National Surveillance of Stroke Quality of Care and Outcomes by Applying Post-Stratification Survey Weights on the Get With The Guidelines-Stroke Patient Registry

Boback Ziaeian (BZiaeian@mednet.ucla.edu)
David Geffen School of Medicine at UCLA https://orcid.org/0000-0001-9787-3649

Haolin Xu
Duke Clinical Research Institute

Roland A. Matsouaka
Duke University

Ying Xian
Duke University

Yosef Khan
American Heart Association

Lee S. Schwamm
Massachusetts General Hospital

Eric E. Smith
University of Calgary

Gregg C. Fonarow
David Geffen School of Medicine: University of California Los Angeles David Geffen School of Medicine

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National Surveillance of Stroke Quality of Care and Outcomes by Applying Post-Stratification Survey Weights on the Get With The Guidelines-Stroke Patient Registry

Boback Ziaeian MD PhD[a,b], Haolin Xu MS[c], Roland A. Matsouaka PhD[c,d], Ying Xian PhD[c,e], Yosef Khan MD PhD[f], Lee S. Schwamm MD[g], Eric E. Smith MD MPH[h], Gregg C. Fonarow MD[a,i]

[a]Division of Cardiology, David Geffen School of Medicine at University of California, Los Angeles, Los Angeles, California
[b]Division of Cardiology, Veteran Affairs Greater Los Angeles Healthcare System, Los Angeles, California
[c]Duke Clinical Research Institute, Durham, North Carolina
[d]Department of Biostatistics and Bioinformatics, Duke University, Durham, North Carolina
[e]Department of Neurology, Duke University Medical Center, Durham, North Carolina
[f]Healthcare Quality Research and Bioinformatics, American Heart Association, Dallas, Texas
[g]Department of Neurology, Comprehensive Stroke Center Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts
[h]Department of Clinical Neurosciences and Hotchkiss Brain Institute, University of Calgary, Calgary, Alberta, Canada
[i]Ahmanson-UCLA Cardiomyopathy Center, University of California, Los Angeles Medical Center, Los Angeles, California

Corresponding Author: Boback Ziaeian, MD PhD, Division of Cardiology, David Geffen School of Medicine at UCLA, 10833 LeConte Avenue, Room A2-237 CHS, Los Angeles, CA 90095-1679
E-mail: bziaeian@mednet.ucla.edu Phone: (310) 876-2602 Fax: (888) 267-3237

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Abstract (258)

Background: The U.S. lacks a stroke surveillance system. This study develops a method to transform an existing registry into a nationally representative database to evaluate acute ischemic stroke care quality.

Methods: Two statistical approaches were used to develop post-stratification weights for the Get With The Guidelines-Stroke registry by anchoring population estimates to the National Inpatient Sample. Post-stratification survey weights were estimated using a raking procedure and Bayesian interpolation methods. Weighting methods were adjusted to limit the dispersion of weights and make reasonable epidemiologic estimates of patient characteristics, quality of hospital care, and clinical outcomes. Standardized differences in national estimates were reported between the two post-stratification methods for anchored and non-anchored patient characteristics to evaluate estimation quality. Primary measures evaluated were patient and hospital characteristics, stroke severity, vital and laboratory measures, disposition, and clinical outcomes at discharge.

Results: A total of 1,388,296 acute ischemic strokes occurred between 2012 and 2014. Raking and Bayesian estimates of clinical data not recorded in administrative databases were estimated within 5% to 10% of the margins of expected values. Median weights for the raking method were 1.386 and the weights at the 99th percentile were 6.881 with a maximum weight of 30.775. Median Bayesian weights were 1.329 and the 99th percentile weights were 11.201 with a maximum weight of 515.689.

Conclusions: Leveraging existing databases with patient registries to develop post-stratification weights is a reliable approach to estimate acute ischemic stroke epidemiology and monitoring for stroke quality of care nationally. These methods may be applied to other diseases or settings to better monitor population health.

Background

The Institute of Medicine's (IOM) report entitled *A Nationwide Framework for Surveillance of Cardiovascular and Chronic Lung Diseases* highlights the lack of systems to monitor the incidence and prevalence of preventable diseases at the national level (1). While the U.S. mandates standardized reporting of causes of death through the National Vital Statistics system, comparable systems are not available for incident disease and the assessment of healthcare quality (2). The IOM's report recommends that surveillance systems be created to track progress on cardiovascular burden and inform efforts to reduce disease burden. Since the IOM's publication in 2011, robust disease surveillance systems for cardiovascular disease have not been developed in the U.S. The glaring need to build such a surveillance system continues to be emphasized (2). Systematically integrating various paper and electronic health record systems across the U.S. remains an insurmountable task. For this study, we sought to overcome these challenges by integrating two existing, large and reliable data sources for future epidemiologic and outcomes research work related to acute ischemic stroke.

A non-representative database may be transformed into a representative one if appropriate post-stratification weights are estimated to rebalance over and under-represented segments of a target population of interest (3). Various methods may be used to weight non-random sample observations to approximate true epidemiologic estimates.

The best estimates for incidence and utilization of hospital services are publicly available through databases sponsored by the Agency for Healthcare Quality and Research's Healthcare Cost and Utilization Project (4). The National Inpatient Sample (NIS) is a structured random sample of U.S. hospitalizations that is then weighted to represent national hospital utilization. However, the database does not include detailed clinical data such as stroke severity, laboratory data, medical treatment received, and patient reported outcomes. A few community cohort and case-control studies are currently featured in the annual American Heart Association (AHA) statistical update on heart disease and stroke statistics but are not nationally representative and inadequate to measure stroke burden and quality of care nationally (5–7).

The AHA sponsored Get With The Guidelines Program (GWTG) program includes rich clinical data for quality improvement and research analyses (8). Yet, registries with volunteer hospitals do not mirror the complete national population (9,10). The purpose of this study is to develop and validate methods to reweight the AHA's GWTG-Stroke registry observations using advanced post-stratification weighting procedures to evaluate clinical characteristics of the total U.S. ischemic stroke population. These methods will form a platform for future national surveillance and health care quality research using these methods.

Methods

Data Source

We used the GWTG-Stroke registry from 2012 to 2014 to evaluate post-stratification weighting procedures to represent the entire U.S. acute ischemic stroke (AIS) population. In GWTG-Stroke, trained personnel abstract reliable deidentified demographic, clinical, and event information from participating hospitals using an internet-based patient management tool (8). Identification of AIS is accurately identified and clinical variables such as admission and discharge stroke severity are systematically included alongside detailed clinical data not available in administrative claims data alone. Details of the GWTG-Stroke program are previously described (11,12). Hospitals participating in the GWTG program do so on a voluntary basis. Even though the GWTG program contains many smaller, rural and non-academic hospitals, these hospital types are under-represented compared to the overall U.S. hospitalized population (9). Therefore, the sampling strategy does not permit the direct estimation for the entire U.S. population as currently structured.

To determine the total number of AIS hospitalizations in the U.S. and marginal population characteristics for post-stratification weights, the NIS sponsored by the Agency for Healthcare Research and Quality's remains the most reliable data source. For 2012 to 2014, the NIS sampled 20% of the administrative discharge records from all participating hospitals (approximately 4,300 hospitals) covering 95% of the U.S. population and 94% of all community hospital discharges (13). While the NIS may be used to understand populations rates of AIS, basic demographics, procedures, and costs, it lacks detailed clinical and outcomes data.

Study Population

The target population for the post-stratification weighting procedure was the total AIS presenting to U.S. hospitals by year. The NIS was used to define the AIS burden nationally stratified between the years of 2012 and 2014 and the 9 U.S. Census regions – preserving the smallest sampling unit recommended by the NIS sponsors.

Data Definitions

AIS was defined by primary discharge International Classification of Diseases, Ninth Revision (ICD-9) codes for hospitalizations in the NIS (14). AIS was defined in GWTG-Stroke based on abstracted discharge diagnoses (online supplement). GWTG-Stroke uses electronic case report form-based data extraction from clinical chart review to document patient-specific comorbid conditions. The NIS diagnostic and procedure estimates are based on administrative coding of ICD-9 diagnostic and procedure codes.

Statistical Analysis

Two parallel methods were used to estimate post-stratification survey weights. Raking is an iterative procedure for minimizing the dispersion of weights to approximate the targeted marginal counts of interest. More recent research has advanced Bayesian interpolation statistical methods to estimate post-stratification weights and fit flexible analytic models. Both raking and the Bayesian interpolation method rely on anchoring estimates to select set of characteristics shared between disparate datasets to improve representativeness of skewed distributions. For this study, select hospital and patient characteristics were added iteratively as anchoring variables to improve skewed representation in GWTG-Stroke. The two post-stratification weighting approaches were used to contrast U.S. population wide epidemiologic estimates.

Standardized differences for all weighted characteristics were estimated for patient and hospital characteristics (anchored and non-anchored variables). We analyzed the distribution of raking and Bayesian weights with histograms and treemaps to provide a perspective on the skewed representation of the GWTG-Stroke raw sample. Iterative model development was used to select the minimal set of hospital or patient characteristics required to limit extreme post-stratification weights while maintaining reliable population estimates for known factors estimated from the NIS.

<u>Overview of the estimation problem</u>

Suppose we want to estimate the proportion of eligible patients for different age categories in the population. For each census division (i.e., sample s), we observe in our registries a number x_k of these patients, with some of them possibly under- (or over-) represented. Using data from the available registry, our goal is to estimate the probability sampling weight w_k such that

$$\sum_s w_k x_k = t_k$$

where t_k is the observed mean for the target population. For this study, we derive the post-stratification weights w_k using two parallel approaches: raking and the Bayesian interpolation.

