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Rounding Behavior in the Reporting of Headache Frequency Complicates Headache Chronification Research

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Abstract

Objectives—To characterize the extent of measurement error arising from rounding in headache frequency reporting (days per month) in a population sample of headache sufferers.

Background—When reporting numerical health information, individuals tend to round their estimates. The tendency to round to the nearest 5 days when reporting headache frequency can distort distributions and engender unreliability in frequency estimates in both clinical and research contexts.

Methods—This secondary analysis of the 2005 American Migraine Prevalence and Prevention study (AMPP) survey characterized the population distribution of 30-day headache frequency

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Timothy T. Houle: Dr. Houle receives research support from GlaxoSmithKline and Merck.

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among community headache sufferers and determined the extent of numerical rounding (“heaping”) in self-reported data. Headache frequency distributions (days per month) were examined using a simplified version of Wang and Heitjan’s (2008) approach to heaping to estimate the probability that headache sufferers round to a multiple of 5 when providing frequency reports. Multiple imputation was used to estimate a theoretical “true” headache frequency.

Results—Of the 24,000 surveys, headache frequency data were available for 15,976 respondents diagnosed with migraine (68.6%), probable migraine (8.3%), or episodic tension-type headache (10.0%); the remainder had other headache types. The mean number of headaches days/month was 3.7 (SD = 5.6). Examination of the distribution of headache frequency reports revealed a disproportionate number of responses centered on multiples of 5 days. The odds that headache frequency was rounded to 5 increased by 24% with each one-day increase in headache frequency (OR: 1.24, 95% CI: 1.23 to 1.25), indicating that heaping occurs most commonly at higher headache frequencies. Women were more likely to round than men, and rounding decreased with increasing age and increased with symptoms of depression.

Conclusions—Because of the coarsening induced by rounding, caution should be used when distinguishing between episodic and chronic headache sufferers using self-reported estimates of headache frequency. Unreliability in frequency estimates is of particular concern among individuals with high-frequency (chronic) headache. Employing shorter recall intervals when assessing headache frequency, preferably using daily diaries, may improve accuracy and allow more precise estimation of chronic migraine onset and remission.

Keywords

Headache frequency; rounding; statistics; headache chronification

Introduction

The widespread prevalence of headache in the United States is well-known, with lifetime migraine prevalence rates of 18% for men and 43% for women.¹ Data on headache frequency are usually gathered through patient self-report—principally by asking for a retrospective account of the frequency of headaches over a defined period of time (eg, days with headache during the last month). Headache frequency is highly consequential in clinical practice as it is used to distinguish among clinical diagnostic groups such as episodic and chronic migraine (CM) as well as episodic and chronic tension-type headache (CTTH). It is also used in treatment guidelines regarding preventive medications. Both CM and CTTH are distinguished from the corresponding episodic disorders by their frequency, in which these chronic disorders require the presence of headache on 15 or more days per month.² Headache frequency is also of importance for research purposes, as change in headache days is the recommended primary endpoint in clinical trials for preventive treatment trials.³

Reporting and measurement issues regarding headache days have been introduced in a prior manuscript in this series.⁴ Diary studies confirm that reporting of headache days over periods of up to 3 months is reasonably accurate.⁵ The number of headache days is often greater than the number of headache attacks because many migraine or TTH attacks extend

over more than a day. The question, “How often do you have headaches?” is ambiguous because it does not distinguish days from attacks. Clinicians should explicitly ask about days with headache and not merely number of attacks in order to obtain the most accurate frequency count.^{6,7}

A related challenge arises from the tendency for individuals to round their reports of headache days. Rounding of such estimates, or “heaping,” results in reports of headache day estimates that cluster around certain common numbers, often multiples of five.⁸ Heaping occurs when individuals are asked to provide precise information (eg, the number of cigarettes smoked per day, age in years, weight in pounds) that they round to a nearby data point either for convenience or due to a lack of precision in their knowledge of the quantity being reported (eg, two packs per day). As Wang and Heitjan (2008) articulate, heaping distorts the distribution of the observed reports, ultimately biasing estimates of central tendency and variability.⁹

The objective of this study was to determine to what extent heaping occurs in self-reported data of headache days. If individuals round headache frequency rates, their estimates of headache frequency will necessarily be imperfectly reliable due to coarsening of the data. This measurement error has consequences for diagnosis and for the conduct of both observational studies and clinical trials that depend upon these fallible estimates. Herein, we model the phenomenon of heaping using population data from the American Migraine Prevalence and Prevention study and consider the consequences of measurement error for practice and research, particularly that related to the subject of headache chronification.

