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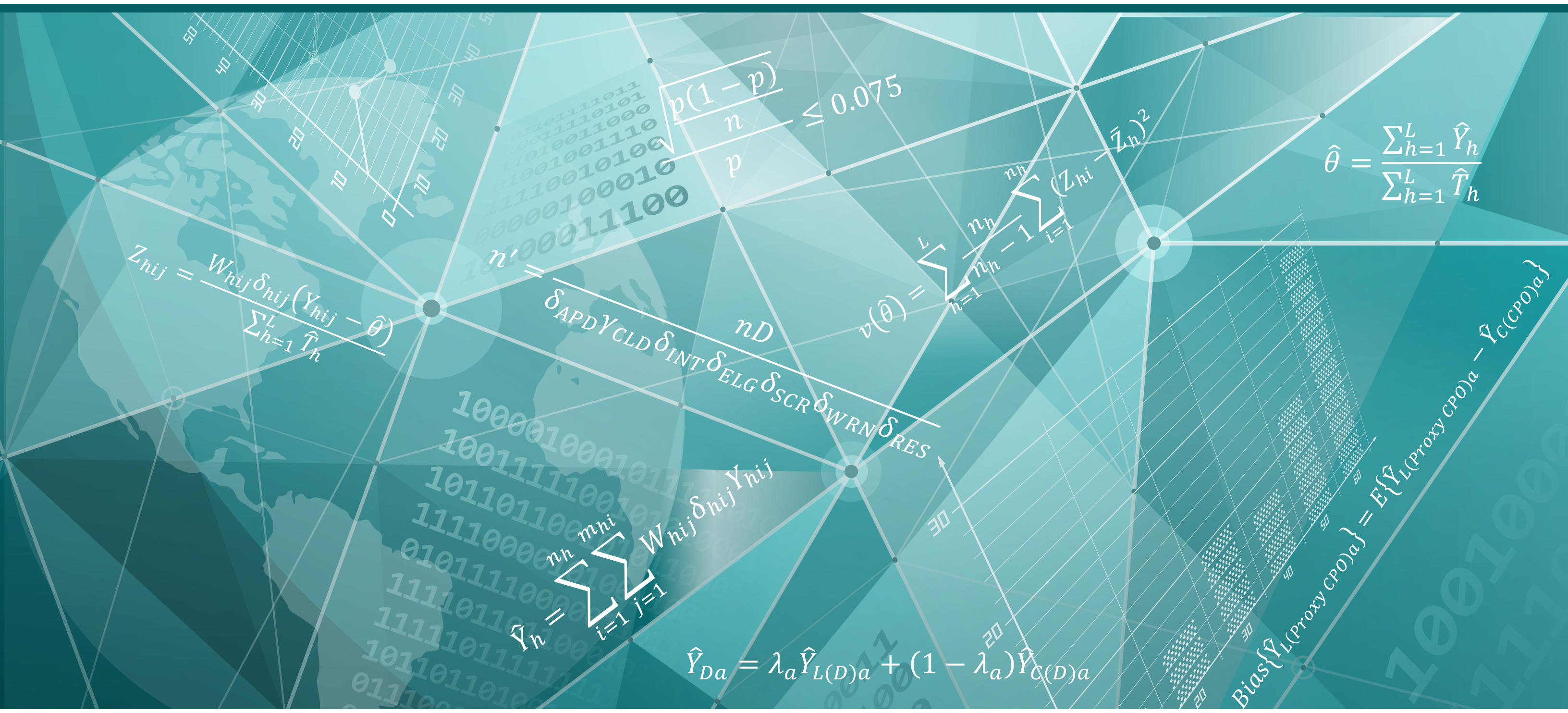

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Data Evaluation and Methods Research

Centers for Disease Control and Prevention
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Survey Weights in the 2018 National Ambulatory Medical Care Survey Adjusted Using Iterative Proportional Fitting

Data Evaluation and Methods Research

U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES
Centers for Disease Control and Prevention
National Center for Health Statistics

Hyattsville, Maryland
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Survey Weights in the 2018 National Ambulatory Medical Care Survey Adjusted Using Iterative Proportional Fitting

by Alexander Strashny, Ph.D., Vladislav Beresovsky, Ph.D., Susan M. Schappert, M.A., and Loredana Santo, M.D., M.P.H.

Abstract

Background

The National Ambulatory Medical Care Survey requires the use of survey weights to produce national estimates of ambulatory care, both at the physician and visit levels. Because of increasing survey nonresponse rates in recent years, a new weight adjustment method was needed that could better address nonresponse bias compared with the previous weighting method.

Methods

This report describes the adjustment of survey weights for the 2018 National Ambulatory Medical Care Survey using iterative proportional fitting (IPF). The IPF weight adjustment method simultaneously performs the following: 1) nonresponse weight adjustment in quantiles defined by response propensity; 2) calibration to population totals in domains defined by calibration variables; and 3) flexible smoothing of adjusted weights. Weight distributions are examined, and selected physician and visit estimates are presented.

Results

Compared with the previous adjustment method, IPF-adjusted weights have a lower maximum value, lower range, lower skewness, and lower design effect. This suggests that IPF-adjusted weights produce more efficient (that is, smaller variance) estimates. Using IPF-adjusted weights, in 2018, an estimated 309,400 office-based physicians were in practice in the United States, and patients made an estimated 872,400,000 visits to these physicians. Weight adjustment using IPF produced overall estimates of office-based physicians and their visits, which were not significantly different from totals based on the previous method.

Conclusion

Although the method used historically for nonresponse bias adjustment is known for strong bias reduction, it also produces large variability of adjusted weights, which may result in reduced stability and efficiency of estimates. IPF addresses these issues by simultaneously performing multiple weight adjustment techniques. The method was successfully implemented with 2018 National Ambulatory Medical Care Survey data.

Keywords: raking • nonresponse bias • participation bias • physician • response rate • National Ambulatory Medical Care Survey (NAMCS)

Introduction

The National Ambulatory Medical Care Survey (NAMCS) is a nationally representative survey of nonfederal office-based physicians and their ambulatory visits. It began in 1973 and has been conducted annually in most years by the National Center for Health Statistics (NCHS). Sample physicians are selected from lists obtained from the American Medical Association (AMA) and the American Osteopathic Association (AOA). Sample data are weighted to produce national estimates of office-based physicians and visits to these physicians.

Both the sampling design and the estimation methods used with NAMCS data have changed over the course of the survey. A report describing the sampling design and estimation procedures that were used historically is available (1). In 2006, the survey was expanded to make estimates of community health center use (2), with health center data collection becoming an independent component of NAMCS in 2012. Also in 2012, the office-based sample was expanded to support reliable estimates for each of the U.S. Census Bureau divisions and the 34 most populous states. In that same year, NAMCS switched to a new form of data collection involving the use of an automated survey instrument. At the same time, response rates decreased substantially, and a nonresponse bias analysis was conducted (3,4).