Raking procedure

Raking procedures are used to generate weights when known marginal counts are available for two or more categorical variable dimensions. The raking algorithms create an initial weight for all observations and then iteratively adjusts them to minimize the spread of weights so no single observation is over- or under-represented in the data.(15) Therefore, if the target male population is 400,000 and the sample population is 200,000 males, an initial raking weight of 2 would apply to all observations across male sex. Raking attempts to minimize the difference between new weights and the initial weight to approximate the targeted population totals.

The initial or base weight d_k based on the population size, such that d_k multiplied by the sample size equals the population size. The goal of a raking procedure is to minimize the sum of the difference between the new weights (w_k) and the base weight (d_k) (16). Raking attempts to estimate a determined t_k target while minimizing the average weight distance from the base weight.

$$Average\ weight\ distance = \sum_{s} (w_k - d_k)^2 / d_k$$

Typically, weighted variance estimation (i.e. the Horvitz-Thomson estimator) of structured data accounts for the inclusion probability of sampled data from a population (17). Post-stratification variance estimation with raking uses an additive analysis of variance (ANOVA) of the residuals to fit the model (15,18). Variables available in both GWTG-Stroke and the NIS were selected as anchoring variables to generate the raking weights using SAS 9.4 (SAS Institute, Inc., Cary, North Carolina). Shortcomings of this frequentist approach to probability weight generation remain. Statistical assumptions may not hold for variance estimation, especially for testing interactions and small-area estimation (19). This procedure may also create negative weights in certain situations (20). Variables evaluated for raking included: age quartiles, sex, race/ethnicity, region, payer, hospital bed size, hospital ownership (government, private non-profit, private investor-owned) and rural/urban status.

Bayesian population interpolation

The Bayesian population interpolation approach frames post-stratification weights as estimated from the posterior distribution of anchoring variables for the target population (i.e. total U.S. AIS population). The Bayesian model allows for greater flexibility and the ability to integrate information from multiple sources that account for the known marginal and joint distributions of various population characteristics over time. For this study, only the NIS was required to calibrate post-stratification weights. The observed proportions from GWTG-Stroke are Bayesian prior information within the model and are non-representative of the target population.

The Bayesian model estimates post-stratification weights when integrating prior and posterior information for the anchored variables. The observed GWTG-Stroke dataset (Bayesian prior) when fit to the marginal distribution of the anchoring characteristics generates post-stratification weights (21,22). The fundamental model is described as such: let $p_m$represent the observed proportion for a given variable m for subgroup with φ_m being the true population proportion. Observed counts are represented by the sample size multiplied by the observed proportion ($\mathrm{n_s p_m}$). Next, we build a multinomial observational model for adjusting the observed and known subgroup proportions:

$$n_s p_m \sim multinomial(\varphi_m n_s^r) \qquad (1)$$

where n_s represents the size of the sample and $n_s p_m$ is the number of patients that fall within different sub-categories (i.e. m=1, 2, 3) of the sample of patients (for which the observed numbers are the naïve estimates). The number n_s^r is the precision of the sampling distribution, which we specify in the application based on n_s. Under this model, the expected value of the proportion p_m is thus φ_m. Finally, for a given cell, $\varphi_m = A_m \pi$, where π is the true (unknown) cell population and A_m is an indicator matrix whose component are equal to 1 when the observed cell is not empty and 0 otherwise.

For each year, the anchoring covariates form joint distributions between the observed GWTG-Stroke observations and target population proportions. The conjugate of the multinomial distribution $\pi_\tau \sim Dir(\pi_{\tau-1}, n^h)$ are Dirichlet models linked through a stochastic relationship (represented by the indexes τ) between each GWTG-Stroke observation and the marginal and joint distributions for the target AIS population derived from the NIS (23). The hyperparameter n^h models the degree of pooling across available registries to which we assign a low prior. The Bayesian model includes permutations of all anchored variable combinations as population subgroups. For variable combinations where GWTG-Stroke lacked observations, non-zero cell populations (i.e., related n^h) were used for estimation. We assumed a flat prior for the GWTG-Stroke observations to approximate the target population characteristics from the NIS. Once the posteriors of $\varphi_m = A_m\pi$ are calculated, we determine the weights w_k as $w_k = p_m$, using the equality (1). All Bayesian analyses were performed in R 3.6.1 (R Foundation, Vienna Austria). Permission for this analysis was granted through the Duke Clinical Research Institute IRB.

Results

A total 1,761 hospitals were included in the GWTG-Stroke registry between 2012 and 2014. We excluded hospitals in which hospital characteristics of interest were not fully recorded in the database. The final cohort included 726,390 patients across 1,546 hospitals representing the raw GWTG-Stroke cohort prior to weighting (Figure I and Online Supplement).

Initially, we attempted a parsimonious model to generate the weights using only select hospital characteristics: ownership, rural/teaching, and bed size stratified by Census division. After observing inadequate representation for select race/ethnic minorities, a decision was made to include patient-level race/ethnicity to derive post-stratification weights. Weights are unique for each hospitalization observed in GWTG-Stroke. The final raking and Bayesian post-stratification weight models used hospital characteristics for ownership, rural/urban and teaching status, bed size followed by race/ethnicity at the patient-level.

There were an estimated 1,388,296 AIS between 2012 to 2014 in the U.S. For the raking method, anchored characteristics in the weighted GWTG-Stroke sample matched the exact population totals estimated from the NIS. This is to be expected unless matching two or more marginal characteristics is mathematically prohibitive (Table I). The Bayesian method generated population totals with no more than 5-10% variance of the NIS estimates. While the NIS estimates AIS presented to rural hospitals 10.29% of the time, the GWTG-Stroke unweighted representation was 3.49% and after post-stratification using Bayesian derived weights was 6.02%, which is 44% lower than expected. Age distributions for both methods were extremely similar. Sex, race/ethnicity, health insurance status, and comorbidities, vital and laboratory measurements, arrival information and hospital characteristics were also similar between the raking and Bayesian methods. Post-stratification estimates stratified by year and U.S. Division are available in the Online Supplement.

The NIS does not provide any clinical data such as medication lists, vitals and laboratory measurements, stroke severity and certain discharge disposition data. The NIS definitions for health insurance status did not align with the GWTG definitions, and therefore were not included in the Table I. In GWTG, there are small differences in the prevalence of comorbidities between the raking and Bayesian weighting methods. NIS comorbidities were based on administrative coding only while GWTG-Stroke is based on chart abstraction. There are minimal differences in summary vital and laboratory measurement, arrival information, baseline medication usage rates, and inpatient outcomes between the two weighting approaches. On admission we note that 49.2% of stroke patients nationally are using antiplatelet medications, 15.5% anticoagulants, 69.1% anti-hypertensives, 43.6% cholesterol lowering medications, 27.4% diabetic medications. With respect to disposition, 47.6% of patients are discharged home 40.2% to transitional care facilities, and 4.6% with hospice-related services.

For the raked post-stratification weights, the median weight was 1.386 and the weights at the 99th percentile were 6.881 with a maximum weight of 30.775 for individual GWTG-Stroke observations (Figure IIA). For the Bayesian post-stratification weights, the median weight was

1.329 and the 99th percentile weights were 11.201 with a maximum weight of 515.689 (Figure IIB).

Color treemaps were made to visualize the strata where larger weights were concentrated on based on select characteristics (Figure III and IV). Overall, given the lower representation of rural hospitals in GWTG-Stroke, rural hospitals received weights in the 6 to 8 range using the raking procedure. The Bayesian approach resulted in mostly smaller weights on average in the rural areas, however post-stratification estimates using the Bayesian method were underestimated with a standard difference of 16% compared to the raking procedure. When looking at the distribution of post-stratification weights by race/ethnicity, raking resulted in average weights in the 6 to 8 range for minorities in the “Other” category. Using the Bayesian method, we observe some more extreme weights for “Other” race/ethnic minorities living in the division 4 and 6.

Discussion

The characteristics and risk factors of patients presenting with stroke nationally are not well understood given the lack of a centralized national surveillance system. Hospital care for AIS is frequently the first and last opportunity to rescue a life and reverse or prevent neurologic disability. Understanding the effectiveness of hospital systems at a national and regional level is needed to insure both consistency and timeliness in the receipt of evidence-based care. We integrate two large data systems to make better population wide clinical estimates of acute ischemic stroke in the U.S. This work demonstrates that methods exist to marry existing databases to make more reliable statistical inferences of population health and health services utilization.

The Greater Cincinnati/Northern Kentucky Stroke Study makes epidemiologic inferences using case ascertainment for an urban population to report stroke incidence rates. The population described is slightly younger, more female, has a higher representation of African-Americans, and higher rates of coronary artery disease and heart failure than is estimated from the NIS or weighted GWTG-Stroke presented (Table II) (24–26).

The approach described in the present paper is a far more robust estimation of the characteristics of stroke presentation and the quality of hospital care nationally. The GWTG-Stroke patient registry captures 58% of all strokes nationally. By anchoring to the NIS, the median weights are reasonable with a median multiplier of 1.3 and very few extreme or outlier weights. The main challenges the model faced was estimation for small cohorts that were under-represented such as rural populations and other minorities in select regions of the U.S. Overall, we provide one of the best estimations for clinical characteristics expected for the entire U.S. population using GWTG-Stroke with post-stratification survey weights.

As patient registries have expanded, advanced statistical methods are available to transform non-random samples into representative population estimates. This research demonstrated that both traditional and Bayesian methods perform well to reshape unstructured data and make inferences regarding the U.S. population. This is the first study to our knowledge that has transformed a patient registry using post-stratification weights to represent a larger population of interest. The ability to translate observations from large registries to a national scale would fill a considerable void in the surveillance of the clinical characteristics, quality of care, and outcomes for AIS hospitalizations nationally (27).

