

Multilevel Regression for Small-Area Estimation of Mammography Use in the United States, 2014

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Abstract

Background: The U.S. Preventive Services Task Force recommends biennial screening mammography for average-risk women aged 50–74 years. County-level information on population measures of mammography use can inform targeted intervention to reduce geographic disparities in mammography use. County-level estimates for mammography use nationwide are rarely presented.

Methods: We used data from the 2014 Behavioral Risk Factor Surveillance System (BRFSS; $n = 130,289$ women), linked it to the American Community Survey poverty data, and fitted multilevel logistic regression models with two outcomes: mammography within the past 2 years (up-to-date), and most recent mammography 5 or more years ago or never (rarely/never). We poststratified the data with U.S. Census population counts to run Monte Carlo simulations. We generated county-level estimates nationally and by urban–rural county classifications. County-level prevalence estimates were aggregated into state and national estimates.

We validated internal consistency between our model-based state-specific estimates and urban–rural estimates with BRFSS direct estimates using Spearman correlation coefficients and mean absolute differences.

Results: Correlation coefficients were 0.94 or larger. Mean absolute differences for the two outcomes ranged from 0.79 to 1.03. Although 78.45% (95% confidence interval, 77.95%–78.92%) of women nationally were up-to-date with mammography, more than half of the states had counties with >15% of women rarely/never using a mammogram, many in rural areas.

Conclusions: We provided estimates for all U.S. counties and identified marked variations in mammography use. Many states and counties were far from the 2020 target (81.1%).

Impact: Our results suggest a need for planning and resource allocation on a local level to increase mammography uptake.

Introduction

In 2016, the U.S. Preventive Services Task Force (USPSTF) updated its recommendations on breast cancer screening after concluding that a net benefit to screening exists. The USPSTF recommended screening every 2 years for average-risk women aged 50–74 years (1).

One of the Department of Health and Human Services' Healthy People objectives was to increase the prevalence of breast cancer screening as recommended to 81.1% by 2020 (2). Analysis of data from the National Health Interview Survey in 2015 showed that 71.5% of women aged 50–74 years reported having had a mammogram in the past 2 years, nearly 10% below the Healthy People 2020 target, and this proportion has been stable for 15 years (3). Underlying this national estimate is considerable variability in screening prevalence by race/ethnicity, income, education, and insurance status (3). Furthermore, variability in these character-

istics occurs at finer geographic scales such as the state or county levels.

State-level cancer screening use is often estimated using data from the Behavioral Risk Factor Surveillance System (BRFSS; ref. 4). However, differences in mammography screening estimates among states do not provide information about the variations within individual states. Local communities may also have substantial variations in mammography use because of diversity in social and economic status, healthcare, and cultural characteristics, which can be masked by state-level analysis.

Recent estimates of mammography prevalence for U.S. counties have utilized BRFSS data from 2012 or earlier. These estimates focused only on the distribution of women with recent mammography and have compared prevalence estimates with older USPSTF recommendations that have since been revised (5–7). A publication of state- and county-level mammography prevalence within 2 years among women aged 40 or older by the NCI found that between 2008 and 2010, there were large geographical variations among states (57.5%–81.9%) and counties (30.69%–94.66%; ref. 8).

Data from small-area analysis, such as county-level analysis, can be useful for describing local variations of mammography use and highlight disparity among counties. County-level mammography screening data could inform state and local public health decision makers about public health resource allocation in counties with low mammography uptake by utilizing state programs funding, such as the Centers for Disease Control (CDC) National Breast and Cervical Cancer Early Detection Programs

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(NBCCEDP). Because some survey samples are insufficiently large to yield stable estimates for some areas, small-area estimates can be generated using models that combine county-level data from different sources, such as the U.S. Census. Using census population data for poststratification allows states to generate estimates for all counties including counties for which no direct estimates are available from BRFSS.

The goal of our study is to apply multilevel small-area estimation (SAE) to obtain county-level prevalence estimates of (i) women who had a mammogram within 2 years (defined as up-to-date) according to the USPSTF recommendations; and (ii) women who had their most recent mammogram 5 or more years before the survey interview or never had one (defined as rarely or never).

Examining small-area differences in mammography use among the group of women who rarely or never had a mammogram is of utmost importance because women who are not screened are more likely to have more advanced disease. In a recent systematic review and meta-analysis, the authors concluded that advanced cancer is reduced with screening for women aged 50 years or older (9). A different systematic review and meta-analysis comparing mammographic screening attendance between immigrant and minority women to that of other women indicated a lower attendance among immigrants and minorities, who are more often diagnosed with advanced breast cancer (10). Our estimates of proportions of women up-to-date with mammography or those who never had a mammogram can potentially reduce geographic disparities in mammography use and reduce late-stage diagnosis.

