Supplementary Data

Statistical Appendix

Data

Death service utilization is calculated by county as the ratio of the number of Medicare beneficiaries who died in 2014 who used at least one day of hospice to the total number of Medicare beneficiaries who died in 2014. Patient characteristics, including gender, race (limited to African American or all other), and diagnosis (consisting of cancer, circulatory illness, respiratory illness, mental disorder/dementia, or other diagnosis), were aggregated by county and converted to percentages of all Medicare decedents.

County-level information was also included in the analysis, consisting of the number of hospices present, percentage of population below the poverty line, percentage of population over the age of 65, and a size indicator of whether the county had over 250 decedents in 2014. In addition, the proportion of each county's population that falls within each hospital referral region (HRR) was determined through census data by taking population counts by census block and summing the total population in the overlap area of each county and HRR using GIS software. All continuous covariates were mean centered.

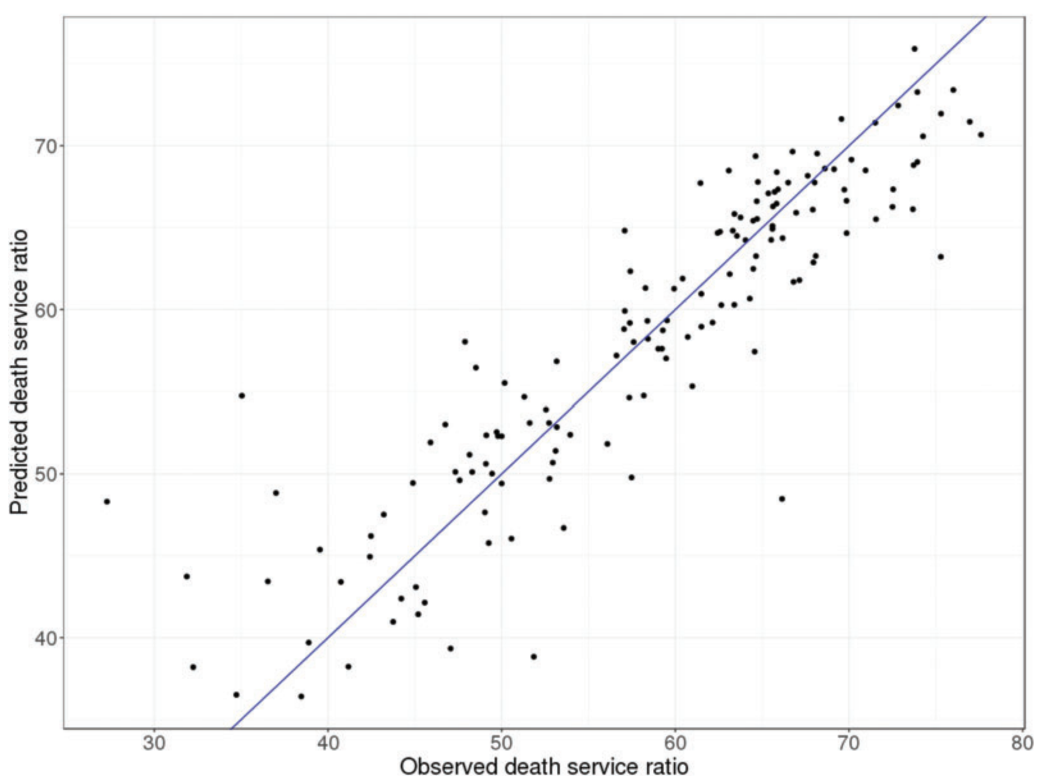
Model formulation

Our primary interest is in whether differences exist in utilization by county after controlling for HRR while still acknowledging random fluctuations in utilization. A standard regression analysis, including indicators for each county, is not appropriate in this setting, since we only have one observation per county. Therefore, we model the death service ratio by county using the following hierarchical model:

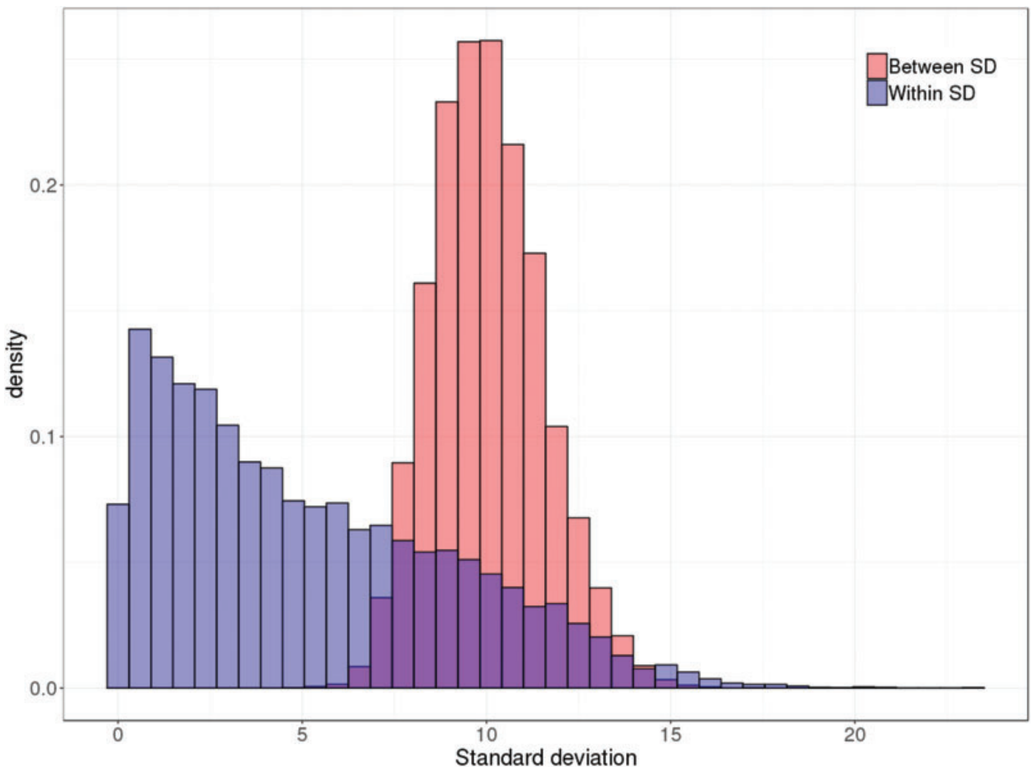
$$y_i = x_i^{'}\beta + b_i + \varepsilon_{is}$$
$$b_i \sim N\left(0,\ \sigma^2_{county}\right)$$
$$\varepsilon_{is} \sim N\left(0,\ \sigma^2_s\right)$$

where β is a vector of the county explanatory variables, b_i is a measure of the county effect on hospice utilization, and s is an indicator of county size (as measured by the number of decedents being less than/greater than 250). Note that the variance of the random unexplained variation is indexed by the county size indicator; since data are aggregated, it is reasonable to expect that smaller counties would have larger sampling variability in their utilizations. We therefore model this explicitly in our formulation.

