Supplemental Online Content

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**eMethods.** Details, verification, and validation of our methodological approach.

**eFigure.** Crude prevalence rate of blindness increases with age for all race and ethnic groups, starting around age 60 years.

**eTable 1.** Estimated prevalence count of people living with visual acuity loss or blindness, stratified by state, as well as prevalence rates (in percent).

**eTable 2.** Estimated prevalence count of people living with blindness, stratified by location, as well as prevalence rates (in percent).

This supplemental material has been provided by the authors to give readers additional information about their work.

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**eMethods:** details, verification, and validation of methodological approach

In this supplementary appendix, we present additional details on the verification and validation of our methodological approach. To better understand the impact of modeling choices, we examined a nested sequence of intermediate models of increasing complexity.

Initially we estimated the numbers of cases of visual acuity loss using only PBS data. We then added NHANES data as reference with PBS data for the estimation, and then merged NSCH data with NHANES data and PBS data in the model and generated estimates of visual acuity loss. We then added ACS data for older ages and group quarters sequentially (denoted ACS-older and ACS-gq in Table 1 below). After that we used ACS data for state-specific prevalence and for year 2017 to generate estimates (denoted ACS-state and ACS-2017 in Table 1 below). In the final model we added interaction terms along with all the datasets to generate visual acuity loss estimates.

*Table 1:* Estimated prevalence counts (in millions) of people living with visual acuity loss or blindness, after each step of the sequence in the model.

| Data Sources                    | Visual acuity loss among age 40+ (in millions) | Visual acuity loss in all ages (in millions) |
|--------------------------------|-----------------------------------------------|---------------------------------------------|
| Population Based Study data (Exam) | 2.92 [2.12, 3.83]                              | 3.47 [2.56, 4.61]                           |
Table 2 presents similar results for the subset of patients who we predicted to be blind.

Table 2: Estimated prevalence counts (in millions) of people living with blindness, after each step of the sequence in the model.
| Data Sources | Blindness among age 40+ (in millions) | Blindness in all ages (in millions) |
|--------------|--------------------------------------|----------------------------------|
| Population Based Study data (Exam) | 0.73 [0.48, 1.10] | 0.77 [0.51, 1.15] |
| Exam, NHANES | 0.71 [0.45, 1.14] | 0.82 [0.56, 1.25] |
| Exam, NHANES, NSCH | 0.73 [0.48, 1.07] | 0.86 [0.59, 1.20] |
| Exam, NHANES, NSCH, ACS-older | 0.69 [0.50, 0.94] | 0.82 [0.60, 1.08] |
| Exam, NHANES, NSCH, ACS-older, ACS-gc | 0.81 [0.59, 1.09] | 0.96 [0.71, 1.24] |
| Exam, NHANES, NSCH, ACS-older, ACS-gc, ACS-state | 0.81 [0.62, 1.04] | 0.96 [0.74, 1.21] |
| Exam, NHANES, NSCH, ACS-older, ACS-gc, ACS-state, ACS-2017 | 0.91 [0.71, 1.12] | 1.06 [0.84, 1.28] |
| Exam, NHANES, NSCH, ACS-older, ACS-gc, ACS-state, ACS-2017, interaction terms | 0.93 [0.74, 1.17] | 1.08 [0.85, 1.34] |
Readers may notice that our reported results when using only PBS data (row 1 of Tables 1 and 2) are lower than those reported by the Vision Problems in the U.S. (VPUS) study which was also based on population-based studies (3). That study (available at visionproblemsus.org) estimated 4.19 million people with vision impairment and blindness, of whom 1.29 million were blind. Based only on population-based studies, our model estimates 2.92 million people who had visual acuity loss or blindness, of whom approximately 730,000 were blind. This difference is driven by the PBS that were used in our model as compared to the earlier VPUS. The studies we included as PBS are described in the data section above. They can be compared to those used by VPUS by reviewing the VPUS Methods and Sources page. In general, the studies that we included reported a lower prevalence of visual impairment and blindness than the studies included in the VPUS and this lower prevalence is reflected in our model estimate.