Materials and Methods

We used data from the 2014 BRFSS, a state-based, cross-sectional, random-digit-dial phone survey administered annually by CDC in collaboration with state health departments and the District of Columbia to noninstitutionalized adults aged 18 years or older. In 2014, the survey's combined landline and cell phone response rates ranged from 60.1% in South Dakota to 25.1% in California, with a median rate of 47%. Further information about the survey can be found on the BRFSS website (4).

Women aged 40 years and older were asked "Have you ever had a mammogram?" and those who answered "No" were assigned as never having had a mammogram. Women who answered "Yes" were asked "How long it has been since you had your last mammogram?" We examined 2 outcomes on the basis of responses to a question about time since their last mammogram: being up-to-date with mammography (most recent mammogram <2 years ago); and rarely or never having had a mammogram (most recent mammogram 5 or more years ago, or never). Our analysis included women aged 50–74 years who answered these questions, consistent with the current USPSTF recommendation for breast cancer screening. For women aged 40–49 years, the USPSTF stated the decision to start screening was a personal one, and for those aged 75 years or older, no recommendation was issued (1). Women who did not know, were not sure, or refused to answer, were excluded.

Because the BRFSS questions did not include details on whether the mammogram was for screening or diagnosis, we consider these questions a general measure of mammography use for all purposes.

Statistical analysis

We linked BRFSS individual-level data with county-of-residence from the 2014 BRFSS restricted dataset by adding the state and county information to each record of the BRFSS data ($n = 130,289$ women age 50–74 years, representing 44.1 million women) after excluding missing mammography information ($n = 8,442$). We then linked the combined data to the 5-year (2010–2014) county-level poverty estimates from the American Community Survey (11). Using these data, we fitted multilevel logistic regression models (12) with fixed effects including age group (50–54, 55–59, 60–64, 65–69, and 70–74), race/ethnicity [non-Hispanic (NH) white, NH black, NH American Indian/Alaska Native (AIAN), NH Asian, NH other (Pacific Islander, other one race, and 2 or more races), and Hispanic], county-level poverty ($\leq 150\%$ of the federal poverty rate), and state- and county-level random effects. The results from each model included parameters for each fixed and random effects. Because estimates of random effects were not available for some counties which did not have BRFSS samples for analysis, we used a local spatial smoothing algorithm, namely a smoothed average of the adjacent counties random effects, to approximate the county random effect of each county without BRFSS respondents (12). We then linked the newly created random effects with the county random effects list. We chose to use a flexible spatial smoothing method to avoid over-smoothing health behavior outcome variations in adjacent counties and by BRFSS data, where direct calculations for some counties were limited (13, 14). Also, a county random effect specifies the local contextual influence on health outcomes and likely would be more similar to its adjacent counties. We poststratified the BRFSS data with U.S. Census county population counts (15) and used them with the updated random effects list in newly developed Monte Carlo simulation models. Our models predicted the individual-level expected probability of being up-to-date with mammography use, or rarely or never having had a mammogram, and generated their county-level prevalence estimates and their SEs.

Our regression models followed the generalized linear mixed models general formula (12, 16):

$$P_{ijcs}(y_{ijcs} = 1) = \text{logit}^{-1}(\alpha_i + \beta_j + x'_c\eta + \mu_c + v_s)$$

y_{ijcs} is the self-reported mammography use by an individual in age group i , $i = 1$ to 5, and race/ethnicity group j , $j = 1$ to 6, from county c in state s , and their respective regression coefficients. x_c is a vector of county-level poverty status covariates and η is a vector of their respective regression coefficients. The prediction model included their product $x'_c\eta$. μ_c and v_s are the county- and state-level random effects, which were assumed to be independent and normally distributed.

Each simulation included 1,000 randomly drawn samples for each of the parameters and their SEs. We used the respective simulation results to summarize the estimated proportions for each outcome by county, state, and the entire United States, and generated predicted mean values, their SEs, and 95% confidence intervals (CIs). The prevalence calculations used the county population counts from the census as weights.

In an additional analysis, we linked our poststratified data (with 2,142 counties) with the 2013 National Center for Health Statistics (NCHS) urban–rural area classification scheme for counties (here after urban–rural area; ref. 17) after excluding 5

counties that were not on the list of the 2014 BRFSS counties. The NCHS urban–rural areas file included 4 metropolitan area categories: area 1, counties of Metropolitan Statistical Areas (MSA) of ≥ 1 million (large central metro); area 2, counties with population ≥ 1 million (large fringe metro); area 3, counties within MSAs of 250,000–999,999 population (medium metro); area 4, counties within MSAs of 50,000–249,999 population (small metro), and two nonmetropolitan areas: area 5, counties in Micropolitan Statistical Areas with a city of 1×10^4 or more population; and area 6, noncore counties not within Micropolitan Statistical Areas (without a city of 1×10^4 or more population). Linking the urban–rural area classification scheme to the poststratified BRFSS data enabled us to point out the difference in mammography screening uptake among the six area classifications.