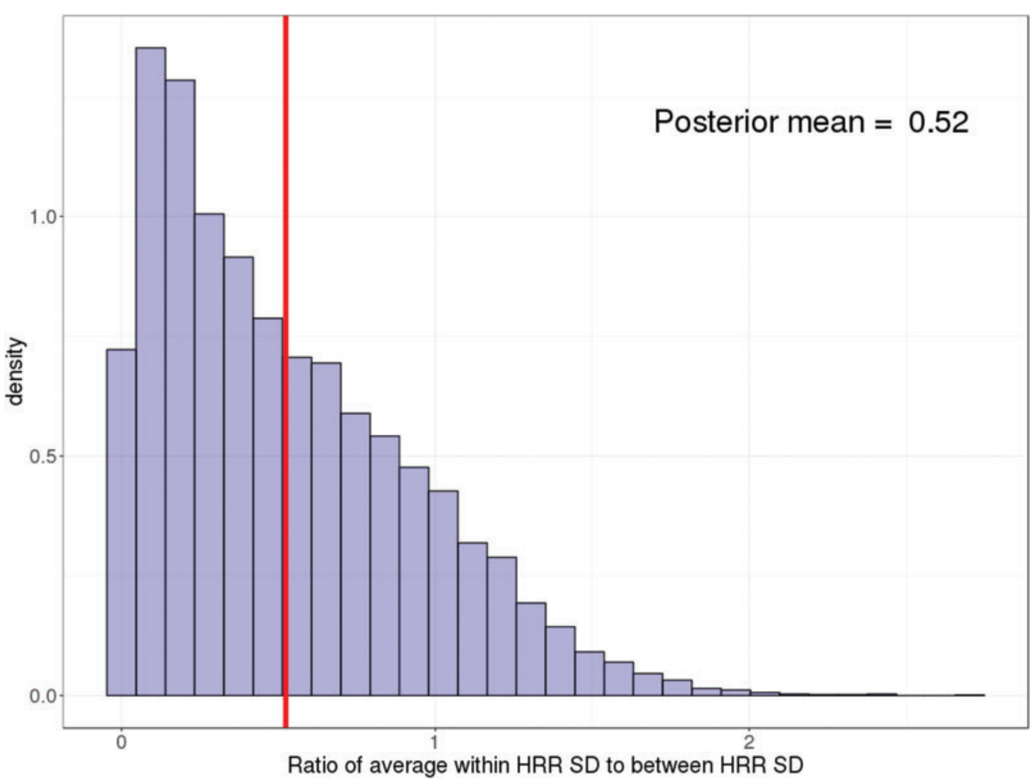
This model as stated is not identifiable because we have two sources of variation at the county level. Without additional information, one could conclude that there are no county effects and all variations from the model are random noise or that there is no random noise and all variations from the model are due to county effects. A Bayesian approach with informative priors on the error variances provides the necessary additional information to estimate the parameters of the model.



SUPPLEMENTARY FIG. S1. Comparison of the observed death service ratio for each county to its predicted death service ratio, based on posterior parameter mean.



SUPPLEMENTARY FIG. S2. Posterior distributions of the standard deviation of the effect of HRR on death service utilization (''between'') compared with the standard deviation of county effects within each HRR, averaged across all HRRs. HRR, hospital referral region.



SUPPLEMENTARY FIG. S3. Posterior distribution of the ratio of the standard deviation of county effects within each HRR, averaged across all HRRs to the standard deviation of the effect of HRR on death service utilization.

Supplementary Table S1. Regression Estimates Using a Gamma Prior for the County Effect Standard Deviation

Variable name	*Mean*	*Marginal posterior summaries* 2.5%	97.5%
Intercept	60.26	56.48	63.95
% African American	−0.22	−0.36	−0.08
% Female	0.57	0.22	0.93
% Circulatory DX	−0.46	−0.94	0.01
% Mental DX	0.05	−0.74	0.84
% Respiratory DX	−1.03	−1.52	−0.54
% Other DX	−1.15	−1.64	−0.68
South Carolina	−8.10	−15.60	−0.88
No. of Hospice	0.06	−0.53	0.65
% Poverty	−0.05	−0.34	0.24
% Age 65+	−0.13	−0.46	0.21
Small County	−4.16	−7.07	−1.26
Atlanta, GA HRR	−15.04	−30.50	−0.07
Augusta, GA HRR	4.11	−7.01	15.05
Savannah, GA HRR	15.00	2.59	27.68
Asheville, NC HRR	−1.73	−7.46	3.95
Charlotte, NC HRR	6.20	1.18	11.26
Greensboro, NC HRR	7.50	−0.35	15.33
Greenville, NC HRR	−7.63	−12.51	−2.70
Hickory, NC HRR	11.91	4.00	19.85
Raleigh, NC HRR	−7.56	−12.48	−2.68
Wilmington, NC HRR	2.55	−3.83	8.92
Winston-Salem, NC HRR	7.68	1.71	13.60
Charleston, SC HRR	9.94	0.84	19.17
Columbia, SC HRR	8.83	0.10	17.92
Florence, SC HRR	10.53	0.30	21.01
Greenville, SC HRR	15.05	5.59	24.75
Spartanburg, SC HRR	10.81	1.15	20.71
Johnson City, TN HRR	−2.07	−19.71	15.39
Norfolk, VA HRR	−12.27	−19.36	−5.00
Noise standard deviation, large counties	4.11	0.97	5.81
Noise standard deviation, small counties	7.54	5.29	9.56
County effect standard deviation	2.11	0.07	5.14