There are limitations to this work. GWTG-Stroke is a voluntary program for quality improvement. Hospitals that do not participate may be more likely to lack systems for quality improvement and therefore measures of the timeliness or completeness of AIS treatment may be biased in a favorable direction. Coding accuracy of comorbid conditions remains an issue for both administrative data from the NIS and abstracted from inpatients charts in GWTG-Stroke. Large post-stratification weights were applied to under-represented patient populations such as those in rural areas and race/ethnic minorities. Applying these methods to smaller sizes may generate less reliable estimates and may not adequately capture the diversity in patient populations. Given there is no gold standard to compare certain statistics we estimated for the U.S. AIS population, we cannot reliably test any biases that might have arisen based on the two approaches used to generate post-stratification weights. These weights were generated only retrospectively, but the same methods will allow for prospective post-stratification and continuous calibration with changes in secular trends of both stroke presentation and GWTG-Stroke center participation.

Conclusion

As healthcare in the U.S. is decentralized, there are immense practical and financial obstacles to building national or regional AIS surveillance systems. Leveraging existing patient registries such as GWTG-Stroke and applying post-stratification weights to reshape unstructured data is an efficient means of providing population surveillance of clinical measurements and outcomes not easily measured otherwise. Both raking and Bayesian approaches provide reasonably accurate estimates for describing health service utilization and the quality of care from a national perspective. We have provided a demonstration for how future researchers may approach non-survey data to achieve better representation of target population of interest. Both the raking and Bayesian interpolation methods of generating post-stratification weights may be applied to more advanced statistical modeling approaches to improve population wide inference and the surveillance of health care quality and outcomes.

Abbreviations

AHA = American Heart Association

AIS = Acute Ischemic Stroke

ANOVA = analysis of variance

GWTG = Get With The Guidelines

ICD-9 = International Classification of Diseases, Ninth Revision

IOM = Institute of Medicine

NIS = National Inpatient Sample

Declarations

Ethics approval and consent to participate: IRB approval granted through Duke University.

Consent for publication: All authors and the American Heart Association approved the manuscript for submission.

Availability of data and materials: Applications for access to protected health information in the registry are available to investigators through the Get With The Guideline – Stroke Registry program. https://www.heart.org/en/professional/quality-improvement/quality-research-and-publications/national-level-program-data-research-opportunities

Competing Interests:

Boback Ziaeian: none

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Lee H Schwamm: Research grants: NINDS, NIA, PCORI; Serves on scientific advisory boards for (1) LifeImage (2) Medtronic clinical trial design for AF related stroke NCT02700945 (3) Penumbra MIND study DSMB NCT03342664, (4) Genentech TIMELESS study NCT03785678 Steering Committee, and expert advisory panel on late window thrombolysis, (5) Diffusion Pharma DSMB PHAST-TSC NCT03763929. Serves as volunteer chair of the AHA/ASA stroke systems of care advisory committee, and ASA Advisory Committee of the AHA Board of Directors [unpaid]

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Author Contributions:

Concept and design: BZ, GCF

Drafting of the manuscript: BZ, HX, GCF

Critical revision of the manuscript for important intellectual content: BZ, HX, GCF

Statistical Analysis: BZ, RAM, YX, GCF

Administrative, technical, or material support: BZ

Supervision: RAM, GCF

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Twitter Handles: @boback, @matsouaka, @gcfmd @Braindoc_MGH

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Tables

Table I. Patient characteristics in the Get With The Guideline – Stroke after post-stratification weights using raking or Bayesian approach.

	GWTG Unweighted	NIS	GWTG Raking Weights	GWTG Bayesian Weights	Standardized Differences, %		
	N=726,390	N=1,388,295	N=1,388,295	N=1,388,296	NIS vs Raking	NIS vs Bayesian	Raking vs Bayesian
Hospital Characteristics							
*Census divisions					0.0	3.9	3.9
Division 1 New England	40,284 (5.55)	59,960 (4.32)	59,960 (4.32)	61,260 (4.41)			
Division 2 Mid-Atlantic	141,026 (19.41)	190,045 (13.69)	190,045 (13.69)	191,365 (13.78)			
Division 3 East North Central	98,744 (13.59)	215,585 (15.53)	215,585 (15.53)	217,076 (15.64)			
Division 4 West North Central	41,280 (5.68)	90,955 (6.55)	90,955 (6.55)	83,707 (6.03)			
Division 5 South Atlantic	159,799 (22.00)	303,745 (21.88)	303,745 (21.88)	314,341 (22.64)			
Division 6 East South Central	39,350 (5.42)	114,565 (8.25)	114,565 (8.25)	107,499 (7.74)			
Division 7 West South Central	66,934 (9.21)	158,475 (11.42)	158,475 (11.42)	160,105 (11.53)			
Division 8 Mountain	37,864 (5.21)	72,795 (5.24)	72,795 (5.24)	66,735 (4.81)			
Division 9 Pacific	101,109 (13.92)	182,170 (13.12)	182,170 (13.12)	186,208 (13.41)			
*Hospital ownership					0.0	5.6	5.6
Government	73,541 (10.12)	165,400 (11.91)	165,400 (11.91)	142,585 (10.27)			
Private, Non-Profit	579,983 (79.84)	1,034,510 (74.52)	1,034,510 (74.52)	1,063,608 (76.61)			
Private, Investor-Owned	72,866 (10.03)	188,385 (13.57)	188,385 (13.57)	182,102 (13.12)			
*Rural/teaching status					0.0	16.0	16.0
Rural	25,374 (3.49)	142,920 (10.29)	142,920 (10.29)	83,637 (6.02)			
Urban nonteaching	149,164 (20.53)	476,970 (34.36)	476,970 (34.36)	477,741 (34.41)			
Urban teaching	551,852 (75.97)	768,405 (55.35)	768,405 (55.35)	826,917			

	GWTG Unweighted	NIS	GWTG Raking Weights	GWTG Bayesian Weights	Standardized Differences, %		
	N=726,390	N=1,388,295	N=1,388,295	N=1,388,296	NIS vs Raking	NIS vs Bayesian	Raking vs Bayesian
				(59.56)			
*Bed Size Categories					0.0	7.4	7.4
Small	92,088 (12.68)	184,630 (13.30)	184,630 (13.30)	159,846 (11.51)			
Medium	198,454 (27.32)	379,405 (27.33)	379,405 (27.33)	357,012 (25.72)			
Large	435,848 (60.00)	824,260 (59.37)	824,260 (59.37)	871,437 (62.77)			
Primary Stroke Center	509,534 (70.15)	N/A	941,419 (67.81)	953,966 (68.71)	-	-	1.9
Comprehensive Stroke Center	110,333 (15.19)	N/A	149,156 (10.74)	179,012 (12.89)	-	-	6.7
Number of Beds, Median (IQR)	374 (243 - 581)	N/A	302 (195 - 464)	350 (205 - 532)	-	-	9.8
Annual Volume of IS Admissions, Median (IQR)	243 (166 - 382)	N/A	208 (143 - 318)	228 (143 - 361)	-	-	8.2
Patient Characteristics							
Age					2.4	1.5	0.8
Mean (SD)	70.49 (14.57)	70.61 (14.10)	70.47 (20.02)	70.29 (20.11)			
Age category							0.8
≤60	184,201 (25.36)	339,800 (24.48)	350,934 (25.28)	356,665 (25.69)			
61-70	160,447 (22.09)	302,770 (21.81)	309,032 (22.26)	309,064 (22.26)			
71-80	169,763 (23.37)	328,650 (23.67)	327,235 (23.57)	326,584 (23.52)			
>80	211,979 (29.18)	417,075 (30.04)	401,094 (28.89)	395,981 (28.52)			
Female	368,770 (50.77)	714,159 (51.44)	704,825 (50.77)	701,281 (50.51)	1.3	1.9	0.5
*Race/Ethnicity					0.0	4.6	4.6
White	506,456 (69.72)	925,390 (66.66)	925,390 (66.66)	923,221 (66.50)			
Black	124,170 (17.09)	217,450 (15.66)	217,450 (15.66)	214,227 (15.43)			
Hispanic	46,836 (6.45)	98,615 (7.10)	98,615 (7.10)	99,818 (7.19)			
Asian & Pacific Islander	22,425 (3.09)	34,935 (2.52)	34,935 (2.52)	45,134			

	GWTG Unweighted	NIS	GWTG Raking Weights	GWTG Bayesian Weights	Standardized Differences, %		
	N=726,390	N=1,388,295	N=1,388,295	N=1,388,296	NIS vs Raking	NIS vs Bayesian	Raking vs Bayesian
(3.25)							
Other	26,503 (3.65)	111,905 (8.06)	111,905 (8.06)	105,896 (7.63)			
Insurance					13.1	14.3	1.7
Private/VA/Champus/Other Insurance	140,727 (23.12)	256,085 (19.01)	259,132 (22.47)	268,964 (23.02)			
Medicaid	39,428 (6.48)	104,045 (7.72)	71,336 (6.19)	73,610 (6.30)			
Medicare	388,813 (63.88)	917,520 (68.10)	741,833 (64.32)	741,999 (63.51)			
Self Pay/No Insurance	39,722 (6.53)	69,685 (5.17)	81,042 (7.03)	83,748 (7.17)			
Stroke Admission Year							
2012	220,387 (30.34)	452,240 (32.58)	452,240 (32.58)	452,240 (32.58)			
2013	242,633 (33.40)	460,400 (33.16)	460,400 (33.16)	460,400 (33.16)			
2014	263,370 (36.26)	475,655 (34.26)	475,655 (34.26)	475,655 (34.26)			
Medical History							
Atrial Fibrillation/Flutter	172,120 (23.76)	343,981 (24.78)	318,990 (23.05)	320,231 (23.14)	4.0	3.8	0.2
Previous Stroke/TIA	222,336 (30.99)	N/A	429,240 (31.31)	423,422 (30.94)	-	-	0.8
CAD/Prior Myocardial Infarction	176,850 (24.65)	378,739 (27.28)	341,816 (24.93)	339,277 (24.79)	5.4	5.7	0.3
Diabetes Mellitus	243,745 (33.97)	553,176 (39.85)	473,934 (34.57)	469,364 (34.29)	10.9	11.5	0.6
Peripheral Vascular Disease	33,481 (4.67)	142,639 (10.27)	64,133 (4.68)	64,556 (4.72)	21.4	21.2	0.2
Hypertension	548,231 (76.41)	1,149,625 (82.81)	1,049,345 (76.54)	1,043,025 (76.21)	15.6	16.4	0.8
Smoker	133,412 (18.59)	433,520 (31.23)	258,994 (18.89)	259,894 (18.99)	28.8	28.5	0.3
Dyslipidemia	325,549 (45.37)	797,295 (57.43)	615,319 (44.88)	613,296 (44.81)	25.3	25.4	0.1
Heart Failure	66,449 (9.26)	199,810 (14.39)	125,027 (9.12)	126,046 (9.21)	16.4	16.1	0.3