We repeated the simulation process described above for the counties in each urban–rural area to generate overall and county-level estimates. We also linked the BRFSS county-level data with the above urban–rural areas by state and county codes and presented the overall direct estimates of our BRFSS outcomes for each urban–rural area by demographic characteristics in the Supplementary Data section. For this analysis, we collapsed the metropolitan areas to two areas on the basis of population size: (i) areas 1 (large central metro) and area 2 (large fringe metro); and (ii) areas 3 (medium metro) and 4 (small metro). Areas 5 and 6 remained the same.

Because the BRFSS is a state-based survey, we evaluated the internal consistency of our model-based state-specific estimates with BRFSS direct state estimates and the six model-based urban–rural area estimates with the corresponding BRFSS direct urban–rural area estimates, using both Spearman correlation coefficients and the mean absolute differences between the model-based and BRFSS estimates. Further details about our methodology are presented by Berkowitz and colleagues (16).

We fitted the BRFSS multilevel logistic regression models with unweighted data using the SAS GLIMMIX procedure, SAS Version 9.3 (SAS Institute, Inc.). The exclusion of weights was based on two validation studies showing that an unweighted model generated more accurate small-area estimates (18, 19). Poststratification is a weighting process in our modeling approach for small-area estimation. We used ArcGIS (Esri) to separately map the model-based county estimates and their SEs by deciles. We calculated direct BRFSS estimates with SAS-callable SUDAAN (Research Triangle Institute, Research Triangle Park, NC).

Results

Our BRFSS data analysis found 93 counties for which random effects were not available. Over 70% of these counties were in the noncore area classification and their mean and median poverty rates among women aged 50–74 were estimated by the American Community Survey at 30%.

Our poststratification file included data from all 3,142 counties. The national 2014 model-based SAE prevalence estimate for up-to-date with mammography was 78.45%, (95% CI, 77.95%–78.92%), the same as the direct 2014 BRFSS estimate: 78.45%, (95% CI, 78.00%–78.90%). The model-based prevalence estimate for rarely or never had a mammogram was 11.19%, (95% CI, 10.91%–11.45%) while the direct 2014 BRFSS estimate was 11.02% (95% CI, 10.70%–11.36%).

Spearman correlation coefficients between our state-level model-based SAE estimates and the BRFSS direct state estimates were 0.98 for up-to-date with mammography and 0.95 for rarely or never had a mammogram, indicating high state-level internal consistency (Table 1). Spearman correlation coefficients for both outcomes for the urban–rural area analysis were 0.94. The means of the absolute differences between both the model-based state-estimates and the NCHS rural–urban area estimates and the respective BRFSS direct estimates for the two outcomes ranged from 0.79 to 1.03. The differences between the model-based mean and median estimates and the BRFSS direct estimates were $<0.5\%$ (Table 1).

Although the majority of women were up-to-date with mammography in 2014, our findings showed large variations in mammography use among states and counties (Table 2; Fig. 1A). The mean estimate for being up-to-date with mammography use by state ranged from 68.72% in Idaho to 87.17% in Massachusetts. States with the highest proportions of up-to-date mammography ($>80\%$) were mostly in New England, and the northern, eastern, and western United States. The seven states with the highest estimates of being up-to-date with mammography, along with New Hampshire, and District of Columbia, had the lowest proportion of women ($<10\%$) who rarely or never had a mammogram. The largest differences (ranges) in estimates for being up-to-date with mammography use across counties within a state ranged from a low of 1.42% in Delaware to a high of 17.19% in Alaska. Alaska also had the lowest up-to-date county estimate (56.67%). Large differences in county estimates ($>13.5\%$) were also observed in Nebraska, Missouri, Idaho, and Arkansas (Fig. 1A).

Table 1. Correlation coefficients and mean absolute differences between model-based state estimates and NCHS urban–rural area estimates, and BRFSS direct state estimates, by test type

Test	Test estimate	Up-to-date with mammography ^a		Rarely or never had a mammogram ^b		
		Mean (%)	Median (%)	Test estimate	Mean (%)	Median (%)
Spearman correlation coefficient	State estimates ($n = 51$)					
Model-based	0.98	77.66	78.44	0.95	11.56	11.27
BRFSS		77.58	78.10		11.60	11.17
Mean absolute differences	0.79			0.95		
Spearman correlation coefficient	NCHS urban–rural estimates ^c ($n = 6$)					
Model-based	0.94	77.72	77.72	0.94	11.68	11.73
BRFSS		77.43	78.09		11.91	11.70
Mean absolute differences	1.03			0.92		

NOTE: BRFSS percentages are weighted to the study population.

^aUp-to-date = having had the most recent mammogram within 2 years;

^bRarely or never = having had the most recent mammogram ≥ 5 years before the survey interview or never.

^cMetropolitan and nonmetropolitan areas were based on the 2013 six categories of NCHS urban–rural classification Scheme for counties.

