Predicting Patterns of Mammography Use: A Geographic Perspective on National Needs for Intervention Research

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Objective. To introduce a methodology for planning preventive health service research that takes into account geographic context.

Data Sources. National Health Interview Survey (NHIS) self-reports of mammography within the past two years, 1987, and 1993–94. Area Resource File (ARF), 1990. Database of mammography intervention research studies conducted from 1984 to 1994.

Design. Bayesian hierarchical modeling describes mammography as a function of county-level socioeconomic data and explicitly estimates the geographic variation unexplained by the county-level data. This model produces county use estimates (both NHIS-sampled and unsampled), which are aggregated for entire states. The locations of intervention research studies are examined in light of the statewide mammography utilization estimates.

Data Extraction. Individual level NHIS data were merged with county-level data from the ARF.

Principal Findings. State maps reveal the estimated distribution of mammography utilization and intervention research. Eighteen states with low mammography use reported no intervention research activity. County-level occupation and education were important predictors for younger women in 1993–94. In 1987, they were not predictive for any demographic group.

Conclusions. Opportunities exist to improve the planning of future intervention research by considering geographic context. Modeling results suggest that the choice of predictors be tailored to both the population and the time period under study when planning interventions.

Key Words. Bayesian hierarchical modeling, mammography, intervention research, geography

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Differential rates of mammography use by age, race, education, and income have been well documented for the United States during the past decade (cf., Mandelblatt et al. 1999). Recognition of these differentials has led to more intervention research involving populations expected to have low utilization rates based on one or more of these characteristics. Although successful strategies to increase breast cancer screening are known, their uneven distribution has resulted in missed opportunities to maximize their potential impact. This study builds on the finding that there are geographic gaps in mammography intervention research (Meissner et al. 1998) and recommends that geographic location be considered when planning intervention research. To advance this recommendation, we introduce a method that estimates mammography rates for every state and explicitly estimates the geographic variation that cannot be explained by age, race, and county-level education and occupation. Estimated state mammography levels for 1993–94 are then contrasted with where mammography intervention research had been initiated prior to 1995. Areas with low mammography utilization and few or no interventions were ascertained. The results of this kind of analysis provide a quantitative basis for researchers and funding agencies to systematically identify areas that could benefit from interventions.

Variation in health status and health services utilization by geographic location has been noted nationally and internationally (Senior 2000; Rosenberg and Wilson 2000). Recent evidence shows strong associations between social and economic environments and population health outcomes (Breen 2000; Amick et al. 1995). Community characteristics are also associated with longevity and health (Waitzman and Smith 1998a; Macintyre, Maciver, and Sooman 1993). An emerging literature confirms that the collective sociodemographic attributes of residences are related to individual health outcomes and behaviors (Kennedy, Kawachi, and Prothrow-Stith 1996; Wallace and Wallace 1998; Waitzman and Smith 1998). Comparable assessments of geographic variation in mammography use have not been conducted,

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although the locations of mammography facilities in the United States have been published (Brown, Kessler, and Rueter 1995). Needs assessments to identify noncompliance with recommended use of mammography have focused primarily on the attributes of individual women or the groups to which they belong (Mandelblatt and Yabroff 1999; Yabroff and Mandelblatt 1999). Little attention has been paid to geographic location except to focus on inner-city and rural disparities in mammography use (Breen and Figueroa 1996; Ansell et al. 1994; Ansell et al. 1993; Burack et al. 1993; Burack et al. 1994; Andersen et al. 2000).

Geographic location could affect mammography intervention planning in two major ways. First, mammography underutilizers may be geographically concentrated. While this concentration may reflect concentrations of particular age, race, or SES groups previously identified as underutilizers, this may not always be the case. Second, geography may pose unique barriers with implications for planning interventions. For example, the challenges poor, older women face utilizing the health care system may differ markedly in Appalachia, the Southwest, or a New York City neighborhood.