	GWTG Unweighted	NIS	GWTG Raking Weights	GWTG Bayesian Weights	Standardized Differences, %		
	N=726,390	N=1,388,295	N=1,388,295	N=1,388,296	NIS vs Raking	NIS vs Bayesian	Raking vs Bayesian
Prosthetic Heart Valve	9,147 (1.27)	20,590 (1.48)	16,757 (1.22)	17,899 (1.31)	2.3	1.5	0.8
Obesity/Overweight	84,405 (11.76)	151,915 (10.94)	148,136 (10.80)	159,219 (11.63)	0.4	2.2	2.6
Chronic Renal Insufficiency	40,204 (5.60)	200,960 (14.48)	74,183 (5.41)	74,472 (5.44)	30.6	30.5	0.1
Vital and Laboratory Measurements							
SBP mmHg, Mean (SD)	157.02 (30.09)	N/A	157.51 (41.69)	157.35 (41.69)	-	-	0.4
BMI, Median (IQR)	27.2 (23.8 - 31.6)	N/A	27.3 (23.8 - 31.7)	27.3 (23.8 - 31.6)	-	-	0.0
HbA1c, % Mean (SD)	6.71 (1.89)	N/A	6.77 (2.57)	6.74 (2.6)	-	-	1.4
Blood Glucose mg/dL, Mean (SD)	142.48 (70.78)	N/A	143.65 (99.06)	143.42 (99.34)	-	-	0.3
Serum Creatinine mg/dL, Median (IQR)	1 (0.8 - 1.3)	N/A	1 (0.8 - 1.3)	1 (0.8 - 1.3)	-	-	0.2
Arrival Information							
Arrival Mode: EMS	328,713 (49.63)	N/A	615,016 (48.88)	608,291 (48.43)	-	-	0.9
Ambulatory Status at Admission					-	-	0.7
Unable to ambulate	140,461 (32.84)	N/A	258,705 (31.75)	261,489 (31.79)			
With assistance from person	117,069 (27.37)	N/A	228,196 (28.01)	232,655 (28.28)			
Able to ambulate independently	170,187 (39.79)	N/A	327,796 (40.24)	328,418 (39.93)			
On-time Arrival (non-holiday weekday 7am-6pm)	351,852 (48.44)	N/A	680,317 (49.00)	676,280 (48.71)	-	-	0.6
Initial NIHSS Score (0-42)					-	-	0.5
Median (IQR)	4 (1 - 9)	N/A	4 (1 - 9)	4 (1 - 9)			
Mean (SD)	6.7 (7.57)	N/A	6.63 (10.43)	6.68 (10.41)			
Medications Prior to Admission							
Antiplatelets	315,626 (49.64)	N/A	597,965 (49.49)	593,907 (49.15)	-	-	0.7
Anticoagulants	70,885 (15.87)	N/A	131,611 (15.49)	132,891 (15.56)	-	-	0.2
Antihypertensives	411,912 (69.26)	N/A	778,405 (69.30)	783,141 (69.14)	-	-	0.3
Cholesterol-Reducers	320,192 (44.35)	N/A	607,248 (43.98)	600,088 (43.55)	-	-	0.9
Diabetic Medications	156,575 (26.98)	N/A	302,257 (27.61)	301,123	-	-	0.5

	GWTG Unweighted	NIS	GWTG Raking Weights	GWTG Bayesian Weights	Standardized Differences, %		
	N=726,390	N=1,388,295	N=1,388,295	N=1,388,296	NIS vs Raking	NIS vs Bayesian	Raking vs Bayesian
				(27.37)			
Outcomes							
Length of Stay, (days), Median (IQR)	4 (2 - 6)	3 (2-6)	4 (2 - 6)	4 (2 - 6)	-	-	0.8
Stroke Unit Admission	394,102 (73.18)		710,891 (70.40)	710,406 (69.84)	-	-	1.2
Discharge Disposition							0.9
Home	343,284 (47.26)	679,755 (48.96)	663,414 (47.79)	660,288 (47.56)	2.3	2.7	
Home Hospice	10,019 (1.38)	N/A	19,336 (1.39)	19,701 (1.42)	-	-	
Hospice Facility	22,950 (3.16)	N/A	43,410 (3.13)	43,532 (3.14)	-	-	
Acute Care Facility	14,739 (2.03)	40,225 (2.90)	33,304 (2.40)	34,595 (2.49)	-	-	
Other Health Care Facility	297,278 (40.93)	592,875 (42.71)	558,726 (40.25)	558,770 (40.25)	4.9	4.9	
Left Against Medical Advice	4,954 (0.68)	10,720 (0.77)	9,644 (0.69)	9,459 (0.68)	-	-	
Expired (in-hospital mortality)	32,540 (4.48)	62,430 (4.50)	59,108 (4.26)	60,650 (4.37)	1.2	0.6	
Discharge Disposition - Other Facilities					-	-	1.5
Skilled Nursing Facility	128,134 (43.40)	N/A	247,379 (44.57)	243,845 (43.93)			
Inpatient Rehabilitation Facility	155,283 (52.60)	N/A	284,112 (51.19)	286,456 (51.61)			
Long Term Care Hospital	6,322 (2.14)	N/A	11,988 (2.16)	12,680 (2.28)			
Intermediate Care facility	2,831 (0.96)	N/A	6,238 (1.12)	6,408 (1.15)			

*Characteristic used to anchor post-stratification weights.

GWTG = Get With The Guidelines, UW = unweighted, W = weighted, TIA = transient ischemic attack, CAD = coronary artery disease, HbA1C = hemoglobin A_{1C}, EMS = emergency medical services

Table II. Comparison of patient characteristics in the National Inpatient Sample, Get With The Guidelines-Stroke, Greater Cincinnati/Northern Kentucky Stroke Study, and Reasons for Geographic and Racial Differences in Stroke Study.

	NIS	GWTG-UW	GWTG-RW	GWTG-BW	GCNKSS (2010)[28]	REGARDS (2003-2007)[29]
Patient Characteristics						
Age, Mean (SD)	70.6 (14.1)	70.5 (14.6)	70.5 (20.0)	70.3 (20.1)	69.0 (15.3)	73 (9)
Female (%)	51.4	50.8	50.8	50.5	55.6	52.5
Race						
Black (%)	15.7	17.1	15.7	15.4	20.3	43.7
Medical History						
Atrial Fibrillation	24.8	18.7	23.1	23.1	22	7.7
CAD/MI (%)	27.3	24.7	24.9	24.8	31.1	40.6
Heart Failure (%)	14.4	9.3	9.1	9.2	17.2	N/A
Hypertension (%)	82.8	76.4	76.5	76.2	79.0	89.1
Diabetes Mellitus	39.9	34.0	34.6	34.3	33	37.2
Smoker (%)	31.2	18.6	18.9	19.0	28.3	21.3
Prior TIA (%)	N/A	31.0	31.3	30.9	13.4	N/A
Vital Measurements						
SBP mmHg, Mean (SD)	N/A	157.0 (30.1)	157.5 (41.7)	157.4 (41.7)	158.3 (31.1)	N/A
Arrival Information						
Baseline NIHSS, Median (IQR)	N/A	4 (1-9)	4 (1-9)	4 (1-9)	3 (1-6)	N/A

NIS = National Inpatient Sample, GWTG = Get With The Guidelines, UW = unweighted, RW = Raking weighted, BW = Bayesian weighted, GCNKSS = Greater Cincinnati/Northern Kentucky Stroke Study

Figures

Figure I. Flow Chart of study population inclusion from the National Inpatient Sample and the Get With The Guidelines-Stroke registry program.