Estimate of county-level effects available as a supplement.
DX, diagnosis; HRR, hospital referral region.

Bayesian estimation

For a given data-generating model, Bayesian inference combines two sources of information. The first is the likelihood of the observed data, which is a function of the model parameters. The second is a prior distribution on the model parameters, which quantifies a researcher's uncertainty about the values the model parameters may take, before observing any data. These two sources are combined using Bayes' theorem to update the prior distribution using the information from the data, resulting in a posterior distribution for the model parameters.[S1]

Determining an analytic formula for the posterior distribution is often not feasible. As a result, Markov chain Monte Carlo (MCMC) methods are normally used to generate values from the posterior distribution.[S2] Parameter values that are frequently drawn indicate that those specific values come from a high probability area of the posterior distribution.

Supplementary Table S2. Ratio of the Posterior Estimate of the Standard Deviation of County Effects within Each Hospital Referral Region to the Posterior Estimate of the Standard Deviation of Hospital Referral Region Effects across All Hospital Referral Regions

HRR	*Marginal posterior summary* Mean	2.5%	50%	97.5%
Atlanta, GA	0.156	0.004	0.109	0.558
Augusta, GA	0.291	0.008	0.211	1.024
Savannah, GA	0.190	0.005	0.135	0.656
Asheville, NC	0.643	0.015	0.427	2.466
Charlotte, NC	0.635	0.015	0.404	2.627
Durham, NC	0.634	0.015	0.417	2.528
Greensboro, NC	0.288	0.008	0.216	0.988
Greenville, NC	0.705	0.017	0.441	2.865
Hickory, NC	0.261	0.008	0.194	0.902
Raleigh, NC	0.562	0.013	0.367	2.258
Wilmington, NC	0.354	0.010	0.251	1.301
Winston-Salem, NC	0.537	0.013	0.359	2.157
Charleston, SC	0.428	0.011	0.288	1.653
Columbia, SC	0.687	0.016	0.430	2.785
Florence, SC	0.407	0.011	0.276	1.571
Greenville, SC	0.361	0.010	0.251	1.399
Spartanburg, SC	0.307	0.008	0.219	1.121
Johnson City, TN	0.122	0.003	0.084	0.453
Norfolk, VA	0.401	0.011	0.276	1.514

For this analysis, all regression coefficients other than the intercept were assigned uninformative independent normal priors. As continuous covariates were mean centered, the intercept was instead assigned a normal prior with mean 50 and standard deviation 20 to reflect a weak prior belief that the average death service utilization by county will be around 50%. The noise error standard deviation σ_s for both large and small counties was assigned a uniform prior on the range (0–25).

For the standard deviation of the county effects, two different priors were used to test for sensitivity to the choice of prior. The first was an exponential distribution with mean 2 and the second was a uniform distribution on 0–10. The exponential distribution is a more conservative choice, since it places a higher probability on small values for the county effect variation, meaning that the resulting estimation of the county effects will be closer to zero. However, results are not significantly different between the two priors. We use the programming language Stan,[S3] which uses a variation of MCMC called Hamiltonian Monte Carlo that accelerates convergence of the sampled values to the true posterior to draw values from the parameter posterior distribution.