Table 2. Model-based SAE state mean estimate (%) and county statistics summarized by state for up-to-date with mammography and rarely or never had a mammogram^a

State	State mean	Up-to-date with mammography ^b							State mean	Rarely or never had a mammogram ^c						
		Min	Q1	Mean	Median	Q3	Max	Range ^d		Min	Q1	Mean	Median	Q3	Max	Range ^d
Massachusetts	87.17	85.03	86.16	86.73	86.80	87.22	88.75	3.72	6.50	5.67	6.41	6.82	6.74	7.31	8.00	2.32
Rhode Island	84.65	83.51	84.03	84.44	84.63	84.69	85.32	1.81	6.92	6.70	6.73	6.94	6.89	7.13	7.25	0.55
Delaware	84.20	83.71	83.71	84.37	84.27	85.13	85.13	1.42	8.05	7.98	7.98	8.04	8.06	8.07	8.07	0.09
Maryland	83.41	75.69	80.88	82.26	82.58	84.05	85.71	10.02	8.57	7.54	8.35	9.15	8.84	9.90	11.76	4.23
Connecticut	83.04	81.50	82.96	83.50	83.39	84.44	84.94	3.45	8.23	7.69	7.84	8.12	7.92	8.43	8.94	1.25
Michigan	82.17	78.64	80.56	81.62	81.78	82.48	84.90	6.26	9.19	8.02	9.47	9.91	9.82	10.50	11.93	3.91
Maine	81.97	76.89	79.13	80.74	80.95	82.39	83.91	7.02	8.74	7.76	8.62	9.33	9.05	10.14	11.17	3.41
Minnesota	81.43	75.75	79.93	80.62	80.67	81.39	83.90	8.15	10.46	9.14	10.44	10.90	10.89	11.28	14.77	5.63
Virginia	81.11	73.32	78.49	79.96	80.11	81.46	83.32	10.11	10.16	8.79	9.96	11.01	10.86	11.85	15.92	7.13
DC	80.91								7.80							
North Carolina	80.87	77.48	79.49	80.53	80.68	81.45	84.02	6.55	10.77	9.15	10.44	11.12	10.92	11.92	13.66	4.52
New Hampshire	80.75	78.54	78.74	79.81	79.04	81.24	82.60	4.05	9.71	8.90	9.35	10.35	10.44	10.94	12.04	3.13
Hawaii	80.57	77.39	77.72	78.85	78.15	79.19	81.80	4.40	10.46	9.93	10.67	11.21	11.09	12.09	12.29	2.37
California	80.29	75.21	78.23	79.49	79.68	80.84	82.77	7.56	10.22	8.79	9.91	10.85	10.77	11.85	13.21	4.43
Iowa	80.21	76.19	78.62	79.45	79.42	80.21	83.85	7.66	11.30	9.45	11.02	11.55	11.52	12.02	13.63	4.17
Wisconsin	80.19	74.75	78.63	79.49	79.66	80.39	83.67	8.91	10.64	8.92	10.50	11.05	11.02	11.50	14.47	5.56
Kentucky	79.58	71.95	76.42	78.12	78.63	79.80	83.41	11.46	11.27	8.63	11.13	12.24	11.93	13.32	16.30	7.67
Georgia	79.57	74.01	77.14	78.39	78.35	79.59	82.45	8.45	10.81	8.96	10.92	11.80	11.88	12.68	15.39	6.43
South Dakota	79.55	71.05	78.53	79.21	79.79	81.13	84.10	13.05	11.16	9.00	10.31	11.63	11.01	11.87	19.31	10.32
Louisiana	79.18	74.23	76.69	77.79	77.79	78.65	82.86	8.63	11.44	9.48	11.66	12.30	12.41	13.03	15.19	5.71
Tennessee	79.08	73.58	76.31	77.60	77.60	78.60	81.49	7.91	11.69	9.29	11.92	12.67	12.73	13.48	15.76	6.46
Vermont	79.01	75.88	77.36	78.49	78.57	78.94	81.81	5.93	10.31	9.34	10.11	10.54	10.27	11.23	12.05	2.71
Florida	78.98	73.09	76.79	78.03	78.01	79.46	82.80	9.71	10.92	9.56	10.79	11.63	11.48	12.22	14.69	5.13
Alabama	78.72	73.43	76.94	77.89	77.72	79.19	81.41	7.98	11.03	9.45	10.73	11.40	11.38	12.01	13.46	4.00