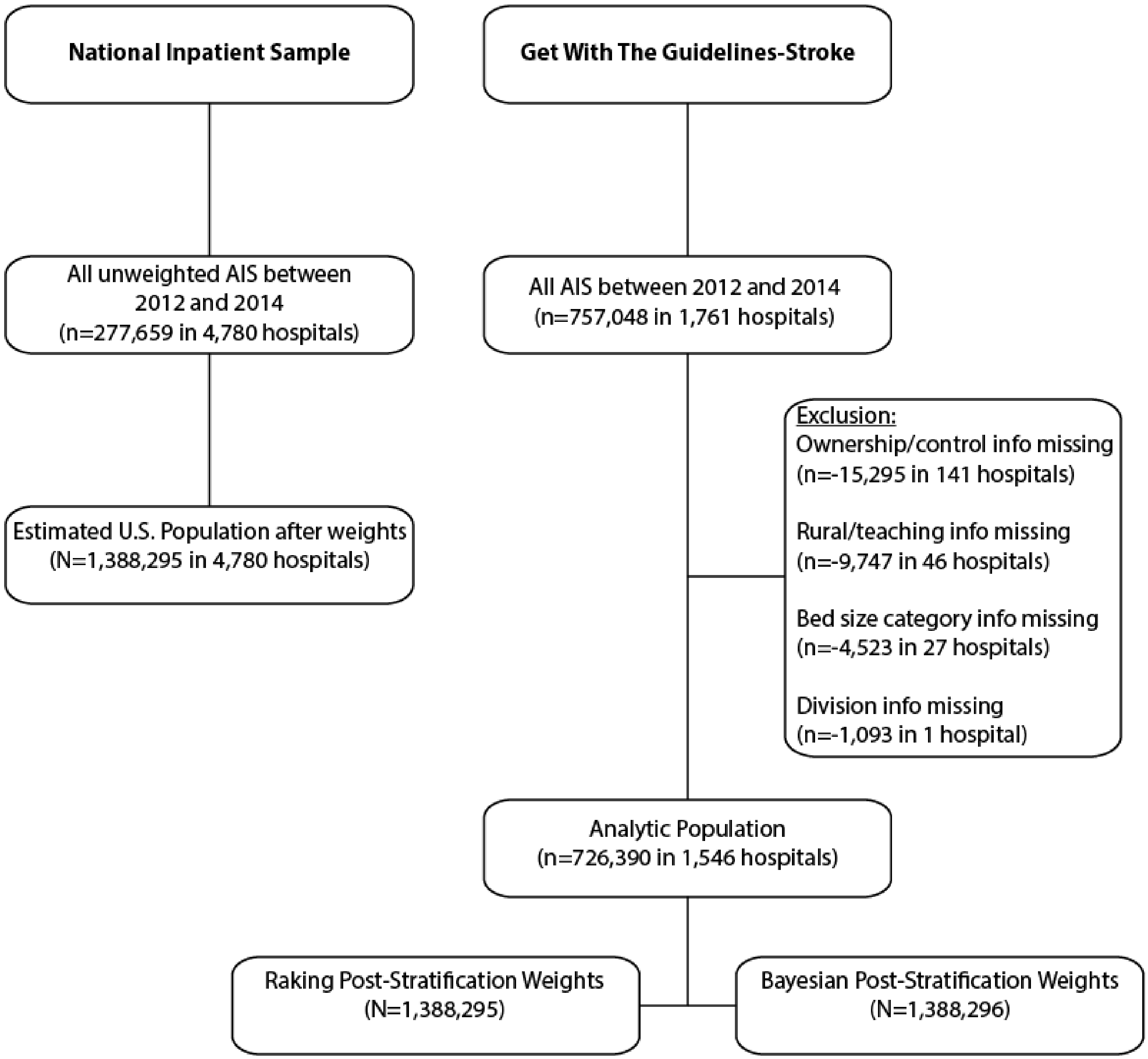
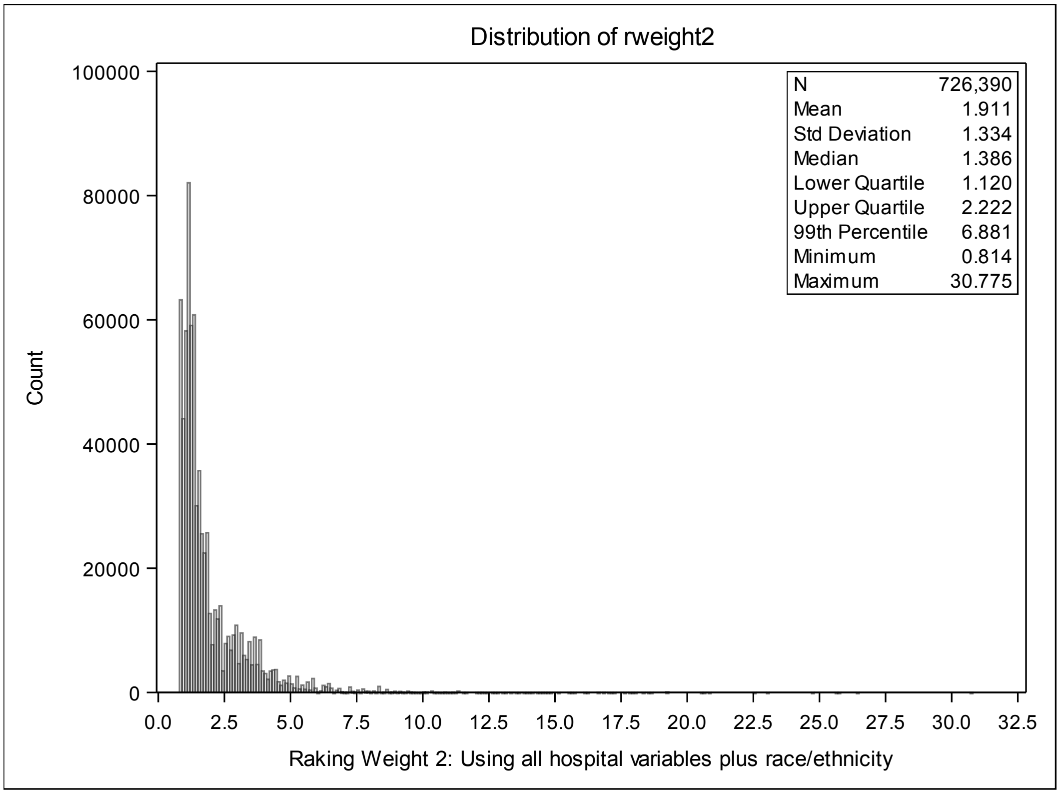


Figure II. Distribution of raking and Bayesian weights.

A: Distribution of raking derived post-stratification weights



B: Distribution of Bayesian post-stratification weights

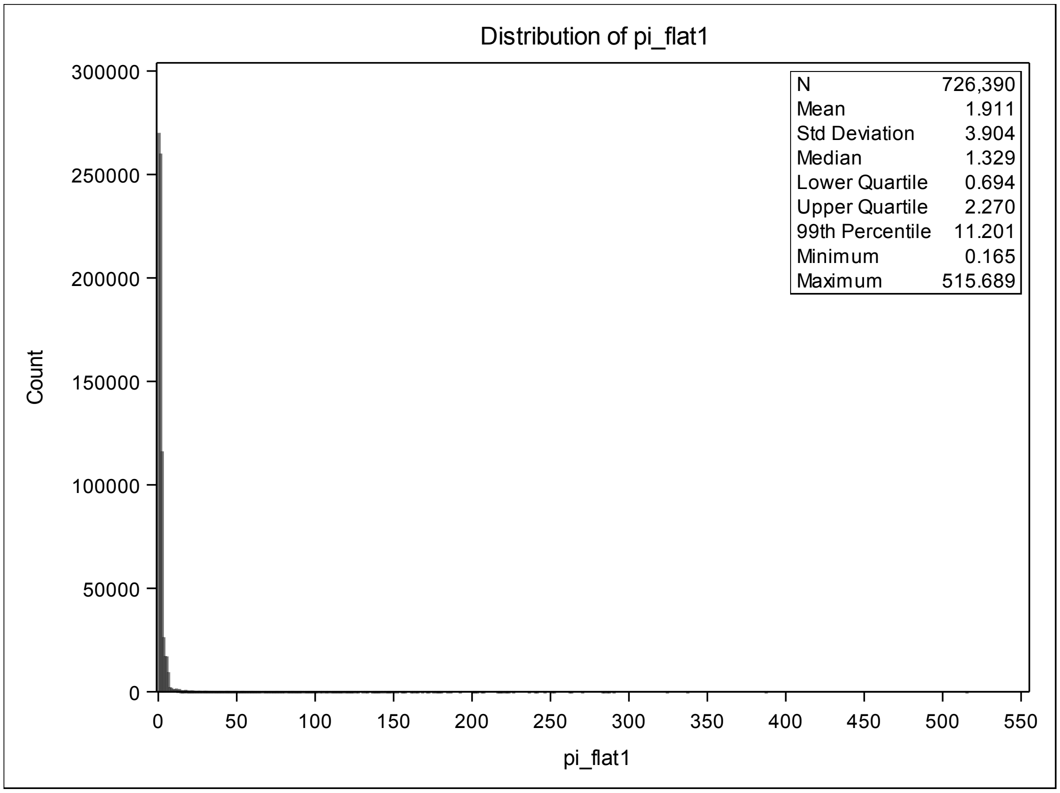
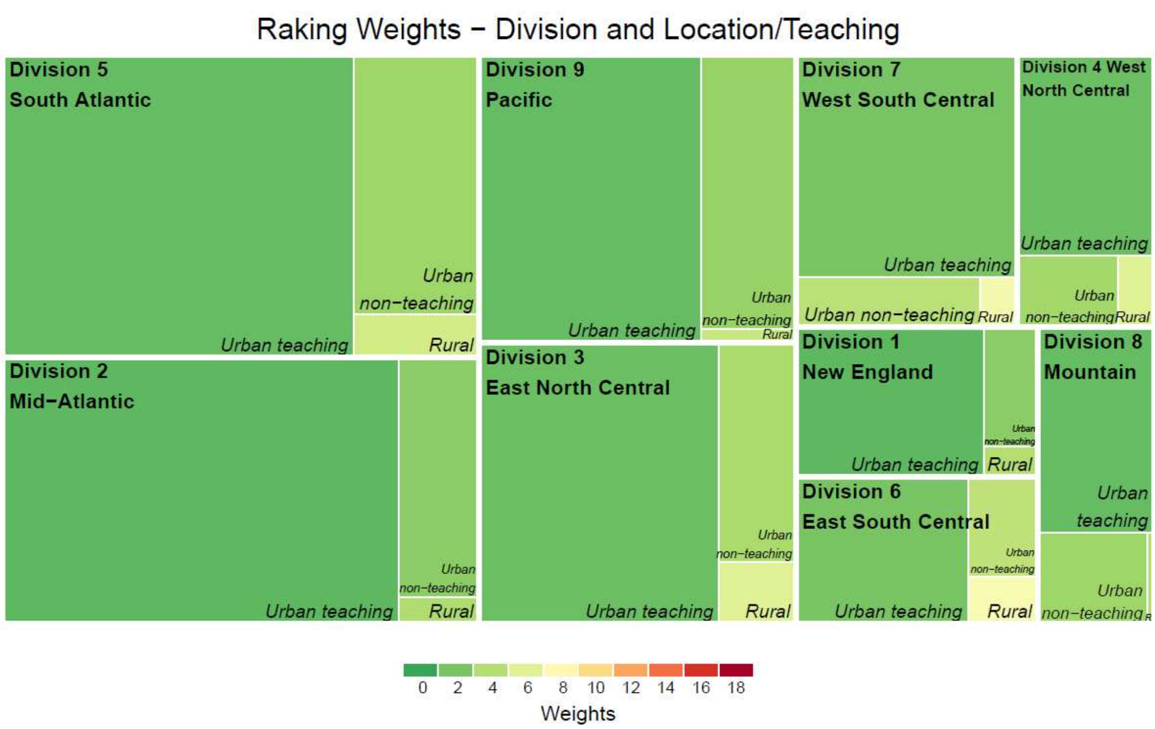
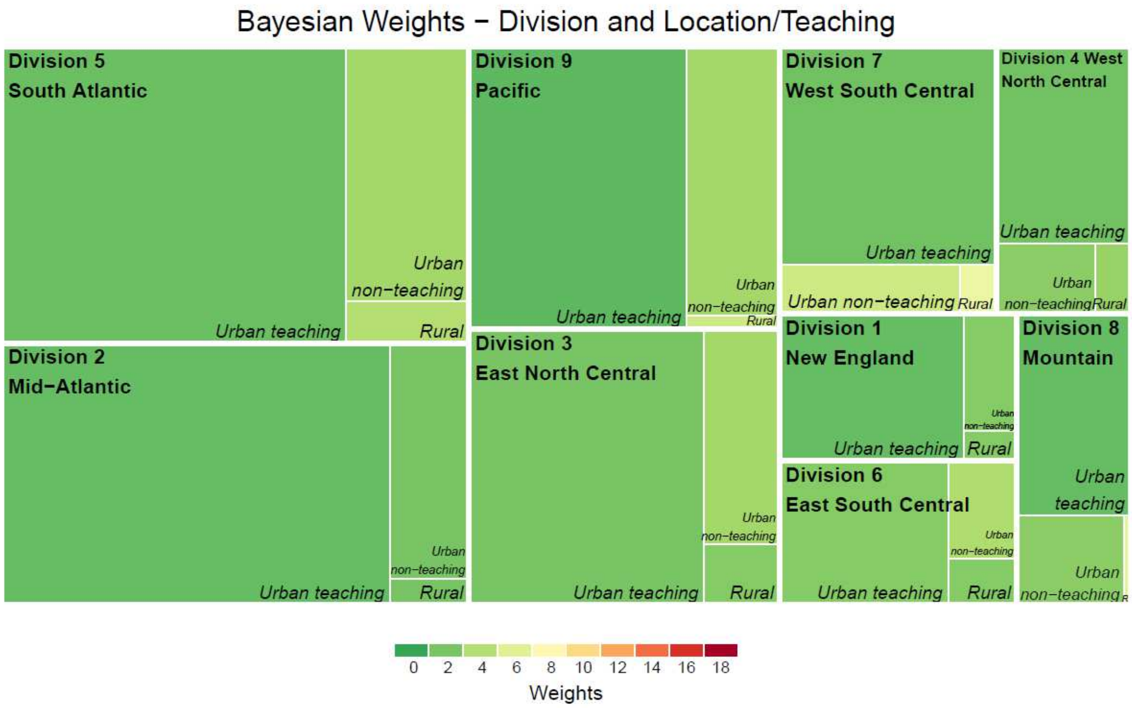