From 2013 through 2015, the survey design was modified to target a steadily decreasing number of states each year

(5–7), until, in 2016, the survey reverted to a design that prioritized national and regional estimates only (8). In 2016, weighted response rates were 46% at the physician level and 33% at the visit level. Response rates were similarly low in the 2018 NAMCS. The potential for nonresponse bias was, therefore, an even more serious concern. The traditional weighting method used in NAMCS (1) was based on adjusting for nonresponse within domains formed by physician practice type (primary, surgical, or medical care) and region. As survey response decreased, the traditional weighting method became less defensible because fewer respondents were available in each of the adjustment domains, leading to increased variance of estimates.

An NCHS workgroup, composed of staff from the Division of Research and Methodology and the Division of Health Care Statistics, was formed in early 2020 to conduct research on nonresponse bias in the 2018 NAMCS data. The goal was to investigate new methods for weighting the data that were less subject to nonresponse bias and the problems noted previously. The workgroup concluded that the iterative proportional fitting (IPF) model should be used to adjust for nonresponse bias in the 2018 NAMCS. This report presents this new method of adjusting weights.

Methods

NAMCS Sampling Design and Estimation Methods Before 2018

NAMCS has traditionally used a multistage probability sampling design. From 1973 through 2011, a three-stage design was used that involved probability samples of primary sampling units, physicians within primary sampling units, and patient visits to those physicians. From 2012 through 2015, NAMCS used a stratified two-stage sample, with physicians selected in the first stage and visits in the second stage. List samples were used to produce separate estimates for states with the largest populations. The 34 most populous states were targeted for individual visit estimation in 2012. This number decreased to 22 states in 2013, 18 states in 2014, and 16 states in 2015. Beginning in 2016, NAMCS used the same stratified two-stage sample design, with the list sample of physicians stratified by Census region and physician specialty. In all survey years, physicians were asked to provide data on a sample of their office visits during a randomly selected 1-week reporting period.

Sample data from NAMCS are weighted to produce national and regional (and, from 2012 to 2015, state-level) estimates of the characteristics of office-based physicians, including physician specialty, demographic characteristics, and practice characteristics, as well as characteristics of visits to office-based physicians. Visit characteristics include patient demographics, such as age, sex, race and ethnicity, and other characteristics, such as episode of care, vital signs, expected source of payment, reason for visit, diagnosis, diagnostic and screening services, procedures, medications, providers seen, and visit disposition.

NAMCS has traditionally used a Horvitz–Thompson estimator to weight the survey data (9). The estimator for visit statistics is an inflation estimator poststratified by the number of physicians in a specialty class. The estimator for physician aggregate statistics is a postratio-adjusted estimator. Both estimators include an adjustment for nonresponse and have been described in detail previously (1).

As an overview, the estimation procedure used before the 2018 NAMCS had four components: 1) inflation by reciprocals of the selection probabilities, 2) adjustment for nonresponse, 3) a ratio adjustment to fixed totals, and 4) weight smoothing. These procedures summarize what is referred to in this report as the traditional weighting method used before the adoption of the IPF method with 2018 data (8).

These components are summarized below:

1. Inflation by Reciprocals of the Selection Probabilities

From 2012 through 2016, because the survey used a two-stage sample design, it included two relevant probabilities:

   a. The probability of selecting a physician within a stratum
   b. The probability of selecting a patient visit within the physician's practice

The strata used for the first probability were determined by sampling strata defined by physician specialty and geographical areas defined by the four Census regions. The second probability was defined to be the number of Patient Record Forms (PRFs) completed, divided by the exact number of office visits during the physician's specified reporting week. To derive annual estimates, all weekly estimates were inflated by the number of weeks annually in which the physician typically sees patients in their practice.

2. Adjustment for Nonresponse

Eligibility for NAMCS is based on several criteria: The physician must be nonfederally employed; primarily engaged in office-based, direct patient care; and not in the specialties of anesthesiology, pathology, or radiology. Estimates were adjusted to account for physicians whose eligibility remained unknown when data collection was completed. This was performed by assuming that the percentage eligible among those with unknown eligibility was the same as the percentage eligible among those with known eligibility. The NAMCS visit estimates were also adjusted to account for in-scope (eligible) physicians who did not provide abstracted PRFs (non-PRF physicians), either because they saw no patients during their sample week or failed to provide abstracted PRFs for visits by patients they did see during their sample week. These adjustments account for nonresponse within physician specialty type (primary care, surgical specialty, or medical specialty) and region. Beginning with 2003 data, the adjustment for non-PRF physicians was revised to include variation in the typical number of weeks worked annually and for variation in visit volume in a workweek. Beginning with 2004 data, changes were made to the nonresponse adjustment factor to account for the seasonality of the reporting period.

3. Ratio Adjustment

A postratio adjustment was made within each of the physician specialty groups and region sampling strata to adjust for changes in the physician population represented in the sampling frame between the time when the sample was selected and the time the survey was conducted. The ratio adjustment is a multiplication factor, calculated by dividing two values. For each physician specialty group and region stratum, the factor's numerator is the known number of physicians in the stratum's universe, obtained from the AMA and AOA master files for the survey year. The factor's denominator is the number of physicians in that specialty group and region obtained from the AMA and AOA master files for the sampling frame year, estimated using sampling-adjusted weights. The result of applying the ratio adjustment is that the estimated total number of physicians within each specialty group and region is equal to the total that is known from the AMA and AOA master files for the survey year.

4. Weight Smoothing

The technique of weight smoothing was used to adjust for sample physicians whose final visit weights were large relative to those for the rest of the sample. If any excessively large visit weights were trimmed, a ratio adjustment was performed to yield the same estimated total visit count as with the unsmoothed weights. The ratio adjustment in this case is a multiplication factor that uses as its numerator the total visit count in each physician group before the largest weights are trimmed and, as its denominator, the total visit count in the same group after the largest weights are trimmed. For 2016, this smoothing was done within each physician group defined by practice type and the nine Census divisions.

In 2018, 2,999 physicians were selected for the NAMCS sample, 1,647 of whom were found to be in-scope and eligible for the survey. Among the in-scope physicians, 496 provided data on 9,953 sampled visits. The response rate for full respondents (those who submitted data for at least one-half of their expected visits during their sampled reporting week) was 29.5%. Because of decreasing response rates, concerns about nonresponse bias and how well it would be addressed through the traditional weighting method were raised. The traditional method also relied on collapsing cells for nonresponse adjustments within defined group parameters. Because of low response, the standards for cell aggregation had to be relaxed, leading to additional concerns. Therefore, NCHS researchers searched for an alternative to the traditional weighting method. These efforts resulted in the development of a model-based approach for weighting NAMCS using IPF.