New York	78.61	76.02	77.64	78.47	78.53	79.07	81.52	5.50	10.85	9.57	10.71	11.17	11.05	11.67	12.54	2.97
New Jersey	78.44	74.86	77.54	78.41	78.52	79.41	81.55	7.00	11.13	9.81	10.92	11.24	11.18	11.64	12.61	2.80
South Carolina	77.96	73.21	76.00	77.44	77.47	79.05	81.93	8.72	10.39	8.12	10.07	10.69	10.73	11.27	12.60	4.48
Oregon	77.67	70.80	74.99	76.22	76.15	77.15	80.99	10.19	11.41	10.25	11.37	11.97	12.01	12.48	14.04	3.79
Washington	77.65	70.63	74.25	75.66	75.58	77.64	81.20	10.57	11.18	9.76	11.54	12.24	12.24	12.86	14.74	4.98
Pennsylvania	77.56	73.18	76.10	76.97	76.96	77.90	80.85	7.67	11.27	9.81	11.29	11.73	11.84	12.27	13.18	3.37
Kansas	77.48	72.43	74.91	75.91	75.88	77.13	82.54	10.10	12.62	10.06	12.61	13.34	13.39	14.14	15.82	5.76
North Dakota	77.26	67.73	75.61	76.14	76.55	77.70	79.72	12.00	11.58	10.14	11.15	12.05	11.75	12.41	17.84	7.70
Illinois	77.21	71.63	75.10	75.90	75.96	77.00	78.97	7.33	10.83	9.78	11.18	11.83	11.76	12.34	15.10	5.32
West Virginia	77.07	73.13	75.46	76.40	76.22	77.44	80.10	6.97	12.98	11.05	12.89	13.49	13.50	14.05	16.37	5.32
Texas	77.03	67.75	74.53	75.43	75.57	76.70	80.64	12.89	12.44	10.05	12.35	13.25	13.17	13.95	18.98	8.93
Arizona	76.68	66.2	70.04	72.02	71.36	75.05	79.04	12.62	11.60	10.23	12.95	14.33	14.08	15.73	18.17	7.95
Ohio	76.15	69.82	74.58	75.29	75.28	76.60	79.41	9.59	12.31	10.04	12.12	12.95	12.94	13.64	15.90	5.86
Nebraska	74.36	61.67	70.08	71.54	71.54	72.94	77.59	15.92	13.09	10.66	14.13	14.77	14.62	15.40	21.40	10.74
Colorado	73.92	64.49	69.08	71.29	71.51	73.18	76.38	11.89	13.92	12.14	14.14	15.36	15.16	16.71	19.72	7.58
Utah	73.43	63.82	69.57	71.21	71.25	73.16	75.35	11.53	13.42	11.78	13.04	14.35	14.09	15.19	19.21	7.43
Mississippi	73.08	69.94	71.53	72.49	72.28	73.20	76.56	6.62	14.88	12.06	14.70	15.32	15.41	15.93	17.53	5.46
Missouri	73.07	63.71	68.76	70.17	70.01	71.58	78.30	14.59	13.33	10.70	14.07	14.92	15.06	15.93	18.56	7.87
Nevada	73.06	66.42	71.36	71.80	72.20	73.02	74.40	7.97	13.67	11.82	13.28	13.81	13.73	14.06	17.94	6.12
Indiana	72.74	68.67	70.60	72.14	71.91	73.00	78.04	9.37	13.24	10.40	12.95	13.63	13.73	14.50	15.55	5.15
Montana	72.60	64.03	71.06	71.84	72.13	73.31	76.92	12.89	13.94	11.86	13.39	14.26	13.98	14.71	18.75	6.88
New Mexico	72.11	64.99	68.72	70.21	70.41	71.31	76.51	11.52	14.37	10.76	14.62	15.41	15.62	16.26	17.96	7.20
Arkansas	71.71	64.19	68.80	70.17	70.06	71.57	77.78	13.59	14.73	11.30	14.58	15.43	15.43	16.39	18.21	6.91
Oklahoma	69.79	63.54	67.41	68.87	68.74	70.37	72.81	9.26	16.18	13.48	15.68	16.70	16.74	17.68	20.03	6.54
Alaska	69.52	56.67	65.75	67.32	67.84	69.08	73.89	17.19	14.11	11.76	13.48	15.09	14.49	16.27	21.65	9.89
Wyoming	69.39	64.41	65.46	68.33	68.38	70.72	73.83	9.42	17.41	15.06	16.04	17.55	17.71	18.38	21.35	6.28
Idaho	68.72	58.80	64.34	66.10	66.29	68.14	72.87	14.08	16.17	14.70	15.84	17.10	16.70	17.99	22.79	8.09