Figure III. Treemaps of weighting stratified by U.S. Census division and rural/teaching hospital status.

A:



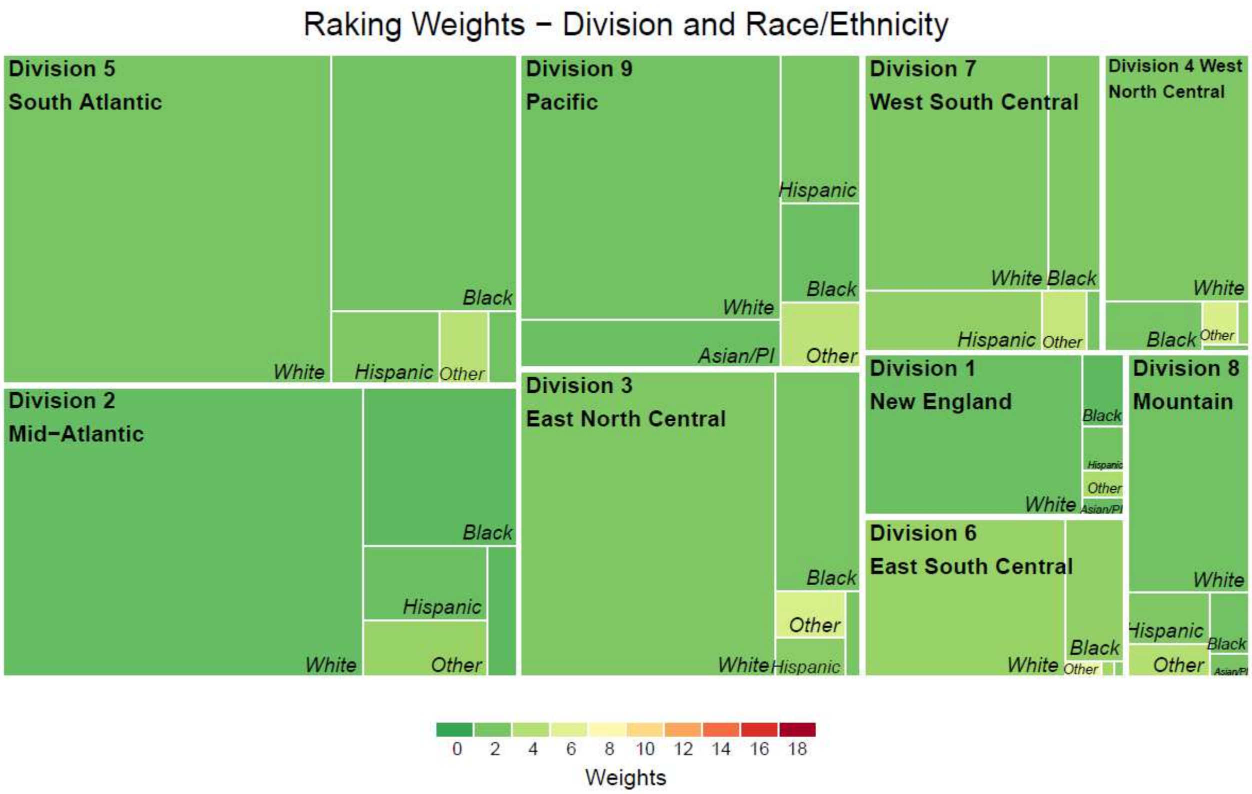
B



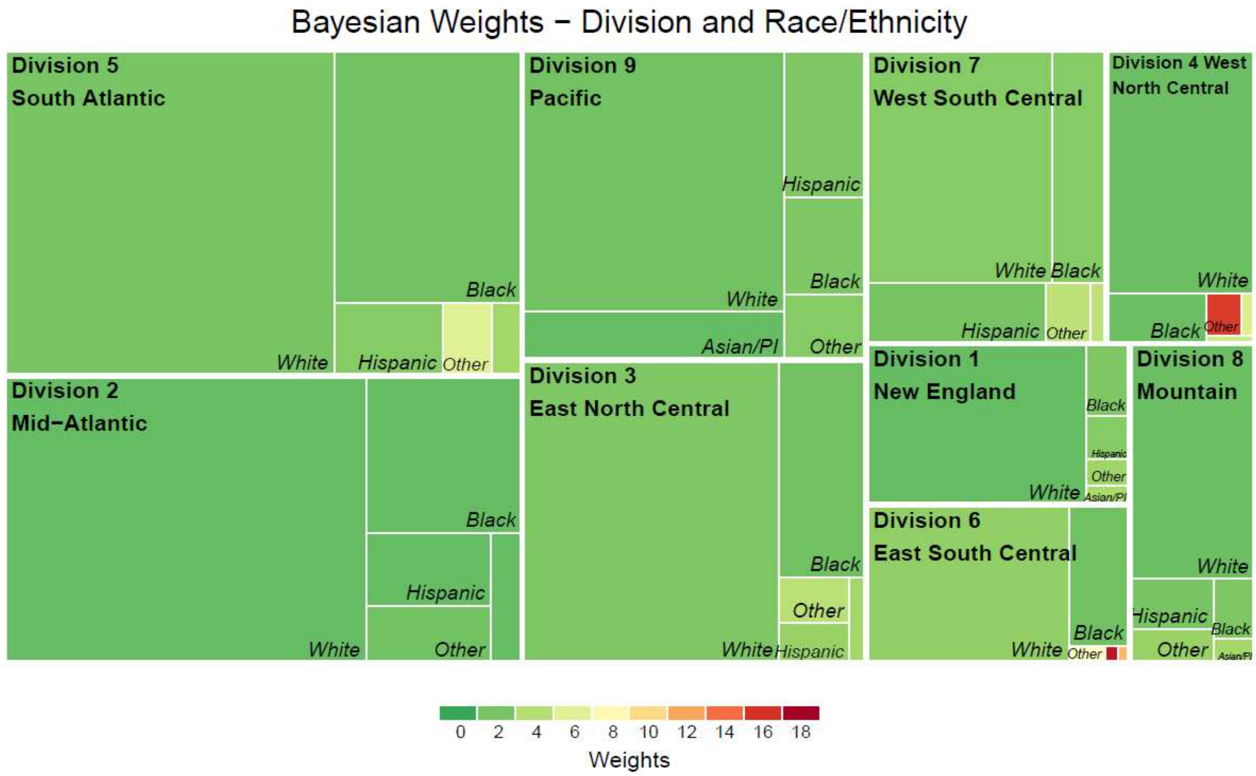
The treemaps provide a perspective of population size (box size) across region and hospital characteristic to describe the target population. The average size of the post-stratification weights used for each observation within Get With The Guideline-Stroke using the post-stratification approach. The more yellow and red regions of the treemaps highlight under-represented populations that required larger relative weights to model the target national population.