Introduction to IPF

Modern weight adjustment techniques include poststratification, generalized regression estimation, raking ratio estimation (also known as IPF), inverse response propensity weighting, and response propensity stratification.

The poststratification method consists of calibrating survey weights of respondents within response cells defined by domains of some categorical variables, so the distribution of weight-adjusted totals estimated from respondents is calibrated to the known population totals or to the weighted totals from all sampled records. This method requires stable estimates of the totals and having enough respondents in all cross-classified domains formed by these categorical variables, which limits the number of calibration domains.

Both the generalized regression estimator and IPF perform calibration on marginal domain totals in multiple overlapping domains. These weight adjustment techniques were initially proposed for variance reduction of survey estimates (10), but later were also used for nonresponse adjustment (11,12). In some cases, generalized regression may result in negative weights, which makes its use impractical for surveys. IPF, on the other hand, does not have this problem. IPF is closely related to poststratification, intuitively simple, and readily implemented using existing software packages, such as R packages "survey" (13) and "sampling" (14). The IPF method updates the same four components used in the previous NAMCS weighting method, described previously in this report, by incorporating straightforward nonresponse adjustments and performing all tasks simultaneously.

The IPF adjustment described in this report achieves two goals. First, it addresses the nonresponse bias problem by calibration in quasi-randomization cells, as explained below. Second, it reduces variances of estimates by calibrating on marginal totals in domains defined by variables that are correlated with healthcare indicators of interest to researchers. The IPF adjustment has a double-robust property—even if the response model that defines the quasi-randomization cells is incorrectly specified, calibration on marginal totals may still correct for biases. The literature cited below has many references to double-robust methods for nonresponse bias adjustment. The approach described here is just one possible implementation. It is comparable to consecutive application of nonresponse adjustment in cells defined by response propensity quantiles, followed by poststratification to population totals in cells defined by corresponding covariates. The described IPF method performs all of these adjustments simultaneously, along with flexible weight smoothing.

Rosenbaum and Rubin (15) proposed using treatment propensity to estimate treatment effects in observational studies. Straightforward application of the propensity score method to survey nonresponse consists of multiplying respondents' sampling weights by the inverse of their response propensity, that is, by performing inverse response propensity weighting. Modeling response propensity makes it possible to account for multiple covariates while taking advantage of machine-learning algorithms, as described in a later section. However, very small estimates of response propensity, which correspond to large, adjusted weights, may cause an undesirable increase of the survey design effect, which can be moderated by using response propensity stratification (16,17). Because survey respondents and nonrespondents may be considered quasi-randomized by their propensity to respond within response propensity quantiles, poststratification in the cells defined by those quantiles can reduce bias of estimates from respondents. According to Cochran (18), five strata are typically sufficient.

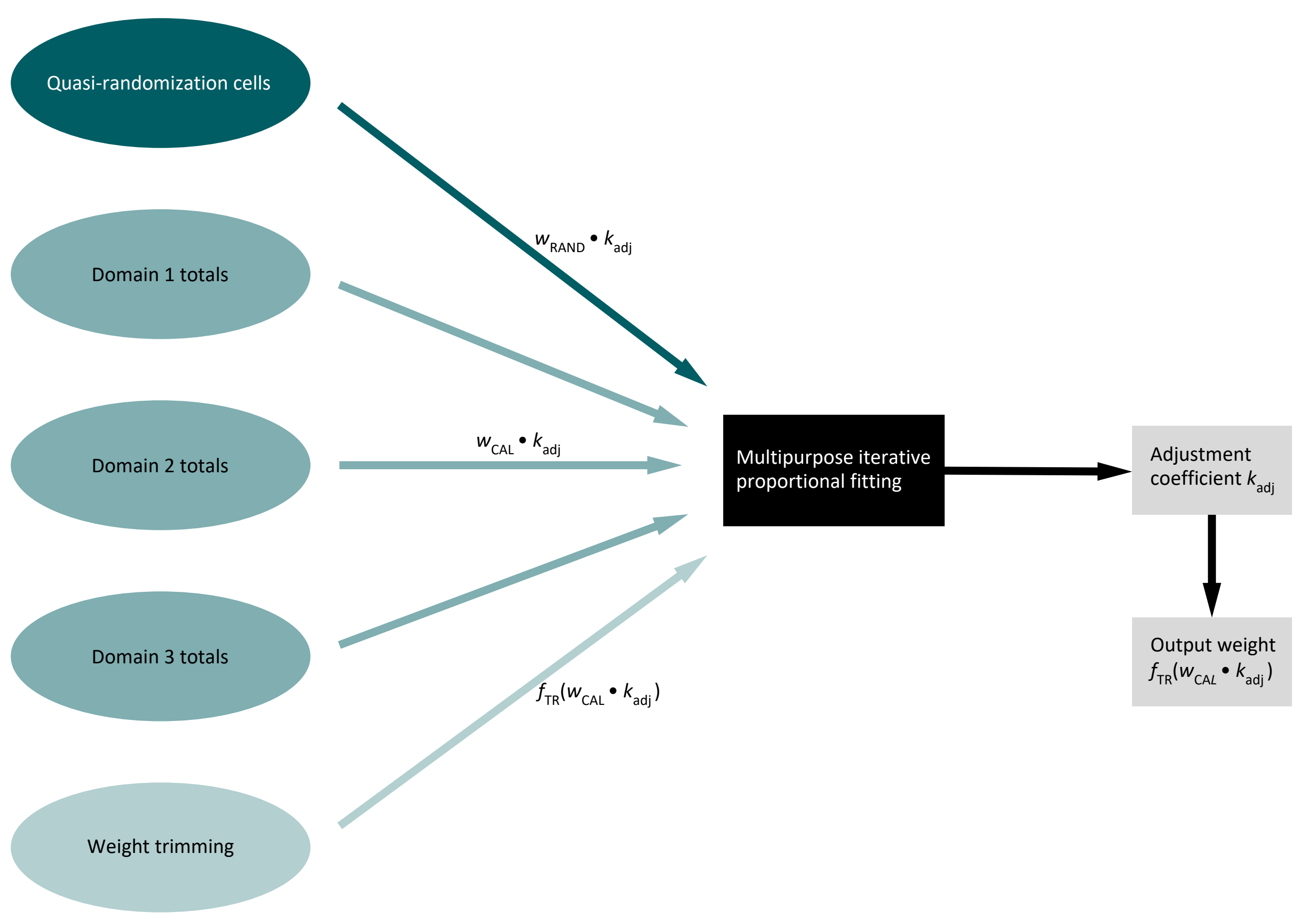
Nonresponse weight adjustment is achieved by either 1) quasi-randomization by response propensity; 2) calibration on marginal domain totals, which is IPF; or 3) sequential application of 1) followed by 2) (19). Because nonresponse weight adjustment may result in an increased design effect, it is usually followed with weight trimming as described by Haziza and Beaumont (19). Under sequential application, only the last-applied weight adjustment is exact, while precision of the rest is approximate.