The purpose of this paper is to describe a method of analysis that produces estimates of state screening rates based on county-level population characteristics. The advantage of this approach is that it also produces an estimate of county-to-county variation in screening apart from that explained by age, race, and county-level occupation or education. To accomplish this, we modeled self-reports of mammography use among women responding to the National Health Interview Survey (NHIS) as a function of age, race, and their county's level of education and occupation. The results were used to estimate mammography utilization for all U.S. counties, sampled and not sampled by NHIS. These county estimates were then aggregated to produce state mammography rate estimates. We used hierarchical modeling because it uses the additional information about each county's education and occupation levels to better estimate each state's rate and it also provides an estimate of the geographic variation in mammography use unexplained by age, race, and county education and occupation. We used a Bayesian approach because it offers a straightforward approach to estimation that accounts for all of the uncertainty in the underlying model of utilization rates.

States are an appropriate unit for this geographic analysis in the United States because states set many public health, education, and social welfare policies. Confidentiality constraints allowed us to present these data only for states and not smaller units. Although the scope of this analysis is national, we anticipate refining this method for use with smaller geographic units. Wells and

Horn (1998) examined the ecological correlates of mammography use using NHIS data for more than 7,000 very small areas (VSAs). While their investigation focused on identifying correlates of low utilization, our objective is to explore the importance of the geographic location itself in planning intervention studies.

Data on mammography from the NHIS is representative of the entire United States, uses a uniform national sampling frame, and has good response rates. One limitation is that not every state was sampled. However, our method can provide indirect estimates of mammography for every state using census data on education and occupation, which is available for every county. It is worth noting that the method we describe does not require the use of NHIS. It can also be applied using alternative data sources such as the Behavior Risk Factors Surveillance System (BRFSS). Nor is it necessary to employ the particular hierarchical model we use. Software to fit hierarchical models has become more widely available since the time our analysis was done, and there are now several different programs that can produce similar estimates of the state rates and geographic variation.

METHODS AND MATERIALS

Most intervention studies in the past two decades targeted women from 50 to 74 years of age because a consistent mortality benefit from mammography has been found for this age group in clinical trials (Fletcher 1993). For this analysis, we computed estimates of mammography use separately for four demographic groups defined by age eligibility for Medicare health insurance coverage (50–64 and 65–74 years of age) and race (black versus nonblack). The NHIS samples are not large enough to allow for separate analyses for every racial group. We analyzed black women separately from the other women respondents based on sample size findings from earlier work by Malec and Mueller (1999).

Individual women's self-report of mammography within the past 24 months for the 1987 and 1993–94 NHIS surveys are the dependent variables for our models. The years between 1987 and 1994 are a period when mammography utilization dramatically increased. The survey year of 1987 was chosen because it represents the earliest national NHIS data available on mammography. Malec and Mueller originally fit their model using 1993–94 NHIS data, which at the time were the most recent data available. Intervention studies to promote mammography were concentrated during this same time period (Meissner et al. 1998).

For this analysis, we used the National Center for Health Statistics (NCHS) Research Data Center (RDC). We took advantage of the opportunity provided by the NCHS that allows researchers to access county-identified data if they work on site at the RDC. The models we used to estimate statewide mammography utilization require county-identified data. Other variables used from the NHIS files are state of residence, age (50–64 years; 65–74 years), race (black; not black), and mammography within the past 24 months. The Area Resource File (ARF) is commissioned by the Health Resource Services Administration to track the supply of health services available in all counties in the United States. Nineteen variables recording county-level characteristics were considered for inclusion in the model (see Table 1). Population figures for each county by age and race are from the 1990 U.S. decennial census. Thus, for every county in the United States, we had ARF and Census covariates regardless of whether the county was sampled by NHIS. For the counties sampled by the NHIS, we also had the number of women who reported having had a mammogram in the past two years.