For each posterior draw, we calculated the weighted standard deviation of the estimated county effects within each HRR, where the weights are the proportion of the county population within the HRR. This gives the posterior distribution of the within-HRR variation for each HRR. The estimate of the standard deviation of the error noise for large counties is 4.1% and for small counties is 7.5%. Based on benchmark of 250 Medicare decedents, there are 79 large counties and 67 small counties across North and South Carolina. As a result, the weighted average error noise standard deviation is 5.7%. There is a 14.4% posterior probability that the standard deviation of the county effect is larger than the standard deviation of random noise in the data.

Summary of results

Regression parameter estimates are shown in Supplementary Table S1 for the model with an exponential prior on the county effect variance. The baseline corresponds to a county in the Durham HRR in North Carolina, with no hospices and all other characteristics at their overall average across North and South Carolina. Model fit was assessed by comparing predicted utilizations from the model to the observed utilization rates by county. A graphical comparison is displayed in Supplementary Figure S1.

The posterior mean standard deviation of within variation averaged over all HRRs is 5.1 percentage points, while the mean standard deviation of between-HRR variation is 10 percentage points (Supplementary Fig. S2). To better understand the relative contribution of different geographic units to hospice utilization, we compared the within-HRR variation to the between-HRR variation by taking a ratio of the two quantities. Supplementary Figure S3 displays the posterior distribution of the ratio of this relative variation. The mean ratio is 0.52, which means that the magnitude of county variation within regions is about 52% of the magnitude of variation between regions. The posterior further quantifies the uncertainty in this ratio; for example, there is a 44.4% posterior probability that the ratio of relative variation is greater than 0.5.

We also ran a sensitivity analysis using a uniform prior on the standard deviation of the county effect (Supplementary Appendix Tables SA1 and SA2 and Supplementary Appendix Figs. SA1–SA3). This corresponds to a prior belief that county effects are likely to be a bigger factor. The results under this assumption are that the point estimate of the weighted noise standard deviation is 4.87% and the county effect is 3.39%. The posterior mean estimate of the ratio of these two quantities is 0.84 with a 36.6% posterior probability that the standard deviation of the county effect is larger than the standard deviation of random noise in the data. This implies that the choice of prior does not unduly impact the conclusion that significant differences in hospice utilization exist within HRRs.

As a result, we conclude that HRRs do not adequately explain geographic differences in hospice utilization, as significant variation exists in utilization at smaller geographic units, such as at the county level. This variation is present even after controlling for observable county characteristics.