Figure IV. Treemaps of weighting stratified by U.S. Census division and race/ethnicity.

A:



B:


Bayesian Weights − Division and Race/Ethnicity
Division 5
South Atlantic
White
Black
Hispanic
Other
Division 2
Mid−Atlantic
White
Black
Hispanic
Other
Division 9
Pacific
White
Hispanic
Black
Asian/PI
Other
Division 3
East North Central
White
Black
Other
Hispanic
Division 7
West South Central
White
Black
Hispanic
Other
Division 4 West
North Central
White
Black
Other
Division 1
New England
White
Black
Hispanic
Other
Asian/PI
Division 6
East South Central
White
Black
Other
Division 8
Mountain
White
Hispanic
Black
Other
Asian/PI
0 2 4 6 8 10 12 14 16 18
Weights

Figures

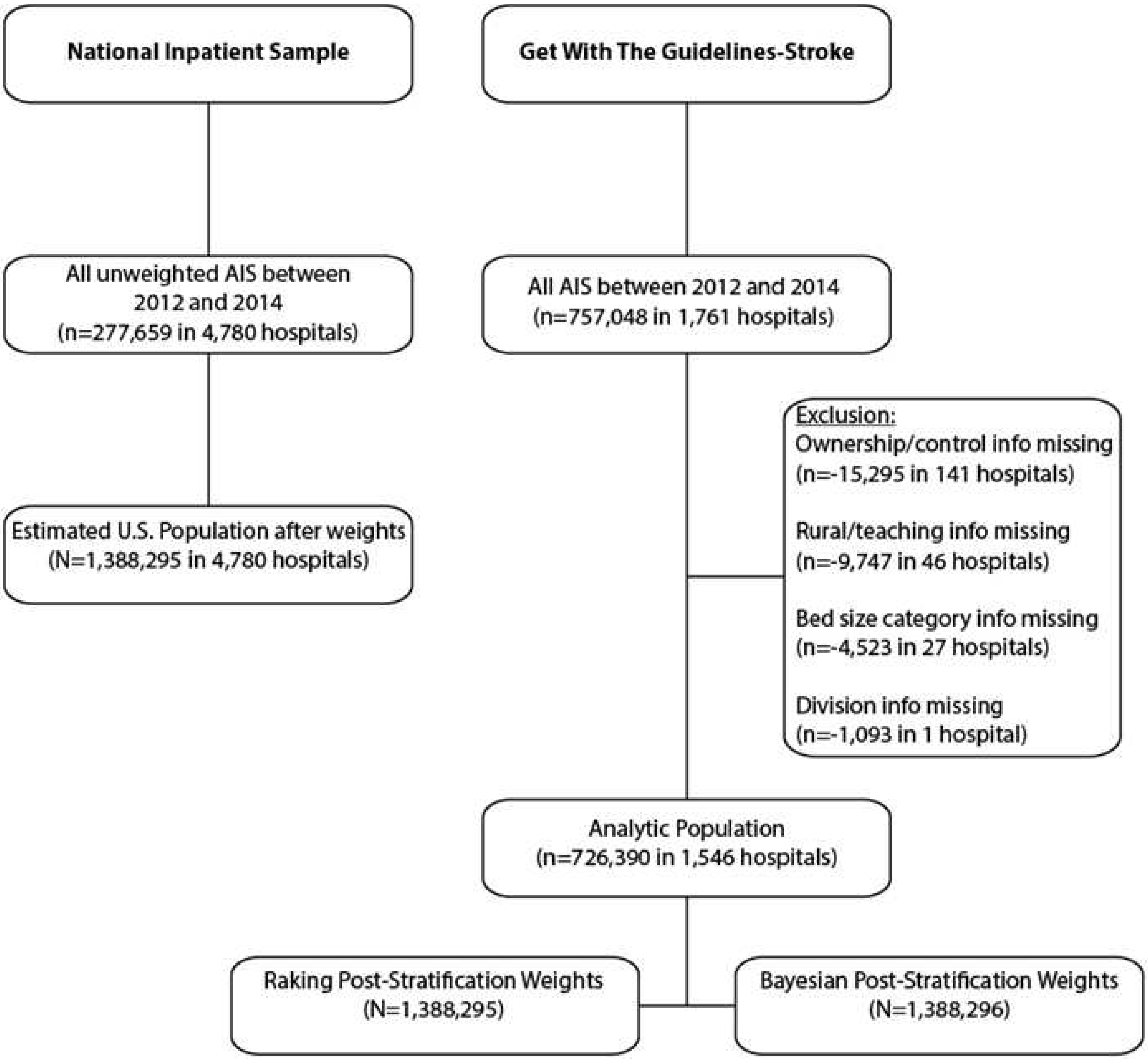
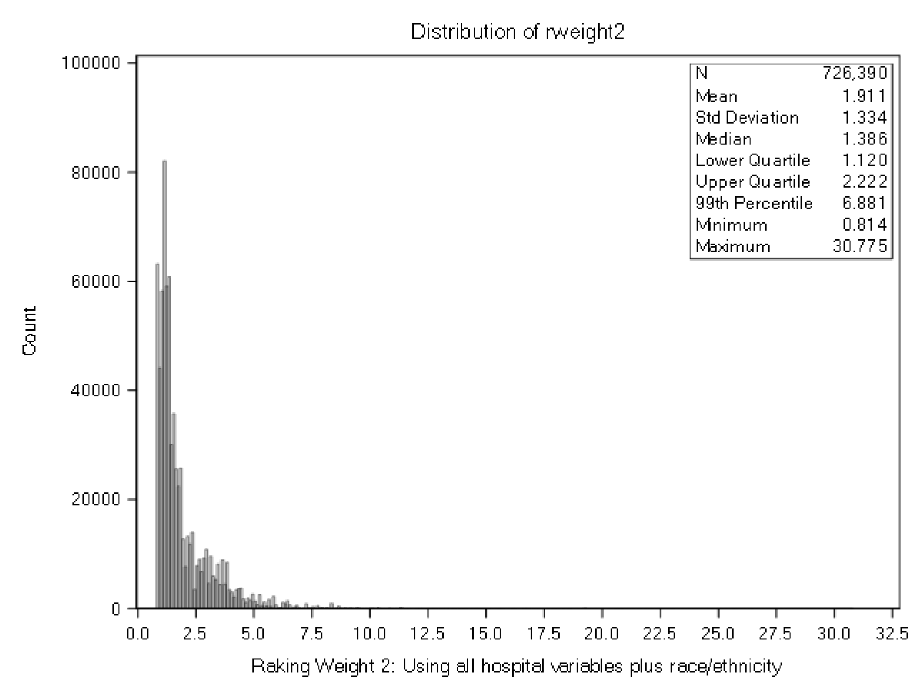


Figure 1

Flow Chart of study population inclusion from the National Inpatient Sample and the Get With The Guidelines-Stroke registry program

A: Distribution of raking derived post-stratification weights



B: Distribution of Bayesian post-stratification weights

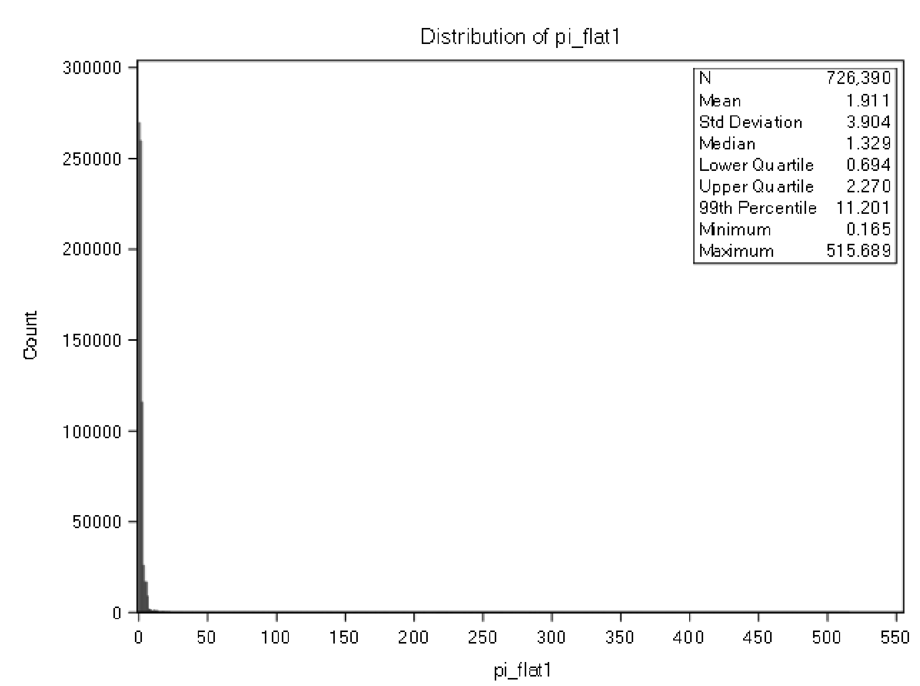
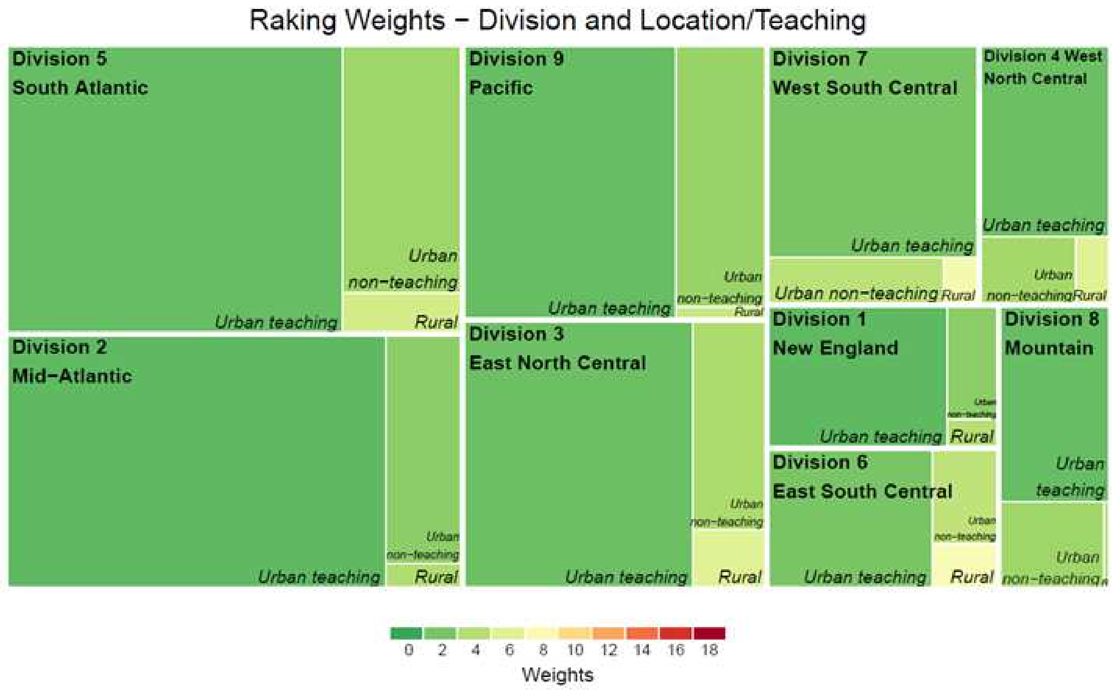