Intervention Study Database

The other integral component for this analysis is the intervention study database previously described (Meissner et al. 1998). This unique database

Table 1: County-level Covariates Considered for Inclusion in the Model

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1) Census regions: North, South, Midwest, and West 1990
2) Unemployment rate
3) Per capita income
4) % renters
5) % hispanic
6) Degree of urbanization
7) % employment in agriculture
8) % employment in construction
9) % employment in white-collar industry
10) % persons aged 25+ who have completed less than nine years of school
11) % persons aged 25+ who have completed high school or more
12) % persons aged 25+ who have completed college
13) Poverty rate
14) % Mexican
15) % Black
16) % White
17) % Asian
18) Population density
19) Median home value

Source: Area Resource File, 1990.

developed by NCI staff includes information on the state where each published mammography intervention study initiated between 1984 and 1994 occurred. Studies were classified according to whether and which special populations were targeted, including blacks and elderly women (65 years and older). While some studies included black or elderly women, we count only those that specifically targeted either one of these groups. States were used to approximate study location because smaller geographic units (e.g., city or county) were not consistently published. Most interventions were not statewide but covered specified communities, counties or other defined populations within one or more states, for example, women enrolled in an HMO. See Meissner et al. (1998) for further details.

Statistical Analysis

The analysis consisted of three steps. The first step used data from the NHIS sampled counties. A woman's probability of self-reporting a mammogram within the past two years was modeled as a function of her county's average education and occupation, taking into account her race and age group plus a county effect not explained by available covariates. The second step used the fitted model from step 1 to estimate the number of women who had mammograms in every U.S. county, including those not sampled by the NHIS. Statewide mammography utilization rates were obtained by summing these county estimates to obtain the total predicted number of women who had mammograms in the state and dividing it by the relevant state population estimate. The last step compared the estimated statewide utilization rates with the intervention study locations.

For step 1, we used a mixed model of the type described in Laird and Ware (1982) with fixed education and occupation effects plus a random effect for each county-demographic group. Our model is hierarchical in that within a county, obtaining a mammogram is modeled as a Bernoulli random variable with parameter p_{id} , where

p_{id} = the expected proportion or probability of women in
demographic group d from county i reporting a mammogram
within the past 24 months.

Note that the random sampling error is accounted for at this within-county level. Between counties, the probabilities, p_{id} , are then modeled as a function of demographic effects, county effects and their interaction as follows:

$$\log(p_{id}) = \theta_d + b_{1d}x_{1i} + b_{2d}x_{2i} + \beta_{id}. \quad (1)$$

At the county level, equation 1 describes how the probability of mammography utilization is affected by:

θ_d = a woman's demographic group,

x_{1i} = the percent of persons in her county ages 25 and older with less than nine years of schooling and

x_{2i} = the percent of the labor force in her county employed in white collar work.

The covariates (x_{1i} and x_{2i}) were selected by Malec and Mueller (1999) from among the potential covariates appearing in Table 1 using stepwise procedures. These variables are referred to here as the county's level of education and occupation, respectively. Main effects were selected first and then interactions with demographics groups were evaluated. Schwarz's criterion was used to select a final set. In addition, the linearity of the predictors was checked graphically. There is strong precedent for the choice of education and occupation variables. Education is widely used because it is invariant over the adult life cycle and strongly correlated with the use of health services. Occupation, in the form of the percent of white-collar workers, is strongly correlated with health insurance coverage, a variable not available from the U.S. Census, and it, too, correlates with availability and use of health services.

The d subscript on the coefficients b_{1d} and b_{2d} indicates that the effect of countywide education and occupation is allowed to differ depending upon a woman's demographic group.

β_{id} = a county demographic-specific random effect

Through the random effect (β_{id}), the model also specifies a county demographic-specific effect that cannot be explained by available county covariates, but exists nonetheless. Note that equation 1 is a model for the parameters, p_{id} , so the random effects explicitly model geographic or county-to-county variation not explained by education and occupation. A multivariate normal distribution was assumed. An advantage of this approach is that these random or county effects are estimated and incorporated into each county's mammography rate estimate. When counties within a state contain a large NHIS sample, these random effect estimates will be relatively precise leading to good state estimates. When few or no women are included in the NHIS sample from a particular county, the information about the county's occupation and education and

the estimated distribution of county-to-county variation are used to provide mammography use estimates with the proper variance. For fitting the model, Bayesian estimation methods with noninformative priors are employed using numerical methods similar to those detailed in Malec et al. (1997).