We believe specific differences between our estimates are attributable to the inclusion of older data from the Baltimore Eye Survey (collected from 1985 and 1988) (1) and the Salisbury Eye Evaluation Project (collected from 1993 and 1995) (2) in VPUS, and our inclusion of data from CHES (collected from 2010-2013), LALES (collected from 2000-2008), and MESA (collected from 2002-2004).

*MICE-Multiple imputation by chained equation*

Missing data in meta-analysis can jeopardize inferences from the study and examination data, and possibly bias the estimates. The vision examination data from NHANES is a key input in our meta-analytic estimates of the prevalence of uncorrectable visual acuity loss or blindness in the United States, but when we mapped this data to dichotomous outcomes for visual acuity loss or blindness, we were unable to determine a value for 11.51% of respondents.
Multiple imputation by chained equations (MICE) is a standard approach to address missing data. MICE constructs a regression model for each column with missing values, using the variables from the other columns as the predictors. If multiple columns have missing values, the MICE procedure iterates through the columns, fitting each with the previously imputed values for the other columns. Simpler approaches, such as complete-case analysis (also called list-wise deletion) and available-case analysis, may produce biased results. The mean age among individuals with incomplete eye exam was 52.8 years, substantially higher than the mean age among individuals with complete eye exam (38.6 years), and since visual acuity loss or blindness prevalence rates increase markedly as age increases, our imputation method must take age into account.

Using equation 1 and 2 below, we imputed missing dichotomous indicators of visual loss and blindness using multiple imputation with chained equations (MICE) with Gaussian perturbations:

\[
\text{Visual acuity loss} \sim C(\text{age Group}) + \text{sex} + C(\text{race_eth}) + \text{vidrva} + \text{vidlva},
\]

\[
\text{Blindness} \sim C(\text{age Group}) + \text{sex} + C(\text{race_eth}) + \text{vidrva} + \text{vidlva},
\]

where \text{vidrva} and \text{vidlva} are presenting visual acuity of the right eye and left eye respectively, \text{C(age group)} respresents a “dummy coding” for age variable grouped in bins (0, 12, 18, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 100) and \text{C(race_eth)} represents a “dummy coding” for our categorical variable for race/ethnicity.

The MICE approach requires some choices: what else should go into the regression formula for the missing variables? Should we use a Gaussian for perturbing the model parameters in the imputation model, or a non-parametric bootstrap? To identify the best
regression formula and perturbation method for imputing missing values of visual acuity loss or blindness, we conducted an out-of-sample validation exercise.

We considered a range of regression equations for our outcomes of interest (visual acuity loss or blindness): (in the formulas below, the notation (var1 + var2)**2 means the variables var1 and var2 are included as main effects and all pair-wise interactions are also included)

1. outcome ~ age + sex + C(race) (where C(race) is a “dummy” coding of the race/ethnicity variable)
2. outcome ~ C(age_group) + sex + C(race) (where C(age_group) is a “dummy” coding of the age variable grouped in bins [0, 12, 18, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 100] )
3. outcome ~ C(age_group) + sex + C(race) + vidrva (where vidrva is the presenting visual acuity in the right eye)
4. outcome ~ C(age_group) + sex + C(race) + vidlva (where vidlva is the presenting visual acuity in the left eye)
5. outcome ~ C(age_group) + sex + C(race) + vidrva + vidlva
6. outcome ~ C(age_group) + sex + C(race) + (vidrva + vidlva )**2
7. outcome ~ C(age_group) + sex + C(race) + vidrova (where vidrova is the best-corrected visual acuity in the right eye)
8. outcome ~ C(age_group) + sex + C(race) + vidlova (where vidlova is the best-corrected visual acuity in the left eye)
9. outcome ~ C(age_group) + sex + C(race) + vidrova + vidlova
10. outcome ~ C(age_group) + sex + C(race) + (vidrova + vidlova)**2
11. outcome ~ C(age_group) + sex + C(race) + vidrva + vidlva + vidrova + vidlova

12. outcome ~ C(age_group) + sex + C(race) + (vidrva + vidlva + vidrova + vidlova)**2

We tested each equation for each outcome for two alternative perturbation methods: (a) the Gaussian perturbation method, which samples from a multivariate normal distribution derived from the fit of the regression equation; and (b) the bootstrap perturbation method, which samples from the conditional model fitted to a bootstrapped version of the data set.