Methods

Study Design

This secondary analysis was conducted on data from the 2005 American Migraine Prevalence and Prevention study (AMPP). The AMPP study is a population-based, longitudinal data collection effort that has been examined in several previous reports.^{10–16} The data were collected using a stratified random sample of 120,000 households in the United States. The response rate and respondent characteristics have been reported elsewhere.¹ Although the study was conducted in two phases over several years, the present analysis uses data from the 2005 survey only. In 2004, 30,721 individuals with severe headache were identified. In 2005, follow-up surveys were mailed to a random sample of 24,000 of these severe headache sufferers.

AMPP 2005 Survey

The survey was a 60-item self-administered questionnaire. The survey obtained demographic data including age, race, and sex. Other data were also collected (eg, income levels) but were not used in this analysis. Headache characteristics required for making diagnoses according to the criteria of the International Classification of Headache Disorders, Second Edition² were collected, including monthly headache frequency. Headache frequency was assessed by inquiring “Please enter the number of headaches you have had in the past month.” Although the exact number of days specified within a month was not

explicitly detailed, all but two responses were 30. (These two responses were reduced from 31 to 30 for the purposes of analysis) Other validated instruments were also imbedded into the questionnaire including measures of headache-related disability (Migraine Disability Assessment [MIDAS])¹⁷ and depression symptomatology (Patient Health Questionnaire-9 [PHQ-9]).¹⁸ For the purposes of analysis, a diagnosis of “no depression” (0 to 4), “mild depression” (5 to 9), “moderate depression (10 to 14), “moderately severe” (15 to 19) or “major depression” (20) was derived from the PHQ-9.

Statistical Analysis

To accomplish the objective of this analysis, the analytical plan was divided into two parts: the observed versus modeled headache frequency distributions and the assessment of heaping behavior. Each part is described separately, although some elements of the estimation tasks were performed simultaneously. All analyses were conducted using SAS 9.2 (SAS, Inc, Cary, NC). Where appropriate, all inferences are two-tailed, and point estimates are presented with 95% confidence intervals.

Headache Frequency Distribution—To identify if heaping occurs and to what extent, the expected proportion of respondents falling into each headache frequency category must first be identified. For this analysis, the number of headache days was queried as frequency count data (ie, respondents were asked to count the number of headache days typically experienced in a 30-day month). Considering headache frequency as count data naturally leads to using the family of discrete probability distributions that include the Poisson distribution and negative binomial distribution to model the observed headache counts. Each of these distributions can be used to predict the expected number of headaches in the population, assuming the distributions each fit the observed data accurately.

After observing the large number of ‘0’ headache counts in the histogram of responses (Figure 1), two additional model forms were selected as viable candidates to model the observed data: zero-inflated Poisson distribution and zero-inflated negative binomial distribution. These two distributions are similar to their non-zero inflated counterparts but allow for a greater number of zero responses. A group of predictors can be used to model the expected number of zero headache days in each month, in addition to separate predictors that can be used to model the mean level of non-zero headache days. (In this analysis we used the same predictors for each part of the model.) Of note, the sampling strategy used in the AMPP survey has particularly selected individuals that are expected to have non-zero headache counts over the course of the month, because they are self-identified headache sufferers. Thus, the number of zero frequency counts in this model will be much lower than if the AMPP sample included non-sufferers as well.

These distributions were fit to the headache frequency counts using Proc Countreg (SAS 9.2), and the fit of each model was evaluated using standard model selection criteria (Akaike’s information criteria: AIC) and $-2 \times \log$ likelihood (LL). In addition, age, sex, race (white versus non-white), PHQ-9 depression status (no depression, mild depression, moderately severe, major depression), and headache diagnosis (migraine, tension-type

headache, and other) were forced into the model to examine their unique roles in predicting headache days/month.

Modeling Heaping Behavior—Heitjan and Rubin developed a framework for applying multiple imputation to account for half-year heaping in the reporting of age among children.⁸ Wang and Heitjan further developed an approach for modeling heaping in the reported number of cigarettes smoked/day, where heaping likely occurred in multiple of 5, 10, and 20.⁹ The present analysis utilized a simplified version of Wang and Heitjan's approach employing a logistic regression model to predict the probability that an observed report was due to heaping. In this model, the observed monthly headache frequency scores were dichotomized (1 = a multiple of '5' (eg, 5, 10, 15, ... 30) or 0 = not a multiple of 5). In this way, the probability that headache frequency was rounded to 5 could be estimated conditional upon a group of predictors that included actual reported monthly headache frequency, demographic variables (age, race, and sex), and depression.