In this case, the multipurpose IPF technique is developed as a nonresponse weight adjustment technique for the simultaneous application of quasi-randomization, calibration on marginal domain totals, and weight trimming. Exactly performing all three weight adjustments becomes possible because multipurpose IPF uses different initial weights for different weight adjustment goals. Consequently, unweighted poststratification is used in quasi-randomization cells, as recommended by Little and Vartivarian (16); sampling weights are used as initial weights for calibration on marginal domain totals; and weight trimming involves yet another set of weights.

Technical Details of Multipurpose IPF

Multipurpose IPF, which is schematically presented in the Figure, is a weight adjustment process consisting of calibration in quasi-randomization cells, calibration in three marginal domains, and weight trimming, all achieved simultaneously. Calibration in quasi-randomization cells updates randomization weights w_{RANDS}, which are initially set to 1, while calibration in marginal domains updates calibration weights w_{CAL}, which are initially set to the sampling weights.

Figure. Schematic presentation of multipurpose iterative proportional fitting



SOURCE: National Center for Health Statistics.

Various choices for the trimming function $f_{TR}(\ldots)$ exist. One choice, used for NAMCS weight adjustment, is to restrict final adjusted weights $w_{CAL} \bullet k_{adj}$ within (.05,.95) quantiles of the distribution. This trimming is a standard practice typically performed with NCHS surveys to improve efficiency. The procedure generates unique weight-adjustment coefficients k_{adj}, which satisfy all stated goals: calibration in quasi-randomization domains, marginal domains, and the stated weight trimming rule. Usually, the trimmed weight $f_{TR}(w_{cal} \bullet k_{adj})$ is related to the calibration weight and is considered to be the output weight of the adjustment process.

Because existing software packages are not equipped to handle multiple initial weights, custom code to implement the functionality of multipurpose IPF was developed. Implementation of the multipurpose IPF code in R is available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/Series_Reports/sr02_202/.

Machine-learning Framework for Survey Response Modeling

Modeling the survey response indicator is typically performed by accounting for all available covariate information. This step is achieved by generating multiple models using diverse machine-learning techniques and by comparing these models within a uniform framework. For modeling survey response propensity, machine learning was selected over the linear regression approach to optimize use of available covariate information. Machine-learning methods allow the systematic exploration of a large variety of models consisting of covariates and interactions, while simultaneously eliminating the models that result in overfitting the data. Response models are generated that use the best subset selection, regularization, and classification and regression trees, or CART, learning algorithms.

K-fold cross validation (CV) was used for optimal model selection. For models with large degrees of freedom, CV is more reliable than Akaike information criterion or Bayesian information criterion, which are used by other software. This is because both Akaike and Bayesian information criterion are asymptotic quantities, but CV is reliable under finite samples. CV was implemented in R, providing for forward, backward, and combined forward-backward covariate selection. The number of covariates included in the model is a model complexity parameter.

Regularization algorithms implemented in the R "glmnet" package (20), including ridge regression, lasso, and adaptive lasso, were used for modeling response indicator. Complexity of the regularization models is controlled by the value of parameter λ, regulating penalty of the target objective function imposed by large absolute values of linear regression coefficients. These coefficients are either shrunk toward zero in the case of ridge regression or assigned a zero value in the case of lasso.

Conditional inference trees (ctree) implemented in R package party (21) was used for modeling response propensity. It is one of multiple implementations of a recursive partitioning inference framework. Ctree uses multiple comparisons to test for possible splits, avoiding bias towards splits by multileveled categorical variables, which affects other recursive partitioning algorithms. Several ctree models can be fitted with different tuning parameters, while their complexity is controlled by the *p* value defining node-splitting criteria.

To compare structurally different models, their maximum strength and validated performance must be uniformly evaluated and scaled in comparable units. A function was developed that uses a common set of cross-validation folds to evaluate previously generated and saved models of best subset selection, regularization, and ctree families. Fit folds are used for fitting the saved models, and validation folds are used to validate the fitted models, resulting in the fitted and validated coefficients of determination R^2_F and R^2_{CV}. R^2_F measures the maximum model strength, which grows monotonically with model complexity, while R^2_{CV} measures validated model strength, achieving maximum value for the optimal value of the complexity parameter and decreasing afterward. The best-performing model is then selected by analyzing a plot jointly presenting fitted R^2_F and validated R^2_{CV} coefficients of determination of competing models.

Application to 2018 NAMCS

NAMCS uses the master files of the AMA and AOA as its frame. From these files, a stratified list sample of 2,999 office-based physicians was selected for the 2018 sample, of which 1,647 were determined from data collection to be eligible (in-scope) for the survey. In-scope physicians were asked to participate in the Physician Induction Interview (PhysII), which collects data on physician and practice characteristics. Of the 1,647 physicians, 825 physicians responded to the interview, resulting in a PhysII response rate of 50.1% [or 825 / 1,647]. Participating physicians were randomly assigned to a 1-week visit reporting period, during which data on a sample of their in-scope office visits were collected using an automated instrument called the PRF. Of the in-scope physicians, 176 were unavailable during the randomly assigned reporting week. At least one-half of the expected number of PRFs were collected from 434 physicians, resulting in a PRF response rate of 29.5% [or 434 / (1,647 – 176)].

IPF was sequentially applied twice to adjust NAMCS physician sampling weights for nonresponse, first at the physician or PhysII level, and then at the visit or PRF level. A third application was performed to calibrate visit weights. Weights generated by one application of the algorithm become initial weights for the next iteration. Table A shows selected NAMCS variables used for nonresponse weight adjustment. Stepwise application of IPF is described as follows.