Notes: Q1, lower quartile; Q3, upper quartile.

^aPercentages are in decreasing order of state prevalence for up-to-date mammography. Percentages for rarely or never match by state.

^bUp-to-date = having had the most recent mammogram within 2 years;

^cRarely or never = having had the most recent mammogram ≥ 5 years before the survey interview or never.

^dRanges with percentages $>10\%$ are in bold font.

At least 10% of women rarely or never had a mammogram in most states; Wyoming had the highest state mean estimate, 17.41% (Table 2). Counties where $\geq 15\%$ of women rarely or never had a mammogram existed in more than half of the states and in five states this percentage exceeded 20% (Nebraska, Oklahoma, Alaska, Idaho, and Wyoming; Fig. 1B). Nebraska and South Dakota had the largest within-state differences in county

estimates of women who rarely or never had a mammogram (10.74% and 10.32%, respectively).

Of the 50 counties with the lowest mean estimates of being up-to-date with mammography, nearly half also had the highest mean estimates ($\geq 18\%$) of women who rarely or never had a mammogram. These counties were in Alaska, Idaho, Montana, Wyoming, Colorado, Nebraska, Oklahoma, Arkansas, Missouri,

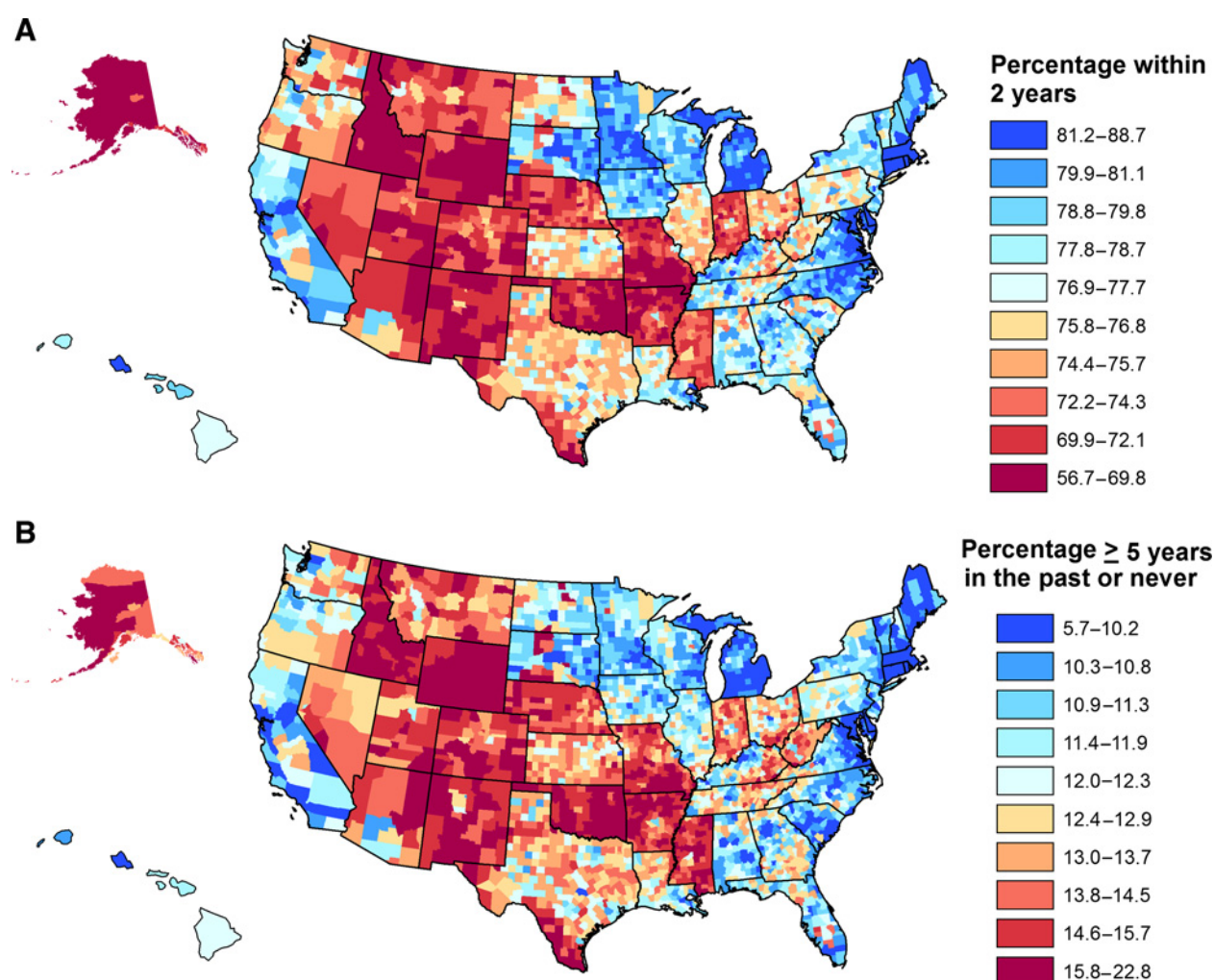


Figure 1.

Model-based county-level mean estimates (%) maps of two outcomes of mammography use: **A**, up-to-date (<2 years). **B**, Rarely or never had a mammogram (most recent mammogram ≥ 5 years before the survey interview or never). The county percentage ranges shown on the right of each map differ by map. Percentage ranges for up-to-date mammography are in decreasing order. Percentage ranges for rarely or never are in increasing order. County-level mean estimates were aggregated by deciles, and a different color was assigned in the legend to each decile.

and Utah. Although not among the above mentioned states, Texas had six counties where 18%–19% of women rarely or never had a mammogram.

Additional details about the predicted SEs of county estimates for being up-to-date with mammography and for rarely or never having had a mammogram are presented in the Supplementary Fig. S1A and S1B.