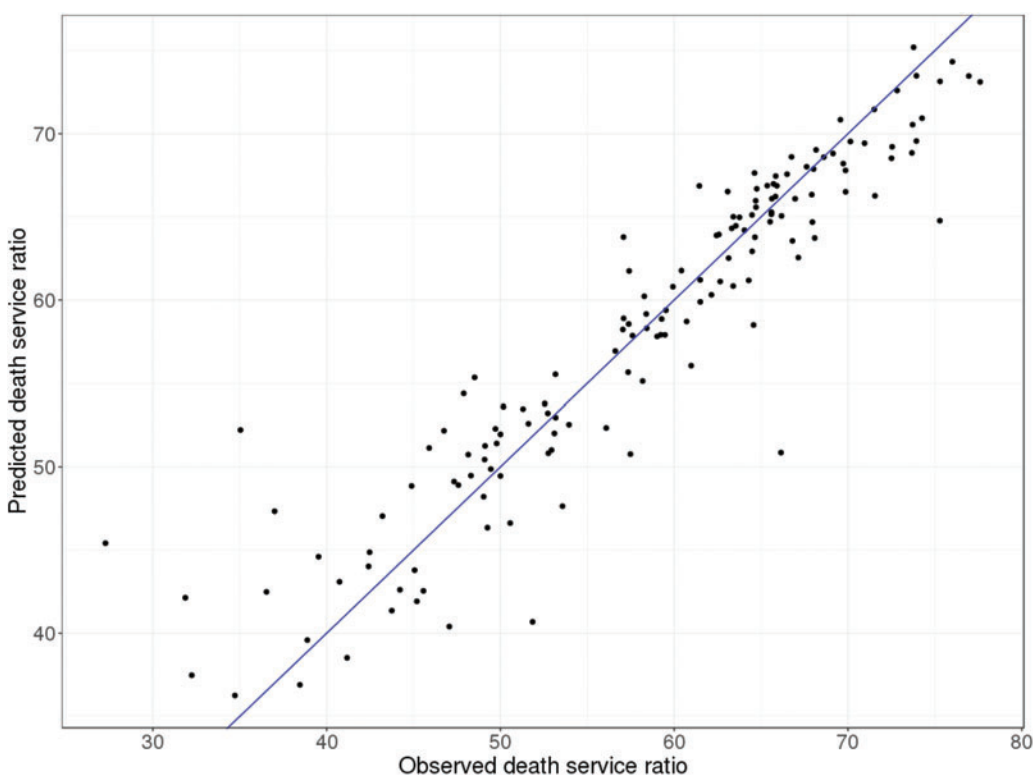
Supplementary References

S1. Hoff PD: *A First Course in Bayesian Statistical Methods, 1st ed.* New York: Springer-Verlag, 2009.

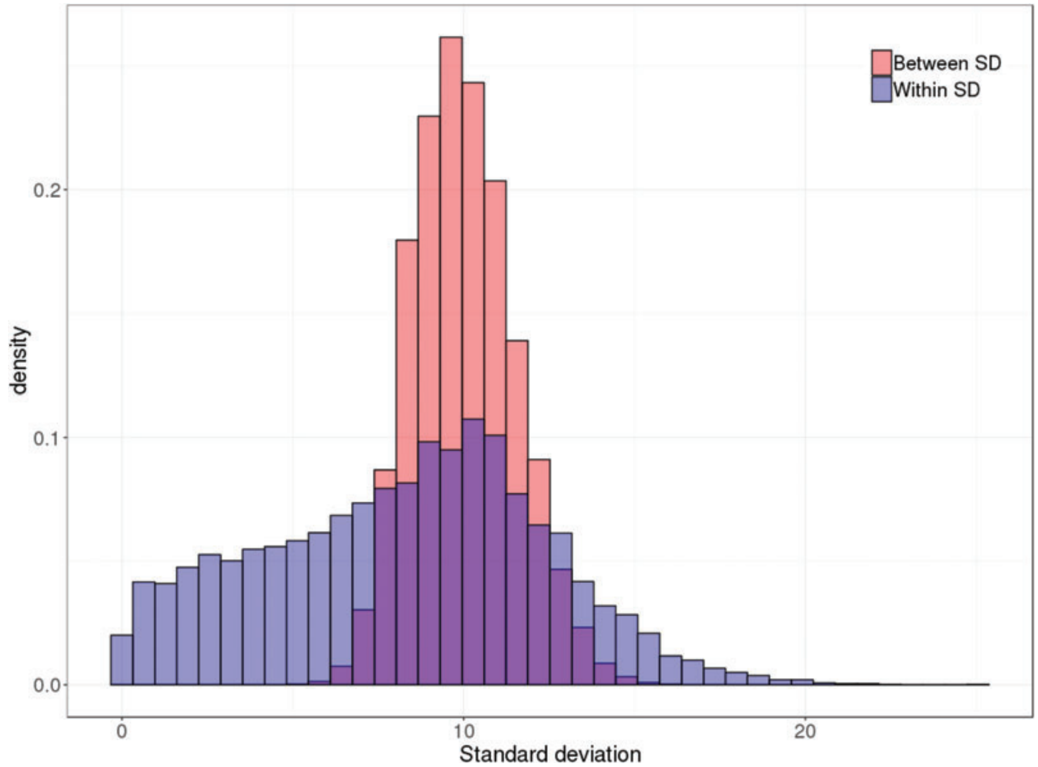
S2. Gelman A, Stern HS, Carlin JB, et al.: *Bayesian Data Analysis, 3rd ed.* Chapman and Hall/CRC, 2013.