Table A. Key variables used for nonresponse adjustment with National Ambulatory Medical Care Survey data

Variable name	Source	Description
RASAMWGT	AMA / AOA	Calibrated sampling weights
SPECR	AMA / AOA	Physician specialty (contains 14 categories)
SPECTYPE	AMA / AOA	Physician specialty type (contains 3 categories)
REGION	AMA / AOA	Census region (contains 4 categories)
FGRAD	AMA / AOA	Medical school (U.S. or foreign) where physician earned degree
MDAGE	AMA / AOA	Physician age (contains 5 categories)
PHYSVV	PhysII	Annual physician visit volume for in-scope physicians
PHYSCOMP	PhysII	Compensation (fixed salary, share of billing, fixed-share mix, or time-based pay)
NUMOFFIN	PhysII	Number of offices where the physician sees patients in reporting week
ESTTOTVS	PhysII	Total estimated number of visits for physician
REVSRC	PhysII	Sources of payment accepted by physician (private insurance, Medicare, or Medicaid)
LNDOT	PRF	Count of PRFs per physician

NOTES: These variables reflect in-house National Ambulatory Medical Care Survey (NAMCS) physician-level files; they are typically not available on NAMCS public-use files. AMA is American Medical Association. AOA is American Osteopathic Association. PhysII is Physician Induction Interview. PRF is Patient Record Form (NAMCS survey instrument). To be in-scope (eligible) for the survey, physicians must be nonfederally employed; primarily engaged in office-based, direct patient care; and not in the specialties of anesthesiology, pathology, or radiology.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

The process of weight adjustment starts with calibrated sampling weights (RASAMWGT). The total sample represents the 2018 population, which is the population targeted in the survey, rather than the population from which the sample was selected. The latter is based on the AMA and AOA files produced before 2018.

The first step of the weight adjustment process is to calculate physician-level weights for PhysII respondents, subsequently referred to as PHYZWT. These are the weights used to produce physician-level estimates. Calibrated sampling weights RASAMWGT are adjusted for PhysII nonresponse resulting in adjusted weights PHYZWT. Calibration is performed on the marginal totals in 12 domains by REGION • physician specialty type (SPECTYPE) and in 14 domains by physician specialty (SPECR). Survey respondents and nonrespondents are quasi-randomized into five quintiles imposed by the PhysII response model selected by the machine-learning framework, which was the best model found using forward selection. Whether a physician responds to PhysII is modeled as a function of REGION and physician age (MDAGE). In the terminology of the Figure, w_{CAL} is RASAMWGT, w_{RAND} is 1, and $f_{TR}(\dots)$ is the identity function.

The second step is to calculate physician-level weights for PRF respondents, which are called PHYSWT. Note that while the PHYZWT weights apply to all PhysII respondents, the PHYSWT weights apply only to PRF respondents. The PHYSWT weights are needed as an intermediate step for calculating visit-level weights. These weights are produced by further adjusting PHYZWT for PRF nonresponse. Calibration domains are the same as for the previous step, and five quasi-randomization quintiles are imposed by the optimally selected best subset forward-selection model of PRF response. Whether enough PRFs are collected from a physician is modeled as a function of REVSRC, REGION, ESTTOTVS, PHYSCOMP, NUMOFFIN, and FGRAD. In terms of the Figure, w_{CAL} is PHYZWT, w_{RAND} is 1, and $f_{TR}(\dots)$ is the identity function.

The third and final step is to calculate visit-level weights, which are called PATWT. Visit-level weights are generated by calibrating the visit volume PHYSWT • PHYSVV of PRF respondents to the visit volume PHYZWT • PHYSVV of physician respondents in the same calibration domains as before. In the terminology of the Figure, w_{CAL} is PHYSWT • PHYSVV. Because visit-level weights are used for estimating patients' visit characteristics, they are defined as PATWT = ($w_{CAL} \bullet k_{adj}$) / LNDOT and are trimmed at every iteration of IPF.

Application of IPF makes weight-adjusted distributions of respondents in calibration domains and quasi-randomization cells sufficiently close to distributions from sampled records before nonresponse. In addition, IPF frequently reduces variability of the adjusted weights, leading to improved efficiency of the estimates, as demonstrated in the following section.

Results

Distributions of Weights

A common concern associated with nonresponse weight adjustment is ensuring the absence of extremely large weights and a heavy upper tail of the weight distribution. Excessive variability of adjusted weights may result in an increased design effect and decreased precision of estimates. Weight distributions were examined to find out whether this was an issue. Design effects were compared to ensure that they were not higher for adjusted compared with unadjusted weights.

Table B presents the distributions of the four sets of weights discussed here, namely the calibrated sampling weights (RASAMWGT); physician-level weights for PhysII respondents (PHYZWT); physician-level weights for PRF respondents (PHYSWT); and visit-level weights (PATWT). For each set of weights, the table presents the five-number summary (minimum, first quartile, median, third quartile, and maximum); skewness (22); and Kish's design effect (23). Comparing the IPF-adjusted physician-level weights (PHYZWT) with the calibrated sampling weights (RASAMWGT), the IPF-adjusted weights have a lower maximum value, lower range, lower

Table B. Distributions of four sets of weights used with 2018 National Ambulatory Medical Care Survey data

Weight	Minimum	First quartile	Median	Third quartile	Maximum	Skewness	Design effect
RASAMWGT	20	60	100	206	1,409	2.83	2.37
PHYZWT	68	125	222	443	1,379	1.60	1.99
PHYSWT	116	179	344	697	2,760	1.93	2.25
PATWT	11,199	24,154	53,200	152,827	389,950	1.28	2.15

NOTE: RASAMWGT refers to sampling weights; PHYZWT refers to iterative proportional fitting (IPF)-adjusted physician-level weights for Physician Induction Interview respondents; PHYSWT refers to IPF-adjusted physician-level weights for Patient Record Form respondents; and PATWT refers to IPF-adjusted visit-level weights.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

skewness, and lower design effect. These findings indicate that the IPF-adjusted weights tend to produce more efficient estimates.

Based on the same characteristics, the IPF-adjusted physician-level weights for PRF respondents (PHYSWT) produce less efficient estimates than the weights for PhysII respondents (PHYZWT). This loss of efficiency is expected, because PHYZWT is already properly calibrated and trimmed, and further adjustment for PRF response results in less efficient weights. Calibration on visit volume leads to a lower skewness and lower design effect for visit-level weights (PATWT). This finding supports the conclusion that the IPF procedure described in this report improves the efficiency for both physician-level and visit-level estimates.

Using the physician-level weights for PhysII respondents (PHYZWT), in 2018, an estimated 309,400 office-based physicians were in practice in the United States. Using the visit-level weights (PATWT), patients made an estimated 872,400,000 visits to these physicians.

Properties of Weights

The effects of weight adjustments on data distributions in calibration domains and quasi-randomization cells, also called response quintiles, are shown in Tables C, D, and E. The tables demonstrate that IPF makes weight-adjusted distributions of respondents in calibration domains and quasi-randomization cells sufficiently close to the corresponding distributions from sampled records before nonresponse.