Findings from our model-based urban–rural analysis indicate an approximately 4% difference in the overall mean estimate of up-to-date mammography use between metropolitan areas with population ≥ 1 million (areas 1 and 2) and the noncore area (area 6, Table 3, a). The total range in county estimates was twice as large in the noncore area as in the large central metro area (area 1). Conversely, the lowest mean estimate for rarely or never mammography use was observed in the largest metropolitan areas (areas 1 and 2) and the highest in the noncore area (Table 3, b). The overall county range was also twice as large in the noncore area as in the large central metro area (area 1). BRFSS direct

estimates were similar to our model-based estimates and their 95% CIs largely overlapped.

A decreasing trend was also observed in BRFSS-NCHS urban–rural linked data, where the overall estimated percentage of up-to-date mammography use was highest in the large central and fringe metro areas (79.97%) and lowest in the noncore area (72.61%, Supplementary Table S1). A similar trend was also observed across age groups in metropolitan and nonmetropolitan areas. A corresponding trend was observed for the percentage of women who rarely or never had a mammogram, with an overall estimate of 9.61% in the large central and fringe metro areas and 15.36% in the noncore area (Supplementary Table S2). An increasing trend in the estimate was also observed across age groups.

Discussion

Between states and within states, our results show large variations in the estimated proportions of women up-to-date with

Table 3. Model-based SAE summary statistics (%) and BRFSS direct estimates for up-to-date mammography use and rarely or never had a mammogram by NCHS metropolitan and nonmetropolitan county population size

NCHS category ^a	No of counties	Mean	95% CI	Min	Lower quartile	Median	Upper quartile	Max	Inter-quartile	Overall range	BRFSS ^b	
											mean	95% CI
Up-to-date												
1 (overall)	68	79.47	78.36–80.52	71.69	78.26	80.20	81.35	87.23	3.08	15.54	80.94	79.89–81.94
Counties		79.72										
2 (overall)	368	79.67	79.00–80.33	67.57	76.43	79.02	81.08	88.7	4.65	21.16	78.92	77.98–79.82
Counties		78.55										
3 (overall)	372	78.02	77.39–78.67	61.02	75.59	77.91	80.09	87.02	4.50	26.00	78.53	77.65–79.39
Counties		77.32										
4 (overall)	358	77.41	76.81–78.07	66.13	75.08	77.43	79.73	86.73	4.64	20.59	77.65	76.36–78.88
Counties		77.00										
5 (overall)	641	76.02	75.49–76.52	61.36	72.30	75.86	78.49	86.53	6.20	25.17	75.95	74.82–77.04
Counties		75.39										
6 (overall)	1335	75.64	75.14–76.11	56.60	71.67	75.68	78.27	86.77	6.61	30.17	72.61	71.34–73.83
Counties		74.90										
Rarely or never												
1 (overall)	68	10.58	9.99–11.18	6.77	9.86	10.47	11.20	15.04	1.34	8.27	8.88	8.20–9.62
Counties		10.60										
2 (overall)	368	10.29	9.94–10.67	5.66	9.98	10.86	12.13	17.33	2.15	11.67	10.40	9.75–11.08
Counties		11.03										
3 (overall)	372	11.50	11.13–11.87	6.26	10.70	11.47	12.98	20.16	2.28	13.90	11.13	10.50–11.80
Counties		11.96										
4 (overall)	358	11.95	11.62–12.34	6.41	10.94	11.97	13.32	18.38	2.38	11.96	12.26	11.22–13.34
Counties		12.22										
5 (overall)	641	12.74	12.44–13.04	7.07	11.58	12.78	14.47	21.58	2.88	14.51	13.42	12.57–14.33
Counties		13.09										
6 (overall)	1335	13.01	12.71–13.29	6.66	11.76	13.09	14.78	22.72	3.02	16.06	15.36	14.38–16.39
Counties		13.39										

NOTE: Up-to-date = having had the most recent mammogram within 2 years; Rarely or never = having had the most recent mammogram \geq 5 years before the survey interview or never. The total number of counties in these areas is 3,142 after deleting 5 counties to reflect the number of counties in the 2014 BRFSS survey.

1. Large central Metropolitan Statistical Areas (MSA) with population \geq 1 million.
2. Large fringe MSA with population \geq 1 million.
3. Medium metropolitan counties within MSAs of 250,000–999,999 population.
4. Small-metropolitan counties within MSAs of 50,000–249,999 population (small metro).
5. Metropolitan counties with a city of 10,000 or more population.
6. Noncore (nonmetropolitan) counties without a city of 10,000 or more population.

^aMetropolitan and nonmetropolitan areas were based on the 2013 six categories of NCHS urban-rural classification Scheme for counties (12).
^bBRFSS percentages are weighted to the study population.

mammography and women who rarely or never had a mammogram. Over three quarters of women were up-to-date with mammography. Fifteen states and the District of Columbia had an estimated mean of 80% or more of women who were up-to-date with mammography and 21 states were within 5% of the 2020 goal of 81.1%. However, many counties were far below 80%. In addition, a large number of states had counties with many women who rarely or never had a mammogram. Overall, we found that 1 in 9 women (~4.9 million) rarely or never had a mammogram, and in some states, this ratio was as high as 1 in 7. This proportion, when applied to the population eligible for mammography, translates into a large number of women.