S3. Carpenter B, Gelman A, Hoffman MD, et al.: Stan: A probabilistic programming language. J Stat Softw 2017;76. DOI: 10.18637/jss.v18076.i18601.

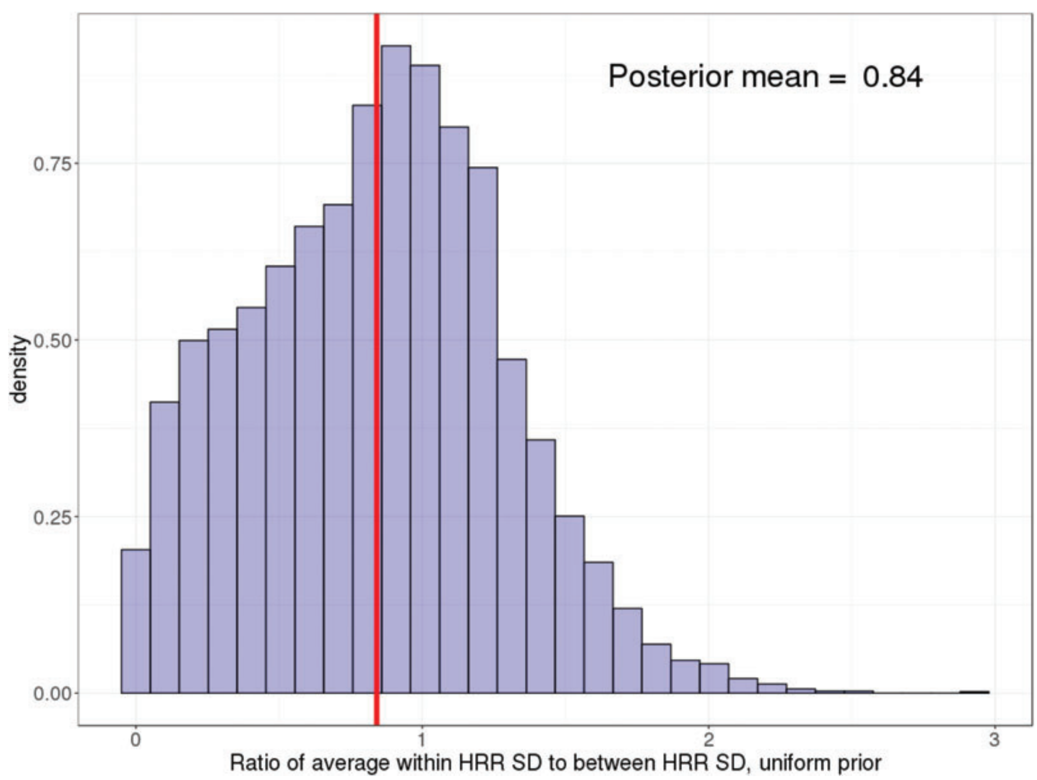
Supplementary Appendix S1. Sensitivity Analysis with Uniform Prior Assumption



SUPPLEMENTARY APPENDIX FIG. SA1. Comparison of the observed death service ratio for each county to its predicted death service ratio, based on posterior parameter mean. This version assumes a **uniform prior** on the standard deviation of the county-level effect.



SUPPLEMETNARY APPENDIX FIG. SA2. Posterior distributions of the standard deviation of the effect of HRR on death service utilization (''between'') compared with the standard deviation of county effects within each HRR, averaged across all HRRs. This version assumes a **uniform prior** on the standard deviation of the county-level effect. HRR, hospital referral region.