The rounding probabilities were then used in a multiple imputation procedure to obtain an estimate of the "true" headache frequency distributions that might be observed in the absence of heaping. If an individual's monthly headache frequency was reported as a multiple of 5, that frequency report was judged a candidate for reassignment based on the high probability that it was rounded (informed from the logistic regression model) and a heaping behavior model. Appendix A displays three models of heaping behavior that assume rounding begins after 0 headache days (A), 3 headache days (B), or 4 headache days (C) per month. To conduct the multiple imputation, 100 replicates of the original data set were first created. If a reported headache frequency score of a multiple of 5 was selected as being rounded (determined from a random Bernoulli trial of a probability informed from the logistic regression model), then that score was replaced using a random number from the uniform distribution with a range determined from the rounding behavior model. For example, if the headache frequency report from a 35 year-old woman without depression was 15 headache days/month, there was a 0.63 probability (Figure 3) that this score was replaced with a uniform random number between 13 and 17 (see Appendix A). This process was repeated for each observation over the 100 replications, with the mean of the replications reported as the expected "true" distribution as described by Heitjan and Rubin.⁸

Results

Sample Characteristics

The 2005 survey sample has been described in several previous reports.^{1,10} Briefly, of the 24,000 headache sufferers that were surveyed, 18,514 (77.1%) surveys were returned. Complete monthly headache frequency data were available on 15,976 individuals, and this sample served as the analytical set. The mean age in this set was 47.6 years (SD 14.4); 12,080 (75.6%) respondents were women, 13,880 (89.0%) were white, and 1,230 (7.9%) were black. The majority of respondents had episodic migraine (68.6%) or probable migraine (8.3%), with the remainder having ETTH (10.0%), CM (4.1%), CTTH (1.0%), or another form of headache and headaches not meeting IHS criteria for a diagnosis.² Most respondents had no (17.1%) or mild (44.7%) symptoms of depression, although a sizeable

proportion reported symptoms consistent with moderate or severe depression based on a PHQ-9 score of 15 or greater (38.2%).

Monthly Headache Frequency Distribution

The 30-day monthly headache frequency distribution for all headache sufferers is displayed in Figure 1. The distribution is highly skewed, with a mean of 3.7 headache days/month (median = 2 headache days/month, SD = 5.6). Examination of the distribution revealed that headache frequency was often reported in multiples of '5', with a disproportionate number of responses (ie, in relation to the adjacent frequencies) centered at 5, 10, 15... 25, and 30.

Statistical Distribution of Monthly Headache Frequency

The predictions and residuals (ie, unexplained variance) for the four discrete probability models considered are displayed in Figure 2. The Poisson (log-likelihood: -65184) and zero-inflated Poisson (log-likelihood: -58118) models systematically over-predicted headache frequency (creating negative residuals) between the low counts of 3 to 10 headache days per month. By comparison, the negative binomial and zero-inflated negative binomial distributions fit the data much more consistently, as indicated by their smaller residuals and lower log likelihood values (both log-likelihoods: -38410), both of which reflect a superior fit.

Including demographics and other patient characteristics statistically improved the model predictions but only modestly improved the model fits. Each of the model fits in Figure 2 were calculated for three separate models: a simple model (without additional predictors), a demographics model (considering age, sex, and race), and a demographics plus depression model that also included depressive symptoms. In all cases, adding covariates enhanced the model fit but had little practical impact on the predictions, especially in both negative binomial models. For example, the demographics plus depression model reduced the log-likelihood in the simple negative binomial model from -38410 to -36379, as well as the AIC value (76823 vs 72770). Males reported 12% fewer headache days than females ($p < 0.0001$), non-whites reported 26% fewer headache days than whites ($p < 0.0001$), and those with moderate or severe symptoms of depression reported 51% more headache days than those with mild depressive symptoms ($p < 0.0001$). The influence of demographic factors on the headache frequency predictions can be seen in Appendix B. For example, whereas 2.2% of non-white, > 50 year-old males without depression are predicted to have 6 headache days/month, 4.8% of white, < 50 years-old males with significant depression are predicted to have 6 headache days/month.