The county maps' deciles highlight the disparity among counties. Many counties with both the lowest estimated proportion up-to-date with mammography and substantial proportions of women who rarely or never had a mammogram were in rural areas. A recent CDC analysis of invasive cancer incidence and mortality over time showed that nonmetropolitan counties had persistently lower incidence rates of breast cancer and late-stage breast cancer among women. However, death rates for breast cancer were higher in nonmetropolitan rural areas than in metropolitan areas with <1million population (20). A county-level analysis of access to screening mammography across the United States from 2003 to 2009 found that more than 27% of counties had no mammography capacity—a finding that was strongly associated with low population density, low primary care physician density, and low percentage of insured residents compared with counties with one or more mammography machines (21, 22).

A longitudinal assessment study of geographic disparities in mammography capacity in the south found that in 2008, Texas contributed the largest percentage of women (44%) living in poor mammography capacity areas, including many rural areas (23). Inadequate health services and low mammography capacity might have decreased the likelihood of women receiving screening mammograms and increased the likelihood of late-stage diagnoses among women with breast cancer (21, 24).

Addressing the challenges of lower mammography use in rural communities requires a multifocal approach. Adults living in rural areas are more likely to have lower educational attainment, lower income, have limited employment, and to be uninsured than those living in urban areas (25–27). In addition, many people in rural areas may have cultural and language challenges which can contribute to low-screening uptake (28). To reduce disparity in mammography uptake between rural and urban areas, evidence-based multifaceted interventions designed to address the needs and concerns of the local populations are needed (29).

In an effort to increase information about small geographical areas, and to plan localized interventions, the CDC, in collaboration with the Robert Wood Johnson Foundation and the CDC Foundation, launched the 500 Cities Project in 2015 (30). Using small-area estimation methods, this project provides estimates of chronic disease measures, unhealthy behaviors, and prevention practices including mammography use at the city and census tract levels. Although the 500 Cities Project covers 33% of the population, it does not include rural areas and cities (except for Wyoming, West Virginia, and Vermont) with populations <66,000. Thus, our county-level mammography estimates fill a critical data need for rural areas and smaller cities, which represent two-third of the total U.S. population.

Our analysis suggests new avenues of research into geographical and sociodemographic barriers to screening. County-level estimates can help with planning and resource allocation at the local level, by identifying areas that might be targeted for interventions to increase screening use. States lacking high-quality county estimates can use our small-area estimation method to generate their own county-level estimates by only including county random effects and excluding the state random effect. Census population data for poststratification can provide information to generate estimates for all counties in each state, including counties for which no direct estimates are available from BRFSS.

Limitations and strengths

We acknowledge several limitations. First, the results of our study are based on self-reported information without medical record validation. Second, the data are cross-sectional, and do not help determine cause and effect relationship between the covariates and the outcome. Third, although there is a possibility of over-reporting mammography use, which can vary by demographic characteristics and may result in misclassification, our internal validation confirmed that the model-based estimates are consistent with the BRFSS estimates. Fourth, our unit-level multilevel model did not incorporate state-level and county-level structured spatial random effects. As a result, the predicted SEs of our model-based small-area estimates tend to be underestimated. Although our multilevel regression and poststratification approach for small-area estimation has been validated internally and externally for county-level small-area estimation (18), further research is needed to explore spatial structure effects on small-area estimates in terms of bias and precision. Fifth, because mammography use included diagnostic and follow-up tests, we were not able to tell whether mammograms were specifically for screening (31). Finally, our predicted percentages of being current with mammography use might be more appropriate for program planning than for program evaluation because we do not include a variable for local interventions in our model.

Despite the limitations, our method provides more current estimates for all U.S. counties. Although a more complex model might have fitted the data better, the results would not necessarily translate into better prediction. Our current model might not be the best model for prediction, but our internal validation confirmed that our models were appropriate to produce small-area estimates, and when aggregated, consistent with reliable direct survey estimates. Our national estimates were very similar to the BRFSS estimates and their 95% CIs largely overlapped. Furthermore, a recent study confirmed that unit-level multilevel models consistently perform better than area-level models in the context of SAE (32).

In conclusion, using data from a nationwide large survey with a linkage to census and the American Community Survey county-level data, our analysis found large variability in the prevalence of mammography use within many of the 50 states. This county-level variability cannot be captured by national- or state-level analyses. Our method, which generated estimates for all the counties, identified many counties far below state-specific and national averages for mammography use. These estimates could be used to target interventions to overcome barriers to mammography in counties with low mammography use.

Disclosure of Potential Conflicts of Interest

No potential conflicts of interest were disclosed.

Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention or the Economic Research Service, U.S. Department of Agriculture.

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