The goal of the second step of the analysis is to obtain statewide estimates. Specifically, in county i , demographic group d , let

N_{id} = the total number of women,
 n_{id} = the number of sampled women, and
 m_{id} = the number of sampled women with a mammogram.

Note that N_{id} is available from the U.S. Census and n_{id} and m_{id} come from the NHIS. The total number of women in county i demographic group, d , with a mammogram is estimated by:

$$m_{id} + (N_{id} - n_{id})\hat{p}_{id}, \quad (2)$$

where $\hat{p}_{id}$ is an estimate of p_{id} using equation 1 based on a county's level of education and occupation from the ARF. For each demographic group, a statewide estimate of the number of women who had mammograms is obtained by summing over all its county estimates as specified by equation 2. Rates were then computed by dividing by the appropriate population total and mapped. We also computed a coefficient of variation by dividing the standard error by the corresponding rate estimate. States with a coefficient of variation greater than 20 percent were cross-hatched on the map.

One indicator of geographic variation is how variable the mammography rates (p_{id}) are from county to county within each demographic group. Here, we analyzed the geographic variation to gain insights into the amount of variation in the mammography rates from county-to-county that can and cannot be explained by county education and occupation levels. This analysis makes use of national demographic-specific "average" mammography rates represented by

p_d = proportion of women in demographic group d reporting a mammogram within the past 24 months at the national average county occupation and education levels.

The variation in the proportion getting mammograms across counties for a given demographic group d , can be approximated as

$$\text{Var}(p_{id}) \doteq p_d^2(1 - p_d)^2 \mathbf{b}'_d \text{Var}(\mathbf{x}_i) \mathbf{b}_d + p_d^2(1 - p_d)^2 \text{Var}(\beta_{id}) \quad (3)$$

An appendix with the derivation of equation 3 is available at <http://www-dccps.ims.nci.nih.gov/SRAB/>. The variation in the county proportions represents the total geographic, county-to-county variation. As demonstrated by equation 3, this variation consists of two terms. The first term is that part of the geographic variation that reflects the variation in the county-level covariates of occupation and education (x_i) and their corresponding effect on mammography for a given demographic group (b_d). The second term reflects the amount of geographic variation unexplained by the county-level covariates by way of the random effects, β_{id} .

As noted earlier, the advantage of using a hierarchical method is that it is possible to explicitly approximate the proportion of variation in screening rates that cannot be explained by county occupation and education. For a given demographic group, d , this is denoted by pv_d where

$$pv_d = \text{proportion of unexplained geographic variation} \\ = \frac{p_d^2(1 - p_d)^2 \text{Var}(\beta_{id})}{\text{Var}(p_{id})}.$$

The final step in the analysis was to determine whether there are states with both low utilization and no mammography intervention research projects during the study period. The number of intervention studies initiated prior to 1995 was mapped with separate maps for studies that specifically targeted blacks or elderly women. Utilization levels are defined using our largest demographic group, young (50–64), nonblack women. State utilization rates were divided into quintiles with the bottom three quintiles designated as low utilization states. States were grouped with respect to utilization and the presence of a published research intervention and a chi-square test of independence of research and utilization was performed.

RESULTS

We present two tables of results and two maps. Table 2 provides indicators of geographic variability of mammography utilization. Table 3 classifies states by mammography use and amount of intervention research. Statewide utilization estimates and intervention studies are mapped in Figures 1 and 2, respectively.

Mammography rates for the “average” county, p_d , are shown in Table 2 for each demographic group and time period. The fitted model indicates that

Table 2: Estimated Mammography Screening Prevalence (p_d) for an Average County¹ and the Percentage of Geographic Variation (pv_d) Unexplained by County Education and Occupation

Demographic Group (d)	1987 NHIS		1993–94 NHIS	
	Screening Prevalence p_d	Percentage of Unexplained Variation, pv_d	Screening Prevalence p_d	Percentage of Unexplained Variation, pv_d
50–64 Blacks	0.134	93.7	0.532	39.5
50–64 Nonblacks	0.195	86.9	0.603	27.9
65–74 Blacks	0.208	83.8	0.493	90.6
65–74 Nonblacks	0.216	84.7	0.549	79.3

¹Average county is defined as having the average percent of the labor force employed in white collar work and the average percent of persons in the county ages 25 and older with less than nine years of schooling among U.S. counties.