Discussion

Nonresponse bias has been a growing concern in numerous official statistics data systems, including NAMCS (3). Starting with the 2018 data collection year of NAMCS, NCHS began using a multipurpose IPF statistical approach to not only address nonresponse bias but also to reduce variances of the resulting estimates. The IPF weight adjustment method may achieve better bias reduction compared with methods that only perform calibration to totals in stratification domains. The IPF method is approximately comparable with inverse response propensity reweighting in quasi-randomization cells defined by quantiles of response propensity followed by calibration in stratification domains, with the one major difference being that IPF performs these tasks simultaneously.

The nonresponse bias adjustment developed for the 2018 NAMCS will continue to be used for future years of NAMCS. This approach can potentially be applied to any data system, not just NAMCS.

Table C. Percent distribution of all in-scope physicians and Physician Induction Interview respondents, by weighting method, specialty type, and region

Specialty type and region	Calibrated sampling weights (RASAMWGT)		Physician-level weights (PHYZWT)[1]
	In-scope physicians	Physician Induction Interview respondents	Physician Induction Interview respondents
Primary care			
Northeast	10.0	8.2	10.0
Midwest	8.6	8.4	8.6
South	17.3	20.6	17.3
West	12.2	11.0	12.2
Surgical specialty			
Northeast	2.8	2.3	2.9
Midwest	2.5	2.4	2.6
South	4.9	6.0	5.0
West	4.2	3.6	4.2
Medical specialty			
Northeast	8.8	7.6	8.8
Midwest	6.2	7.3	6.2
South	11.8	15.0	11.7
West	10.6	7.5	10.6

[1]Physician-level weights for Physician Induction Interview respondents.

NOTE: Numbers may not add to 100 due to rounding.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

Table D. Percent distribution of all in-scope physicians and Physician Induction Interview respondents, by weighting method and physician specialty group

Physician speciality group	Calibrated sampling weights (RASAMWGT): In-scope physicians	Calibrated sampling weights (RASAMWGT): Physician Induction Interview respondents	Physician-level weights (PHYZWT)[1]: Physician Induction Interview respondents
General and family practice	15.5	15.6	15.5
Internal medicine	12.7	13.5	12.7
Pediatrics	10.6	10.2	10.6
General surgery	2.6	2.5	2.6
Obstetrics and gynecology	6.9	7.2	6.9
Orthopedic surgery	4.6	4.6	4.6
Cardiovascular diseases	4.1	3.5	4.1
Dermatology	2.6	2.5	2.6
Urology	1.8	1.2	1.8
Psychiatry	5.2	5.0	5.2
Neurology	2.2	2.1	2.2
Ophthalmology	4.1	4.2	4.1
Otolaryngology	1.9	1.9	1.9
Other specialties	25.2	26.1	25.2

[1]Physician-level weights for Physician Induction Interview respondents.

NOTE: Numbers may not add to 100 due to rounding.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

Table E. Percent distribution of all in-scope physicians and Physician Induction Interview respondents, by weighting method and response quintile

Response quintile	Calibrated sampling weights (RASAMWGT): In-scope physicians	Calibrated sampling weights (RASAMWGT): Physician Induction Interview respondents	Response rate[2]	Physician-level weights (PHYZWT)[1]: Physician Induction Interview respondents
	Percent distribution			Percent distribution
1	29.6	23.5	0.40	29.6
2	16.2	13.3	0.41	16.1
3	17.4	18.3	0.53	17.4
4	20.1	22.8	0.57	20.1
5	16.8	22.1	0.66	16.8

[1]Weighted in quasi-randomization cells of the iterative proportional fitting model.
[2]Before adjustment, the Physician Induction Interview response rate monotonously increased between response quintiles. Nonresponse adjustment makes response rates balanced between cells.

NOTE: Totals may not add to 100 due to rounding.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

References

1. Bryant E, Shimizu I. Sample design, sampling variance, and estimation procedures for the National Ambulatory Medical Care Survey. National Center for Health Statistics. Vital Health Stat 2(108). 1988.

2. National Center for Health Statistics. 2006 NAMCS microdata file documentation. Hyattsville, MD. 2009. Available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/.

3. Hing E, Shimizu IM, Talwalkar A. Nonresponse bias in estimates from the 2012 National Ambulatory Medical Care Survey. National Center for Health Statistics. Vital Health Stat 2(171). 2016.

4. National Center for Health Statistics. 2012 NAMCS microdata file documentation. Hyattsville, MD. 2015. Available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/.

5. National Center for Health Statistics. 2013 NAMCS microdata file documentation. Hyattsville, MD. 2017. Available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/.

6. National Center for Health Statistics. 2014 NAMCS microdata file documentation. Hyattsville, MD. 2018. Available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/.

7. National Center for Health Statistics. 2015 NAMCS microdata file documentation. Hyattsville, MD. 2017.

Available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/.

8. National Center for Health Statistics. 2016 NAMCS microdata file documentation. Hyattsville, MD. 2019. Available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/.

9. Särndal C-E, Swensson B, Wretman J. Model assisted survey sampling. New York, NY: Springer. 1992.

10. Deville J-C, Särndal C-E. Calibration estimators in survey sampling. J Am Stat Assoc 87(418):376–82. 1992.

11. Särndal C-E, Lundström S. Estimation in surveys with nonresponse. New York, NY: John Wiley & Sons, Inc. 2005.

12. Jelke B. Working with response probabilities. J Off Stat 36(3):647–74. 2020.

13. Lumley T. Analysis of complex survey samples. J Stat Softw 9(8):1–19. 2004.

14. Tillé Y, Matei A. Package 'sampling.' 2022. Available from: https://cran.r-project.org/web/packages/sampling/sampling.pdf.

15. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. Biometrika 70(1):41–55. 1983.

16. Little RJ, Vartivarian S. On weighting the rates in non-response weights. Stat Med 22(9):1589–99. 2003.

17. Roderick JAL. Survey nonresponse adjustments for estimates of means. Int Stat Rev 54(2):139–57. 1986.

18. Cochran WG. The effectiveness of adjustment by subclassification in removing bias in observational studies. Biometrics 24(2):295–313. 1968.

19. Haziza D, Beaumont J-F. Section 6.1: Weight trimming. In: Construction of weights in surveys: A review. Statist Sci 32(2):206–26. 2017.

20. Friedman J, Hastie T, Tibshirani R. Regularization paths for generalized linear models via coordinate descent. J Stat Softw 33(1):1–22. 2010.

21. Hothorn T, Hornik K, Zeileis A. Unbiased recursive partitioning: A conditional inference framework. J Comput Graph Stat 15(3):651–74. 2006.

22. Moments, cumulants, skewness, kurtosis and related tests. R documentation (Version 0.10.1) [computer software]. 2015.

23. Kish L. Weighting in Deft2. The Survey Statistician: International Association of Survey Statisticians. 1987.

24. Santo L, Kang K. National Ambulatory Medical Care Survey: 2019 National Summary Tables. 2023. Available from: https://www.cdc.gov/nchs/data/ahcd/namcs_summary/2019-namcs-web-tables-508.pdf.

