8.5**	0.7	**8.8**	0.7	6.7	1.0
Becker	11.3	0.5	13.9	1.4	11.3	1.1	14.5	1.7	8.9	1.8
Beltrami	13.7	0.7	17.4	2.6	13.5	1.4	18.2	2.2	10.9	2.1
Benton	8.5	0.6	6.0	1.7	8.5	1.3	8.0	1.3	8.6	1.6
Big Stone	8.5	0.7	4.7	1.7	8.4	1.5	8.2	1.8	9.8	2.0
Blue Earth	10.1	0.6	8.2	1.6	10.6	1.2	7.1	0.9	11.5	1.9
Brown	8.7	0.6	10.0	1.1	9.0	1.3	8.4	1.0	7.0	1.4
Carlton	10.7	0.7	8.5	1.6	11.1	1.3	10.4	1.3	8.3	1.7
Carver	7.2	0.5	7.9	1.6	**7.2**	1.0	**5.8**	1.5	6.9	1.2
Cass	10.0	0.5	9.8	1.9	9.7	1.0	12.8	1.7	11.3	2.3
Chippewa	9.2	0.7	11.2	1.3	9.3	1.8	8.8	1.4	8.6	1.7
Chisago	9.3	0.5	10.8	1.5	9.2	1.0	9.1	1.2	8.4	1.4
Clay	8.6	0.6	8.8	2.4	8.5	1.1	8.5	1.1	8.5	1.5
Clearwater	13.1	0.7	21.5	2.6	12.7	1.3	16.9	2.1	12.0	2.0
Cook	8.9	0.7	1.8	2.5	8.5	1.2	10.9	2.2	14.7	2.7
Cottonwood	8.8	0.6	6.4	1.4	9.0	1.4	7.7	1.5	8.6	1.7
Crow Wing	10.9	0.5	12.6	1.6	11.0	1.1	10.2	1.1	8.7	1.7
Dakota	8.8	0.5	11.7	1.8	**9.2**	0.8	**6.6**	0.6	7.8	1.1
Dodge	7.7	0.6	5.6	1.5	7.6	1.1	7.3	1.4	8.9	1.5
Douglas	8.6	0.5	7.5	1.8	8.4	1.0	9.2	1.2	8.8	1.7
Faribault	10.1	0.7	22.4	2.9	9.9	1.3	9.2	1.4	9.2	1.9
Fillmore	8.4	0.6	7.8	1.5	8.0	1.0	10.2	1.5	10.8	2.0
Freeborn	8.5	0.6	13.8	1.5	8.3	1.1	8.4	1.4	8.9	1.7
Goodhue	8.5	0.6	12.1	1.4	8.4	1.2	8.7	1.2	7.2	1.3
Grant	9.0	0.6	10.9	1.5	8.5	1.3	8.5	1.6	10.9	2.1
Hennepin	9.5	0.2	10.8	2.9	**9.4**	0.4	**9.5**	0.4	8.5	0.9
Houston	7.5	0.6	10.0	2.1	7.2	1.1	9.0	1.7	7.9	1.5
Hubbard	12.1	0.6	17.8	2.1	11.9	1.2	15.5	1.9	10.3	1.7
Isanti	9.6	0.5	12.3	1.5	9.5	1.1	9.6	1.4	8.8	1.5
Itasca	9.4	0.5	13.6	1.6	9.2	0.8	12.0	1.5	8.7	1.8
Jackson	8.9	0.7	2.6	1.9	9.1	1.3	7.9	1.5	8.6	1.7
Kanabec	11.3	0.6	18.9	2.0	11.4	1.3	10.8	1.3	8.1	1.6
Kandiyohi	8.9	0.5	6.2	1.4	9.0	1.0	7.3	1.1	9.4	1.7
Kittson	6.8	0.5	9.7	1.7	6.6	1.1	5.4	1.0	9.6	2.0
Koochiching	9.7	0.7	11.8	1.9	9.5	1.3	12.6	2.3	8.6	1.8
Lac qui Parle	9.1	0.6	4.1	1.4	9.1	1.5	8.5	1.2	10.6	2.0
Lake	9.4	0.8	9.2	2.3	9.3	1.6	12.3	2.8	8.5	1.7
Lake of the Woods	13.0	0.9	4.7	2.0	13.3	2.0	17.8	3.2	12.7	2.4
Le Sueur	8.5	0.6	13.2	1.7	8.2	1.2	8.4	1.2	8.7	1.5
Lincoln	9.3	0.7	6.9	1.7	9.1	1.6	8.5	1.3	11.3	2.1
Lyon	9.5	0.7	5.3	2.0	9.5	1.4	9.2	1.1	9.7	1.7
Martin	8.6	0.6	16.6	1.6	8.5	1.3	6.6	1.4	8.6	1.6
McLeod	11.6	1.2	11.0	1.2	14.0	1.9	19.0	3.0	7.5	1.5

See footnotes at end of table.