Table 3: Number of States Classified by Number of Published Intervention Studies from 1984 to 1994 (as of 8/2000) and Mammography Utilization Estimated from 1993–94 NHIS.

State Mammography Utilization	Published Intervention Studies as of 8/2000	
	No Studies	One or More Studies
Low utilization ¹	18	13
High utilization ²	8	12
Number of states	26	25

¹States in the lower three quintiles of mammography utilization for nonblacks, 50–64 years of age.

²States in the upper two quintiles of mammography utilization for nonblacks, 50–64 years of age.

average mammography use is higher for all groups of women in 1993–94 than in 1987. The coefficients for these fitted models (not shown) indicate that the effect of education on mammography use among nonblacks was similar in magnitude for the two time periods, whereas for blacks it was larger in 1993–94 than it was in 1987. Counties with larger percentages of white-collar workers were associated with higher mammography use and counties with higher proportions of persons with less formal education (ninth grade or less) correspond to lower use. Coefficients of variation were well below the 20 percent threshold for all demographic groups except for older, black women. For this group, fifteen states had coefficients of variation ranging from 21 to 28 percent (ID, DE, UT, WI, SD, RI, AK, WY, OR, HI, NV, ND, NE) reflecting the

Figure 1: Model-Based Estimates of the Proportion of Women Reporting a Mammogram within Two Years Using NHIS 1993–94 Survey Data

fact that few, if any, older black women were included in the NHIS sample for these states. To alert the reader, these states are cross-hatched on this demographic group’s map.

The proportion of geographic variation unexplained by occupation and education, pv_d , is reported as a percentage and appears in the last column of Table 2 for each time period. The county covariates explain the largest amount of geographic variation for the 1993–94 data on women aged 50–64 years: 60.5 percent and 72.1 percent ($= 100 - pv_d$) of the variation in the expected county proportions is explained by the county-level covariates of occupation and education for blacks and nonblacks, respectively. The county covariates explain far less of the geographic variation in mammography rates for older women: 90.6 percent and 79.3 percent ($= pv_d$) of the geographic variation is unexplained after taking into account county occupation and education for blacks and nonblacks, respectively. The results for 1987 also reveal uniformly higher percentages of unexplained geographic variation. The statewide estimates for 1993–94 for each demographic group are mapped in Figure 1.

Figure 2: Number of Published Mammography Intervention Studies Initiated Prior to 1995

Intervention Study Location

Figure 2 presents the locations of published mammography intervention research from 1984–94 by state for all populations, for studies focusing on blacks, and for studies targeting elderly women. Table 3 shows the number of states with high or low mammography utilization levels according to the presence or absence of published intervention studies. Eighteen states with low mammography utilization reported no published intervention research activity during our study period (1984–94). During the years 1993–94, only 3 of the 10 states with extremely low mammography rates, that is, in the lowest quintile (Tennessee, Arkansas, and North Carolina), were sites of published intervention studies. Of the 11 states (including the District of Columbia) with the very highest rates, only Maryland, Utah, and D.C. did not host published intervention studies.

DISCUSSION

Hierarchical modeling to assess geographic disparities is an important tool for policymakers trying to decide where to focus limited resources. With our model, it was possible to use national survey data to produce statewide mammography estimates based on county-level occupation and education. These estimates enabled us to identify states that warrant concentrated efforts to improve breast cancer screening rates. The residual variation estimated by our model suggested that geographic locations merit consideration, in their own right, when planning intervention research.