25. Santo L, Okeyode T. National Ambulatory Medical Care Survey: 2018 National Summary Tables. 2022. Available from: https://www.cdc.gov/nchs/data/ahcd/namcs_summary/2018-namcs-web-tables-508.pdf.

Appendix I. Assessment of Estimates Using Initial and Refined Weighting Methods

2018 NAMCS Initial Data Release

The main body of this report describes the iterative proportional fitting (IPF) methodology that is currently in use with National Ambulatory Medical Care Survey (NAMCS) data. This is reflected in the 2019 NAMCS public-use file (PUF), the "National Ambulatory Medical Care Survey: 2019 National Summary Tables" (24), and the November 2022 file of refined weights for the 2018 NAMCS PUF.

An initial version of this methodology was used to calculate the weights used to produce the 2018 NAMCS PUF (released in April 2021) as well as the "National Ambulatory Medical Care Survey: 2018 National Summary Tables" (25). However, after the initial release of the 2018 PUF and the publication of the 2018 tables, it was discovered that the initial weighting method did not take full advantage of additional adjustments within the response domains. As a result, a refined IPF weighting method, described in the main text of this report, was used in the 2019 NAMCS PUF, the 2019 tables (24), and the November 2022 file of refined weights for the 2018 NAMCS PUF. The refinement of the IPF method resulted in slight differences in estimates based on the refined weights compared with both the previously released 2018 summary table estimates and with estimates made from the first release of the 2018 PUF. Consequently, an assessment of estimates using the initial IPF weights and the refined weights is presented in this Appendix.

In this Appendix, the initial version of the weights (used in the 2018 PUF release and accompanying summary tables) is referred to as summary table weights, and the weights that are based on the refined methodology are referred to as refined weights. Several tables from the 2018 summary tables were reproduced using both summary table and refined weights to assess differences in the estimates. The change in the weights resulted in mostly small and, with some exceptions, not statistically significant ($p > 0.050$) changes in the estimates. A file containing the refined visit and physician weights for 2018 NAMCS is available for downloading at the NAMCS website from: https://www.cdc.gov/nchs/ahcd/ahcd_questionnaires.htm, along with instructions on how to merge this file with the 2018 NAMCS PUF.

Comparison of Estimates Using Refined Weights With Those Using Summary Table Weights

Tables I and II in Appendix II present selected physician- and visit-level estimates generated using both summary table and refined weights. The differences between the count estimates are measured using relative percentage difference (RPD), with the denominator being the average of the two estimates. The differences between estimates of percentages are measured in percentage points.

When comparing physician estimates using the refined weights with those using the summary table weights, the total number of physicians was the same (Table I). For most categories, the differences in counts were small and not statistically significant ($p > 0.050$). The largest differences were for physicians aged 35–44 (RPD = 15.2%, $p < 0.001$), non-MSA location (RPD = 14.3%, $p = 0.002$), and physicians aged 65 and over (RPD = 8.9%, $p < 0.001$). The next highest difference, for doctors of osteopathy (RPD = 5.9%), was not statistically significant ($p = 0.226$). All other differences were small (RPD < 5.0%) or not statistically significant ($p > 0.050$).

For percentages, the biggest difference was for physicians aged 35–44 (3.8% points). Some differences in physician estimates were expected because the revised model accounted better for the results of the response propensity modeling. Physician age was used in both models, but the calibration in the earlier model tended to moderate some features of that modeling.

When comparing visit estimates using the refined weights with those using summary table weights, the difference in the total number of visits was small (RPD = 1.4%) and not statistically significant ($p = 0.800$) (Table II). The largest difference in counts was for visits to doctors of osteopathy (RPD = 22.8%; $p < 0.001$). All other differences were small (RPD < 5.0%) or not statistically significant ($p > 0.050$). For percentages, the biggest differences were for visits to doctors of osteopathy and visits to doctors of medicine (1.6% points each).

Appendix II. Supporting Tables

Table I. Comparison of estimates of physicians using summary table weights and refined weights, by selected characteristics: National Ambulatory Medical Care Survey, 2018

Physician characteristic	Summary table weights		Refined weights		p value in number	Relative percent difference in number	Point difference in percent
	Number of physicians (standard error)	Percent distribution (standard error)	Number of physicians (standard error)	Percent distribution (standard error)			
All physicians	309,400 (2,200)	100.0 …	309,400 (2,300)	100.0 …	1.000	0.0	...
Professional identity							
Doctor of medicine	291,000 (2,200)	94.1 (0.1)	289,900 (2,200)	93.7 (0.2)	0.650	0.4	0.4
Doctor of osteopathy	18,400 (300)	5.9 (0.1)	19,500 (800)	6.3 (0.2)	0.226	5.9	0.4
Specialty type[1]							
Primary care	137,200 (3,100)	44.3 (1.1)	135,300 (3,400)	43.7 (1.1)	0.342	1.4	0.6
Surgical specialty	66,700 (4,400)	21.6 (1.4)	66,400 (4,400)	21.5 (1.4)	0.750	0.5	0.1
Medical specialty	105,500 (5,500)	34.1 (1.7)	107,700 (5,400)	34.8 (1.7)	0.120	2.1	0.7
Metropolitan status[2]							
MSA	286,400 (4,700)	92.6 (1.3)	282,900 (4,600)	91.5 (1.4)	0.109	1.2	1.1
Non-MSA	22,900 (3,900)	7.4 (1.3)	26,400 (4,500)	8.5 (1.4)	0.002	14.3	1.1
Age (years)							
Under 35	* *	* *	* *	* *	*	…	…
35–44	72,100 (6,400)	23.3 (2.1)	84,000 (7,300)	27.1 (2.2)	0.000	15.2	3.8
45–54	93,600 (7,200)	30.2 (2.3)	89,900 (6,900)	29.1 (2.3)	0.001	4.0	1.2
55–64	79,100 (6,600)	25.6 (2.1)	75,400 (6,300)	24.4 (2.1)	0.002	4.7	1.2
65 and over	61,500 (5,500)	19.9 (1.8)	56,300 (5,200)	18.2 (1.7)	0.000	8.9	1.7
Sex							
Female	98,300 (6,600)	31.8 (2.1)	100,700 (6,900)	32.5 (2.2)	0.167	2.4	0.8
Male	211,100 (6,700)	68.2 (2.1)	208,700 (6,600)	67.5 (2.2)	0.229	1.1	0.8
Race[3]							
White	205,200 (7,200)	66.3 (2.3)	204,500 (7,400)	66.1 (2.4)	0.748	0.3	0.2
Black or African American	* *	3.5 (0.9)	* *	3.5 (1.0)	0.930	…	0.0
Other groups[4]	58,700 (6,000)	19.0 (2.0)	60,300 (6,300)	19.5 (2.0)	0.171	2.7	0.5
Unknown or blank	34,600 (4,800)	11.2 (1.5)	33,600 (4,700)	10.9 (1.5)	0.193	2.9	0.3
Ethnicity							
Hispanic or Latino	25,400 (4,700)	8.2 (1.5)	25,300 (4,800)	8.2 (1.5)	0.879	0.3	0.0
Not Hispanic or Latino	257,800 (6,000)	83.3 (1.9)	258,700 (6,200)	83.6 (1.9)	0.725	0.3	0.3
Unknown or blank	26,200 (4,100)	8.5 (1.3)	25,400 (3,900)	8.2 (1.3)	0.264	3.1	0.3