Although the negative binomial models fit the data reasonably well throughout the entire range of headache frequencies, the heaped reports in multiples of 5 biased the model fits because they were consistently under-predicted. These values essentially functioned as outliers, serving to bias the predicted values upward. This can be seen in the residuals of the negative binomial models (Figure 2), wherein the majority of residuals lie below zero. To account for this rounding effect and to more accurately predict the population monthly headache frequency, this rounding behavior was further explored.

Probability of Heaping

The results of the logistic regression that predicted the probability an individual would report a monthly headache frequency as a multiple of '5' are displayed graphically in Figure 3. The odds that a headache frequency was rounded to '5' increased by 24% with each one-day increase in headache frequency (OR: 1.24, 95% CI: 1.23 to 1.25). Women tended to round more than men (OR: 1.25, 95% CI: 1.08 to 1.45), and rounding behavior decreased with each year of increasing age (OR: 0.99, 95% CI: 0.98 to 0.99) and increased with symptoms of depression (moderate/severe depression versus mild depression; OR: 1.15, 95% CI: 1.02 to 1.30). The individuals with the lowest, median, and highest probability of rounding to '15' are displayed in Figure 3. (The actual lowest group, non-depressed, > 50 year-old men were not well-represented in the sample and are not displayed.) Although substantial variability was observed across individuals, all individuals had a greater than 64% chance of rounding to '20', and more than an 81% chance of rounding to '25'.

Adjusting for Heaping

After applying the multiple imputation procedure to "smooth" the heaped data, the "true score" distribution of headache frequency was estimated. Figure 4 displays the AMPP reported headache frequencies versus the smoothed predictions. As predicted from the model, higher headache frequencies had a greater likelihood of being rounded and were thus more affected by the smoothing model. For example, at a headache frequency of 5 days/month, the measured value of 5.4% is adjusted downward by 9.3% through the multiple imputation to a value of 4.9%. At 25 days/month, the prediction was adjusted downward by 68.4%, from 0.0057% to 0.0018%. Thus, as the model predicts that more rounding occurs at higher headache frequencies, the heaped data are smoothed to a greater extent at the higher headache frequencies (ie, the higher reported frequencies are more substantially shifted downward).

The percentile ranks for the number of headaches experienced in the population are presented in Table 1 for four different models: the original AMPP data, the negative binomial model predictions, the multiply imputed (smoothed) data, and the negative binomial model predictions on the smoothed data. The negative binomial model was selected for presentation because without the use of additional information (eg, demographics), its predictions are identical to its zero-inflated counterpart. The predictions for each model become more theoretical as more assumptions are used to generate the predictions (ie, moving from left to right in the Table). Whereas the predictions from the more theoretical models are similar to the AMPP reports, they do not exhibit the large probability masses that occur on the '5's among the AMPP frequency reports. Because it is implausible that 'true' headache frequency occurs with greater probability at multiples of '5' than at any other numbers, the employed models more accurately reflect the actual distribution of headache frequency in the population.

Discussion

This study set out to determine whether and the extent to which heaping (or rounding) occurs in self-reports of headache frequency. Using a simple representation of rounding

behavior, the analysis revealed that multiples of 5 occur at a higher rate in reports of headache frequency than would be predicted by chance. If the process followed the best approximations (ie, zero-inflated negative binomial), the frequency of non-rounded numbers should be distributed evenly along the distribution of reports. Yet, monthly headache frequencies were disproportionately reported in multiples of 5, and this phenomenon was particularly evident when reported headache frequencies were > 15 days/month. This rounding heuristic was sufficiently common to distort the resulting population estimates of headache frequency. Thus, when a model was used to adjust the headache reports to account for heaping, subtle but meaningful differences were observed in the distributions that could exert a substantial impact in population-based studies, particularly those focused on events with very low base rates such as headache chronification.

Certain groups were more likely to engage in heaping. Women were more likely than men, younger patients more likely than older, and depressed more likely than non-depressed patients to round their frequency reports to a multiple of '5'. This information has a significant impact on both clinical practice and research. In clinical practice, headache days are used to distinguish nosological entities such as episodic and chronic migraine or episodic and chronic THH. A determination of headache days based on self-reported recall may be inaccurate for multiple reasons. First, as headache frequency changes over time, any particular recall interval may or may not be representative of a patient's experience, especially if the recall interval is short. Second, patients may not accurately recall their headache frequency but tend to excessively report headache days per month in multiples of 5. Third, random error in measurement results from the fact that retrospective recall is inherently imperfect.