Our methodology does not require the use of any particular data set. We chose the NHIS because data are uniformly collected and yield comparable measures across states. However, data from the Behavioral Risk Factor Surveillance System or the Centers for Disease Control (CDC) Breast and Cervical Cancer Early Detection Program could also be usefully incorporated into a hierarchical model for screening. It would be useful to validate our findings with one or more of these other data sets. Other approaches to hierarchical modeling that also yield estimates of geographic variation could be employed. We used a FORTRAN program to fit a hierarchical Bayesian model (Ghosh and Rao 1994; Rao 1999). However, a number of alternative approaches and computational resources are now accessible (e.g., SAS PROC NLMIXED [Littell et al. 1996] and WINBUGS [Spiegelhalter 1999]).

Other studies using the NHIS show that a minority of women were being screened in 1987. The subsequent rapid increase in use of mammography

(Breen and Kessler 1994) reflected changed public awareness of the need for early detection and the acceptability of mammography. The mammography estimates from our fitted model reflect this strong secular trend. Our results confirm previous findings that the determinants of underutilizers changed over time as mammography became widely recommended by health care providers and adopted by women (Makuc et al. 1999; Anderson et al. 1995).

What is new about our findings is that where people live may be an independent factor in mammography use. Several authors have reported associations between neighborhood and disease, for example, see Roux et al. (2001) for results concerning coronary heart disease and neighborhood of residence. However, our findings show that health behaviors may also be related to particular locales. Other studies are needed to confirm this. Collaborations among behavioral and social scientists and statisticians are needed to elucidate what it is about locality that influences mammography use above and beyond the individual characteristics of underutilizers. These results are needed to inform policy concerning where and how programs are implemented.

The Intervention Study Data Base we used allowed us to identify states where published intervention research took place. Using it and the results from our analysis of the NHIS data, we inferred that eighteen states have both low utilization and no published intervention research. These eighteen states represent untapped opportunities for expanding the current knowledge base of intervention research.

Most published studies showed mammography use increased significantly in the populations they targeted. However, we cannot infer how these studies affected mammography rates in the broader populations where interventions took place. Many interventions focused on only a limited area within a state. Moreover, local interventions are unlikely to dramatically impact county or state mammography rates. It is possible that states that hosted studies but continued to exhibit low utilization would have fared even more poorly in the absence of intervention research. In addition to scientific research, government sponsored demonstration programs and other aspects of health care delivery have promoted use of mammography.

Nonresearch programs serving poor and uninsured women play an important part in promoting mammography use and their impact is not captured in this analysis. The widespread CDC National Breast and Cervical Cancer Early Detection Program (NBCCEDP) is a good example. Nevertheless, our results are consistent with the level of nonresearch programmatic activity taking place at the time. Using NHIS data, we found that the

proportion of black women reporting mammograms in the southeastern United States was low and, in Illinois, it was low for black women 65 and older. Not one study in our Intervention Research Database specifically targeted women 65 years or older in any of these states between 1984 and 1994. Of the southeastern states, no intervention research targeting blacks occurred in Tennessee, Mississippi, Louisiana, Alabama, South Carolina, or Florida at that time either. Half of the states without CDC comprehensive screening programs in 1995 also did not have intervention research studies identified using the Intervention Study Data Base. (These states include, NV, ID, MT, WY, ND, SD, KT, MS, and AL [Henson et al. 1996]). These results strongly suggest opportunities for intervention research in states where it has not yet occurred.

The Health Plan Employer Data and Information Set (HEDIS) was introduced between the study periods (1987 and 1993–94). The HEDIS, which provides an indication of mammography use in managed care settings, created an incentive for managed care organizations to promote screening mammography among their enrollees. This increase, which affects only insured women, is reflected in the average screening prevalence we estimated in Table 2 and we expect it to continue to increase.

Medicare began covering biennial routine screening mammography in 1991. Our findings using NHIS reflect increased use of the benefit by women 65 years and older who reported higher rates in 1993–94 than in 1987. In 1998, Medicare began covering annual mammography and removed the deductible for screening mammography. This improvement in the Medicare benefit is expected to further boost mammography screening rates for women 65 and older.