SUPPLEMETNARY APPENDIX FIG. SA3. Posterior distribution of the ratio of the standard deviation of county effects within each HRR, averaged across all HRRs to the standard deviation of the effect of HRR on death service utilization. This version assumes a **uniform prior** on the standard deviation of the county-level effect.

Supplementary Appendix Table SA1. Regression Estimates Using a Uniform Prior over the Range (0–10) for the County Effect Standard Deviation

Variable name	*Marginal posterior summaries* Mean	2.5%	97.5%
Intercept	60.22	56.52	63.97
% African American	−0.22	−0.36	−0.08
% Female	0.56	0.21	0.92
% Circulatory DX	−0.47	−0.94	0.01
% Mental DX	0.05	−0.76	0.86
% Respiratory DX	−1.04	−1.53	−0.56
% Other DX	−1.16	−1.63	−0.68
South Carolina	−8.02	−15.71	−0.49
No. of hospice	0.06	−0.53	0.68
% Poverty	−0.05	−0.34	0.25
% Age 65+	−0.14	−0.48	0.21
Small County	−4.13	−7.18	−1.26
Atlanta, GA HRR	−4.92	−29.64	−0.36
Augusta, GA HRR	4.05	−7.12	15.25
Savannah, GA HRR	15.1	2.72	27.41
Asheville, NC HRR	−1.65	−7.51	4.20
Charlotte, NC HRR	6.26	1.29	11.28
Greensboro, NC HRR	7.63	−0.10	15.47
Greenville, NC HRR	−7.59	−12.57	−2.60
Hickory, NC HRR	11.94	4.14	20.30
Raleigh, NC HRR	−7.49	−12.46	−2.49
Wilmington, NC HRR	2.6	−3.84	8.99
Winston-Salem, NC HRR	7.73	2.00	13.66
Charleston, SC HRR	9.91	0.92	19.16
Columbia, SC HRR	8.79	−0.20	17.87
Florence, SC HRR	10.46	0.18	20.90
Greenville, SC HRR	15.08	5.59	24.67
Spartanburg, SC HRR	10.85	0.91	20.78
Johnson City, TN HRR	−1.88	−19.35	15.39
Norfolk, VA HRR	−12.14	−19.32	−5.07
Noise standard deviation, large counties	3.08	0.24	5.54
Noise standard deviation, small counties	6.99	4.48	9.27
County effect standard deviation	3.39	0.26	5.69

Estimate of county-level effects available as a supplement.
HRR, hospital referral region.

Supplementary Appendix Table SA2. Ratio of the Posterior Estimate of the Standard Deviation of County Effects within Each Hospital Referral Region to the Posterior Estimate of the Standard Deviation of Hospital Referral Region Effects across All Hospital Referral Regions, Assuming a Uniform Prior

HRR	*Marginal posterior summary* Mean	2.5%	50%	97.5%
Atlanta, GA	0.245	0.013	0.206	0.695
Augusta, GA	0.460	0.028	0.399	1.272
Savannah, GA	0.294	0.017	0.248	0.800
Asheville, NC	1.045	0.053	0.850	3.128
Charlotte, NC	1.027	0.051	0.745	3.436
Durham, NC	1.034	0.053	0.779	3.312
Greensboro, NC	0.458	0.030	0.399	1.228
Greenville, NC	1.138	0.060	0.810	3.706
Hickory, NC	0.405	0.026	0.351	1.123
Raleigh, NC	0.920	0.051	0.677	2.923
Wilmington, NC	0.564	0.036	0.447	1.659
Winston-Salem, NC	0.845	0.048	0.649	2.675
Charleston, SC	0.691	0.041	0.531	2.144
Columbia, SC	1.097	0.052	0.804	3.530
Florence, SC	0.645	0.038	0.497	1.975
Greenville, SC	0.564	0.036	0.431	1.781
Spartanburg, SC	0.482	0.030	0.403	1.423
Johnson City, TN	0.195	0.011	0.161	0.564
Norfolk, VA	0.642	0.039	0.522	1.913