This tendency to round headache frequency estimates can prove to be a critical issue with respect to formulating chronic headache diagnoses. For individuals with migraine who round down from 16, 17 or 18 days/month to 15, diagnostic accuracy will not be influenced by underestimates of headache frequency; these individuals will be classified as chronic migraine. However, when individuals with migraine and 12, 13 or 14 headache days per month (who thus do not meet diagnostic criteria for CM) round up to 15 days/month, CM may be overdiagnosed.

These findings also have major implications for research. In clinical trials, self-reported headache frequency at baseline is used to determine eligibility for a diary run-in phase. Persons with more than 15 headache days/month who round down to 15 will still be enrolled in the diary phase to determine baseline frequency. But those with 13 or 14 headache days/month who instead round up will be initially misclassified as CM, and enrolled in the baseline diary phase. If the diary reveals a frequency of less than 15 headache days per month, they will be judged ineligible for a CM study.

These problems are well exemplified in the PREEMPT studies.¹⁹ The investigators found that about half of the patients the physician thought had CM in fact did not have the requisite number of headache days based on the daily telephone diary. One reason may be the phenomenon of rounding up. A high exclusion rate after the diary run-in is expensive and time-consuming for clinicians and patients but does not necessarily challenge the validity of

a randomized controlled trial (RCT). On the other hand, an erroneously high inclusion rate or atypical baseline frequencies may negatively affect the conclusions derived from an RCT. When patients by chance have a bad month during the diary run-in, they are enrolled in the RCT and then, independent of treatment group, regress to their mean. This may produce an artificially high placebo rate as exemplified by the PREEMPT program, as well as high treatment response rates.

In addition to their potential influence in clinical trials, heaping may influence observational studies. Heaping may lead to spurious conclusions about change over time by contributing to underestimation or overestimation of change in headache days per month. Alternatively, “real” changes in headache frequency may be obscured by the inaccuracy that occurs whenever a participant approximates their headache frequency to a round number. The results of this analysis underscore the need for concern when evaluating supposed changes in self-report headache frequency. The current data indicate that between 3.3% (negative binomial smoothed model) and 5.1% (AMPP data) of the general headache population could be diagnosed as chronic headache sufferers depending on rounding behavior (see Table 1), suggesting that prior studies may have overestimated chronification rates by not accounting for heaping behavior. More precisely estimating these rates will assist in the appropriate allocation of resources to help treat these individuals on a community and national level.

This analysis has several limitations that must temper the conclusions. First, only rounding to multiples of ‘5’ were considered whereas headache sufferers might use a host of rounding patterns when reporting headache frequencies. For example, for individuals with high frequencies of headache, it may be cognitively easier to consider how many days on which one does *not* have a headache and simply subtract from 30. Under this process, different numbers will be observed such as multiples of ‘4’ (eg, one headache-free day each week). Further, the model assumed that low headache frequencies are not rounded but that rounding occurs uniformly after some frequency (eg, 3 headaches/month). The extent to which these assumptions are accurate cannot be ascertained in this setting and it is likely that these models do not comprehensively account for all of the factors that are at work in the observed heaping behavior. Finally, the models examining rates of heaping across demographic groups are simply associations and could be due to a host of unmeasured/confounding variables. For example, higher rates of depressive symptoms can be hypothesized to encourage rounding behavior due to reduced cognitive resources associated with depression, but it is not intuitive why women would round headache frequency to a greater extent than men. Despite these notable limitations, the study supports the notion that heaping occurs quite often in global reports of headache frequency.

Although use of daily headache diaries is endorsed as the gold standard for headache assessment in the research community,² global reports of headache frequency nevertheless are still being used to assess outcomes of clinical interventions and are routinely used in headache chronification research.⁴ Such global assessments (eg, “How many headaches did you experience this month?”) should be expected to have subtle forms of bias, including but not limited to, rounding heuristics.

To reduce the impact of rounding and to improve the accuracy of headache frequency estimates, data collection methods other than simple global, retrospective self-report must be used. For example, reports from others knowledgeable of the patient's headache frequency could be employed along with the patient's report. Another method is to ask the patient to report twice covering the same time period, but soliciting one of the reports at a later date (eg, a week later than the prior report) and then comparing the two reports. This should be done by the patient without benefit of the data she presented in the first report. One could also shorten the time period covered in the reporting (eg, one week rather than one month), for the data implies that heaping occurs less with low frequency reporting, although a short duration may not be entirely representative of the patient's longstanding headache pattern. A final option, if resources and time permit, is to use daily headache diary methods that do not rely so heavily on patient memory. In the final companion manuscript, several recommendations are offered to reduce the impact of these and other confounds in research on headache chronification.