Table 3: Comparison of Modeled Minnesota County Uninsurance Estimates with Inputs to the SEM – Continued

	Final SEM Results		2009 MNHA (SAE)		2009 ACS (County)		2008 ACS (County)		2007 SAHIE (Adjusted)	
County	**Rate**	**SE**	**Rate**	**SE**	**Rate**	**SE**	**Rate**	**SE**	**Rate**	**SE**
Mahnomen	7.9	0.6	17.3	4.0	7.8	1.1	7.4	1.1	9.1	2.0
Marshall	9.1	0.6	9.2	1.4	8.7	1.2	7.1	1.3	12.0	2.2
Meeker	8.8	0.5	11.6	1.3	8.8	1.0	7.1	1.0	8.4	1.6
Mille Lacs	11.4	0.6	14.9	1.8	11.4	1.1	10.8	1.2	9.3	1.9
Morrison	9.1	0.6	13.6	1.5	8.8	1.1	9.9	1.4	8.9	1.7
Mower	9.5	0.6	7.7	1.6	9.5	1.2	10.5	1.5	8.4	1.6
Murray	8.9	0.6	3.8	1.6	8.7	1.3	7.2	1.4	11.9	2.1
Nicollet	7.9	0.9	1.8	1.8	9.1	1.6	4.6	1.2	7.4	1.3
Nobles	11.4	0.8	4.5	2.6	11.3	1.6	11.5	1.7	12.5	2.0
Norman	8.8	0.6	10.3	1.6	8.5	1.2	8.6	1.2	9.8	2.0
Olmsted	5.4	0.4	6.3	2.4	**5.1**	0.7	**5.9**	0.8	7.0	1.2
Otter Tail	8.7	0.5	9.1	1.3	8.5	1.0	8.4	1.2	10.1	1.7
Pennington	8.4	0.6	11.6	1.3	8.1	1.4	8.0	1.4	8.5	1.7
Pine	11.7	0.6	13.5	1.6	11.8	1.2	11.5	1.2	9.0	1.7
Pipestone	9.2	0.6	10.1	1.6	9.3	1.2	8.2	1.4	8.6	1.7
Polk	8.7	0.6	9.4	1.9	8.6	1.3	8.7	1.3	8.6	1.7
Pope	7.8	0.5	5.4	1.4	7.6	1.0	6.9	1.2	10.1	1.9
Ramsey	10.4	0.3	11.0	2.7	**10.5**	0.7	**9.5**	0.5	8.8	1.1
Red Lake	7.5	0.7	7.9	1.9	7.1	1.3	6.2	1.3	12.0	2.2
Redwood	9.5	0.7	7.7	1.5	9.6	1.7	9.2	1.3	9.3	1.8
Renville	9.5	0.5	10.1	1.4	9.3	1.2	7.9	1.2	11.0	2.0
Rice	9.1	0.7	12.0	1.8	8.8	1.4	9.3	1.4	9.7	1.7
Rock	8.4	0.6	4.2	1.7	8.5	1.2	6.9	1.3	8.9	1.7
Roseau	7.7	0.6	4.7	1.7	7.6	1.3	7.1	1.3	9.1	1.6
Sibley	9.8	0.5	4.8	1.8	**10.1**	0.8	**6.2**	1.0	12.0	2.0
St. Louis	9.0	0.5	12.5	1.7	**8.9**	1.0	**9.4**	1.3	7.8	1.3
Scott	8.0	0.5	6.0	1.8	**7.6**	1.0	**9.4**	0.9	7.5	1.2
Sherburne	8.9	0.6	9.2	1.7	9.0	1.2	7.4	1.2	7.7	1.4
Stearns	7.9	0.4	11.3	1.3	**7.7**	0.7	**7.1**	0.7	9.4	1.6
Steele	7.8	0.5	12.8	2.0	7.6	0.9	7.3	1.2	8.2	1.5
Stevens	9.1	0.6	5.4	1.5	9.0	1.4	9.2	1.7	10.7	2.0
Swift	7.8	0.5	9.2	1.4	7.7	1.1	7.1	1.4	8.4	1.7
Todd	9.1	0.6	7.0	1.4	9.0	1.2	10.1	1.4	9.1	1.8
Traverse	8.7	0.7	10.6	1.9	8.3	1.3	8.0	1.6	11.4	2.4
Wabasha	7.2	0.5	6.2	1.5	6.9	1.0	8.5	1.6	8.7	1.6
Wadena	9.9	0.7	15.6	1.5	9.8	1.5	11.5	1.8	7.6	1.5
Waseca	7.0	0.7	12.8	1.6	7.7	1.3	2.3	1.0	7.9	1.5
Washington	6.4	0.4	9.3	2.0	**6.7**	0.7	**4.8**	0.5	7.2	1.1
Watonwan	10.1	0.8	8.9	2.5	9.9	1.5	9.2	1.7	12.7	2.1
Wilkin	7.4	0.6	7.4	2.9	7.3	1.2	6.5	1.5	8.2	1.6
Winona	9.3	0.5	10.4	1.6	9.0	0.9	12.0	1.5	9.5	1.6
Wright	9.8	0.6	11.0	1.9	**9.9**	1.2	**8.6**	1.2	8.2	1.4
Yellow Medicine	9.4	0.7	8.9	1.7	9.5	1.5	9.2	1.2	8.2	1.7

SE: Standard Error. Direct ACS county estimates, from single-year ACS files, indicated in bold.

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