Figure 2

Distribution of raking and Bayesian weights. A: Distribution of raking derived post-stratification weights B: Distribution of Bayesian post-stratification weights

A:



B

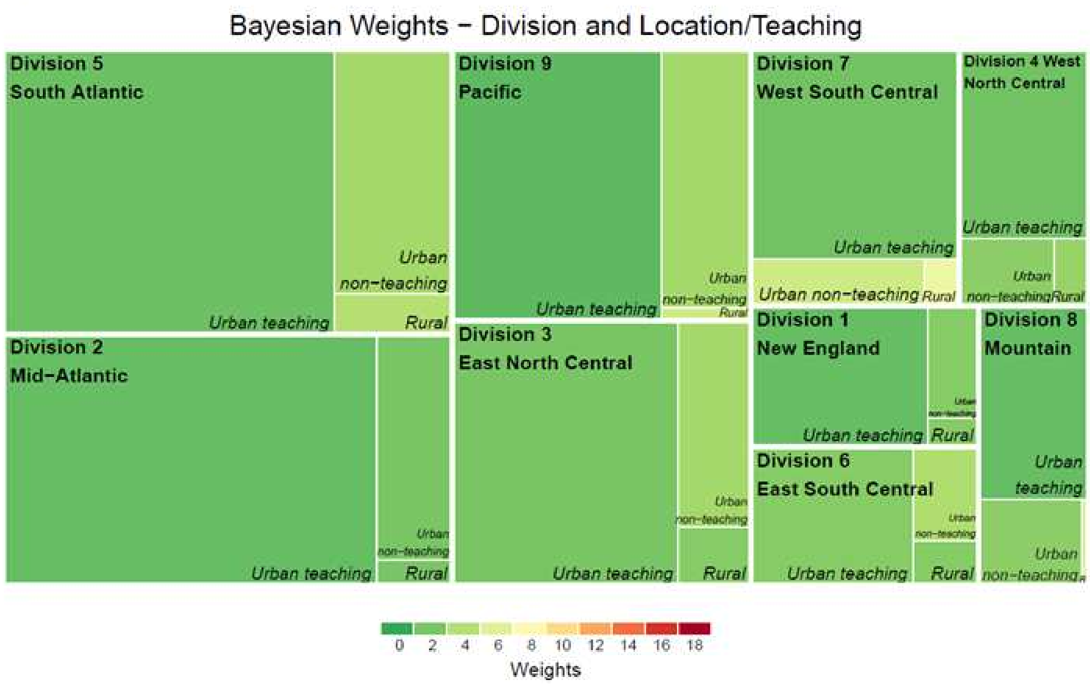
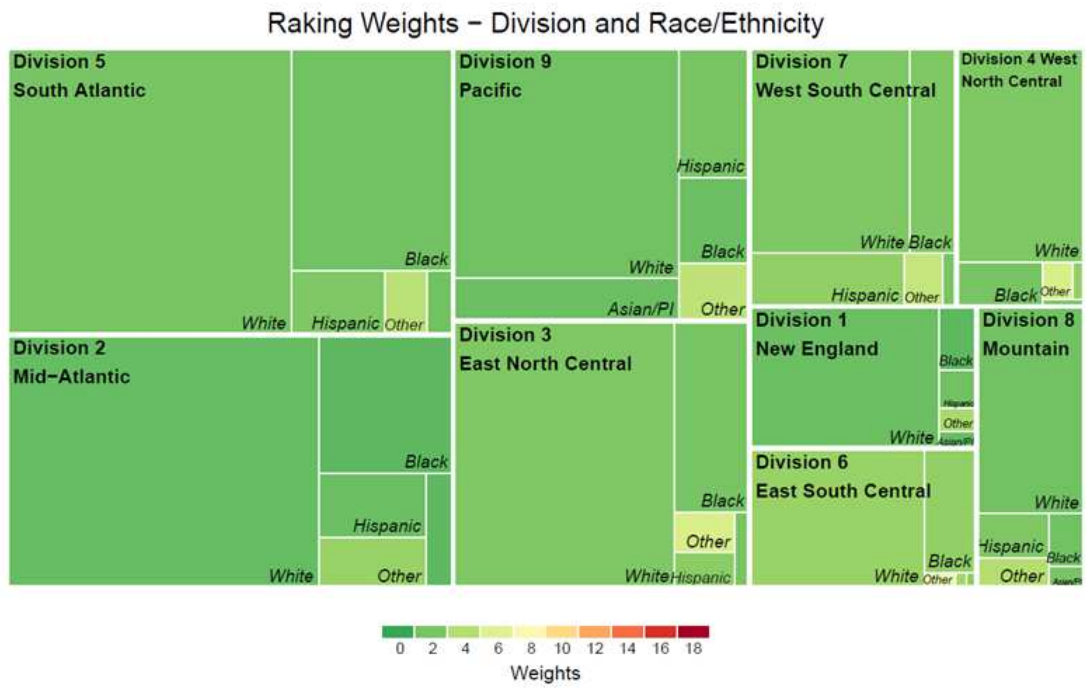


Figure 3

Treemaps of weighting stratified by U.S. Census division and rural/teaching hospital status. The treemaps provide a perspective of population size (box size) across region and hospital characteristic to describe the target population. The average size of the post-stratification weights used for each observation within Get With The Guideline-Stroke using the post-stratification approach. The more yellow and red regions of the treemaps highlight under-represented populations that required larger relative weights to model the target national population.

A:



B:

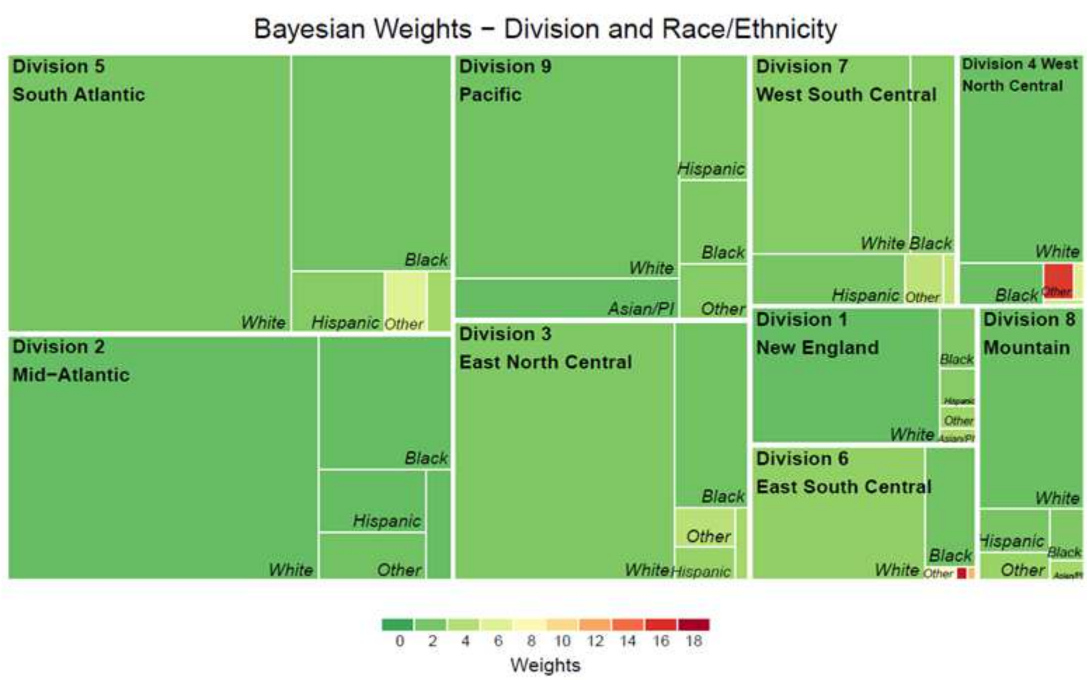


Figure 4

Treemaps of weighting stratified by U.S. Census division and race/ethnicity.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- GWTGStrokePostStratificationWeightsSupplement.docx