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Appendix A. Rounding models

Rounding behavior assuming respondents have rounded their “true” headaches/month to nearest ‘5’. Each model assumes that reported scores with multiples of ‘5’ could have true scores within the specified range. For example, a report of ‘10’ headaches/month could result from a true score of 8 to 12. The three models below assume that rounding starts beginning at 0 (A), 3 (B), and 4 (C) headaches/month.

A																													
0	0	0	5	5	5	5	5	10	10	10	10	10	.	.	.	25	25	25	25	25	30	30	30						
0	1	2	3	4	5	6	7	8	9	10	11	12	.	.	.	23	24	25	26	27	28	29	30						

B																													
0	1	2	5	5	5	5	5	10	10	10	10	10	.	.	.	25	25	25	25	25	30	30	30						
0	1	2	3	4	5	6	7	8	9	10	11	12	.	.	.	23	24	25	26	27	28	29	30						

C																													
0	1	2	3	5	5	5	5	10	10	10	10	10	.	.	.	25	25	25	25	25	30	30	30						
0	1	2	3	4	5	6	7	8	9	10	11	12	.	.	.	23	24	25	26	27	28	29	30						

Appendix B. Zero-inflated negative binomial model predictions

The Figures plot the statistically significant but practically small differences in the predicted proportions of individuals at various headache frequencies as a function of sex (A), headache diagnosis (B), age category (C), and racial group (D). Panel E presents all of the zero-inflated model predictions for all predictors and two-way interactions.

American Migraine Prevalence and Prevention (AMPP) Study (N = 15,796)

Figure 1. Histogram of headaches per 30-day month derived from the 2005 American Migraine Prevalence and Prevention Survey (N=15,796). The survey was a 60-item self-administered questionnaire. The survey presented questions related to demographics such as age, race, and sex. The respondents were asked to count the number of headaches they typically experience in a 30-day month.

Figure 2.

Simple model predictions and residuals/errors for four discrete probability models. The four models are the Poisson, the Zero inflated Poisson (ZIP), the Negative Binomial (NB) and the Zero-Inflated Negative Binomial (ZINB). To the right of each of the four models are their respective residual/errors.

Figure 3. Probability of rounding to the nearest '5'. The results of the logistic regression model that predicted the probability an individual would report a monthly headache frequency in a multiple of '5'.

Figure 4.

The results of the multiply imputed smoothing model. The observed responses of the AMPP survey are represented by grey circles and the smoothed predictions are presented with the black line. As predicted by the model, greater headache frequencies are more smoothed than lower frequencies.

Table 1

Cumulative proportion of persons with migraine with headache days at or below the critical value using AMPP survey data and model-based estimates of headache day distributions.

Headache Days/Month	AMPP sample data	NB model prediction	MI smoothed data	NB smoothed prediction
0	23.4	28.2	23.4	28.2
1	47.5	44.4	47.5	44.4
2	60.8	56	60.8	56
3	71.3	64.6	71.4	64.7
4	76.3	71.4	76.5	71.5
5	81.7	76.7	81.4	76.8
6	86.2	81	86.1	81.1
7	86.8	84.4	86.8	84.5
8	88.8	87.2	88.9	87.3
9	89.1	89.4	89.4	89.5
10	91.9	91.3	91.6	91.4
11	92.4	92.8	92.3	92.9
12	92.9	94	92.9	94.2
13	93.7	95.1	93.8	95.2
14	93.8	95.9	94	96
15	94.9	96.6	94.7	96.7
16	95.5	97.2	95.4	97.3
17	95.5	97.6	95.5	97.8
18	95.5	98	95.6	98.1
19	95.5	98.4	95.9	98.5
20	96.8	98.6	96.5	98.7
21	97	98.9	96.9	99
22	97.1	99.1	97.1	99.2
23	97.4	99.2	97.5	99.3
24	97.5	99.3	97.7	99.4
25	98	99.5	97.9	99.5
26	98.5	99.5	98.5	99.6
27	98.5	99.6	98.5	99.7
28	98.8	99.7	99	99.8
29	98.8	99.7	99.7	99.8
30	100	99.8	100	99.9

Abbreviations: NB=Negative Binomial model predictions, MI = Multiple Imputation smoothed data, and NB smoothed = Negative Binomial (NB) smoothed model predictions