… Category not applicable.
* Estimate does not meet National Center for Health Statistics standards of reliability.
[1]Physician specialties within each type are listed in the 2018 National Ambulatory Medical Care Survey public-use file documentation, available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/doc2018-508.pdf.
[2]MSA is metropolitan statistical area.
[3]The race groups White, Black or African American, and Other groups include people of Hispanic and non-Hispanic origin. People of Hispanic origin may be of any race.
[4]Includes Asian, Native Hawaiian or Other Pacific Islander, American Indian or Alaska Native, and people of more than one race.

NOTE: Significant differences were assessed using one-sample t test of null hypothesis for the sample total sum ($W_1 \bullet Z$) of the derived variable $Z = Y \bullet (1 - W_2 / W_1)$, where Y is the variable of interest, W_1 is the refined weight, and W_2 is the summary table weight.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

Table II. Comparison of estimates of physician office visits using summary table weights and refined weights, by selected characteristics: National Ambulatory Medical Care Survey, 2018

Characteristic	Summary table weights: Number of visits in thousands (standard error)	Summary table weights: Percent distribution (standard error)	Refined weights: Number of visits in thousands (standard error)	Refined weights: Percent distribution (standard error)	*p* value in number	Relative percent difference in number	Point difference in percent
All visits	860,400 (37,900)	100.0 …	872,400 (36,300)	100.0 …	0.800	1.4	…
Physician characteristic							
Professional identity:							
Doctor of medicine	803,400 (37,200)	93.4 (0.9)	800,800 (35,100)	91.8 (1.0)	0.460	0.3	1.6
Doctor of osteopathy	57,000 (7,600)	6.6 (0.9)	71,700 (9,200)	8.2 (1.0)	0.000	22.8	1.6
Specialty type[1]:							
Primary care	440,200 (31,500)	51.2 (2.3)	439,700 (28,400)	50.4 (2.2)	0.569	0.1	0.8
Surgical specialty	204,000 (21,600)	23.7 (2.3)	213,900 (21,800)	24.5 (2.2)	0.616	4.8	0.8
Medical specialty	216,300 (19,000)	25.1 (2.2)	218,800 (18,000)	25.1 (2.0)	0.951	1.2	0.0
Metropolitan status[2]:							
MSA	764,800 (37,500)	88.9 (2.4)	771,600 (35,900)	88.4 (2.4)	0.836	0.9	0.5
Non-MSA	95,600 (21,900)	11.1 (2.4)	100,800 (21,900)	11.6 (2.4)	0.375	5.4	0.5
Patient characteristic							
Age (years):							
Under 15	109,900 (14,300)	12.8 (1.6)	110,800 (12,300)	12.7 (1.4)	0.904	0.8	0.1
15–24	58,800 (5,000)	6.8 (0.5)	59,000 (4,600)	6.8 (0.5)	0.784	0.5	0.0
25–44	158,800 (12,800)	18.5 (1.3)	156,400 (11,100)	17.9 (1.1)	0.328	1.5	0.6
45–64	251,500 (14,900)	29.2 (1.0)	259,000 (15,900)	29.7 (1.1)	0.625	2.9	0.5
65–74	147,000 (9,600)	17.1 (0.8)	151,200 (9,500)	17.3 (0.8)	0.605	2.8	0.2
75 and over	134,400 (10,800)	15.6 (1.0)	136,100 (10,100)	15.6 (0.9)	0.942	1.3	0.0
Sex:							
Female	507,100 (25,500)	58.9 (1.3)	510,600 (24,100)	58.5 (1.2)	0.786	0.7	0.4
Male	353,300 (18,800)	41.1 (1.3)	361,800 (18,000)	41.5 (1.2)	0.633	2.4	0.4
Race[3]:							
White	723,000 (32,200)	84.0 (1.6)	735,700 (32,000)	84.3 (1.4)	0.877	1.7	0.3
Black or African American	72,600 (7,400)	8.4 (0.8)	74,100 (7,100)	8.5 (0.8)	0.851	2.0	0.1
Other groups[4]	64,800 (14,100)	7.5 (1.5)	62,700 (12,300)	7.2 (1.3)	0.208	3.3	0.3
Ethnicity:							
Hispanic or Latino	128,000 (13,200)	14.9 (1.4)	124,800 (11,500)	14.3 (1.2)	0.161	2.5	0.6
Not Hispanic or Latino	732,400 (34,100)	85.1 (1.4)	747,600 (33,500)	85.7 (1.2)	0.776	2.1	0.6

… Category not applicable.
[1]Physician specialties within each type are listed in the 2018 National Ambulatory Medical Care Survey (NAMCS) public-use file documentation, available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/doc2018-508.pdf.
[2]MSA is metropolitan statistical area.
[3]The race groups White, Black or African American, and Other groups include people of Hispanic and non-Hispanic origin. People of Hispanic origin may be of any race. Starting with 2009 data, the National Center for Health Statistics adopted the technique of model-based single imputation for NAMCS race and ethnicity data. The race imputation is restricted to three categories (White, Black, and other) based on research by an internal work group and on quality concerns with imputed estimates for race categories other than White and Black. The imputation technique is detailed in the 2018 NAMCS public use file documentation, available from: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NAMCS/doc2018-508.pdf. For 2018, race data were missing for 32.38% of weighted visits, and ethnicity data were missing for 32.12% of weighted visits (based on refined weights).
[4]Includes Asian, Native Hawaiian or Other Pacific Islander, American Indian or Alaska Native, and people of more than one race.

NOTE: Significant differences were assessed using one-sample *t* test of null hypothesis for the sample total sum ($W_1 \bullet Z$) of the derived variable $Z = Y \bullet (1 - W_2 / W_1)$, where Y is the variable of interest, W_1 is the refined weight, and W_2 is the summary table weight.

SOURCE: National Center for Health Statistics, National Ambulatory Medical Care Survey, 2018.

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