In order to build on existing research findings and more effectively use programs that deliver health services, we need to develop a collaborative infrastructure for disseminating and diffusing effective interventions in areas where need is identified. States without studies are largely rural and have relatively little research infrastructure. Conducting scientific interventions in areas without research infrastructure poses special difficulties. However, it is possible to do so with creativity and commitment. Government agencies, other funders, and researchers need to work together to overcome obstacles posed by limited infrastructure in these geographic areas.

The independent variables for our model were originally chosen on statistical grounds; however there is strong justification in economic theory for using the predictors of occupation and education. Previous studies have shown that white-collar workers are more likely to have insurance. Conversely, areas

with a low percentage of white-collar workers may have fewer health services because effective demand is reduced since less of the population is insured. Interventions to promote mammography would be especially useful in these areas. Mammography services could be located in public clinics or delivered using mobile vans, for example.

Our objective for this analysis was to provide a scientific basis for planning future mammography interventions. To do this, we quantified geographic differences in mammography utilization and compared them to intervention research. Our approach of taking into account geographic context and location is even more critical now, in an era of widespread adoption, because hard-to-reach populations may remain outside the focus of intervention research. We encourage investigators to tailor proven research to populations in locations where it is most needed. We also encourage funders to explicitly solicit such research projects. Though our paper addresses interventions to promote mammography, this approach can be generalized to other health services.

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APPENDIX

Let p_{id} represent the proportion of women in demographic group d from county i reporting a mammogram within the past 24 months. The influence of demographic effects, county effects and their interaction on p_{id} are modeled as follows:

$$\text{logit}(p_{id}) = \theta_d + \mathbf{x}_{id}^t \mathbf{b}_d + \beta_{id}, \quad (1)$$

where

$$\text{logit}(p_{id}) = \ln \left\{ \frac{p_{id}}{1 - p_{id}} \right\}$$

and $\boldsymbol{\beta}_i = (\beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4})^t$ has a multivariate Normal distribution with mean $\mathbf{0}$ and variance-covariance $\boldsymbol{\Gamma}$, independent across counties where

$$\boldsymbol{\Gamma} = \begin{bmatrix} \text{var}(\beta_1) & \text{cov}(\beta_1, \beta_2) & \text{cov}(\beta_1, \beta_3) & \text{cov}(\beta_1, \beta_4) \\ \text{cov}(\beta_2, \beta_1) & \text{var}(\beta_2) & \text{cov}(\beta_2, \beta_3) & \text{cov}(\beta_2, \beta_4) \\ \text{cov}(\beta_3, \beta_1) & \text{cov}(\beta_3, \beta_2) & \text{var}(\beta_3) & \text{cov}(\beta_3, \beta_4) \\ \text{cov}(\beta_4, \beta_1) & \text{cov}(\beta_4, \beta_2) & \text{cov}(\beta_4, \beta_3) & \text{var}(\beta_4) \end{bmatrix} \quad (2)$$

Expanding p_{id} around $\bar{\mathbf{x}} = (\bar{x}_1, \bar{x}_2)$ and $\beta_{id} = 0$ where $\bar{\mathbf{x}}_k = \sum_{i=1}^N x_{ik} / N$ where N refers to the number of counties and

$$p_{id} \doteq p_d + p_d(1 - p_d)\mathbf{b}_d'(x_i - \bar{\mathbf{x}}) + p_d(1 - p_d)\beta_{id}$$

where

$$\text{logit}\{p_d\} = \theta_d + \bar{\mathbf{x}}' \mathbf{b}_d.$$

Also,

$$\text{Var}(p_{id}) \doteq p_d^2(1 - p_d)^2 \mathbf{b}_d' \text{Var}(\mathbf{x}_i) \mathbf{b}_d + p_d^2(1 - p_d)^2 \text{Var}(\beta_{id}).$$

where $\text{Var}(\mathbf{x}_i)$ is the population variance of $\mathbf{x}_i = (x_{i1}, x_{i2})'$ and $\text{Var}(\beta_{id})$ is the variation in the random effects terms for demographic group d .