For our testing approach, we used an out-of-sample cross-validation approach from machine learning, where we withheld the presenting and best corrected visual acuity measurements for a randomly selected subset of data (our “test dataset”) and compared the model predictions for these individuals to the true values of blindness and visual acuity loss.(3) To be precise,

1. First, we selected 25% of the rows of NHANES data and redacted their vidrva, vidlva, vidrova, and vidlova values (which are all numeric values measured for presenting and best corrected visual acuity in the right and left eye; these values are always sufficient to derive the values of the visual acuity loss and blindness variables, and certain patterns of missing values among these measurements lead to missing values of the dichotomous visual acuity loss and blindness variables). For these rows, we also redacted the visual acuity loss or blindness values derived from these measurements.

2. Second, we imputed the masked values using MICE 1,000 times and took the average of these values as a probability prediction of the outcome of interest (visual acuity loss or blindness).
Third, we compared those imputed values and actual values using the ROC curve in which the true positive rate (Sensitivity) is plotted as a function of the false positive rate (100-Specificity) for different cut-off points of a parameter. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. We measured the area under the ROC curve (AUC) as a summary metric for performance of the MICE formulation.

**MICE validation results**

Missing values were best imputed using the variables age, sex, race, vidrva and vidlva, as shown in Table 3.

*Table 3: Table showing the AUC score of all the models with different parameters*

| Method / Equation | VL Gaussian | VL Bootstrap | Blindness Gaussian | Blindness Bootstrap |
|-------------------|-------------|--------------|--------------------|--------------------|
| Age + Sex + C(Race) | 70.11       | 69.74        | 73.15              | 72.95              |
| C(Age_group) + Sex + C(Race) | 72.21       | 71.18        | 72.51              | 70.39              |
| C(Age_group) + Sex + C(Race) + Vidrva | 75.81       | 75.86        | 80.14              | 81.09              |
| C(Age_group) + Sex + C(Race) + Vidlva | 74.72       | 75.66        | 77.05              | 83.89              |
| C(Age_group) + Sex + C(Race) + Vidrva + Vidlva | **75.51**   | 74.66        | **80.75**          | 78.53              |
| Model                                           | AUC 1 | AUC 2 | AUC 3 | AUC 4 |
|------------------------------------------------|-------|-------|-------|-------|
| \( C(Age\_group) + Sex + C(Race) + (Vidrva + Vidlva)^2 \) | 74.98 | 75.74 | 78.70 | 78.93 |
| \( C(Age\_group) + Sex + C(Race) + Vidrova \)       | 75.04 | 74.49 | 82.95 | 70.89 |
| \( C(Age\_group) + Sex + C(Race) + Vidlova \)       | 75.29 | 74.81 | 77.66 | 79.59 |
| \( C(Age\_group) + Sex + C(Race) + Vidrova + Vidlova \) | 74.19 | 74.99 | 75.22 | 72.04 |
| \( C(Age\_group) + Sex + C(Race) + (Vidrova + Vidlova)^2 \) | 74.25 | 72.43 | 69.24 | 75.48 |
| \( C(Age\_group) + Sex + C(Race) + Vidrva + Vidlva + Vidrova + Vidlova \) | 74.66 | 72.97 | 70.27 | 67.53 |
| \( C(Age\_group) + Sex + C(Race) + (Vidrva + Vidlva + Vidrova + Vidlova)^2 \) | 72.60 | 71.26 | 77.00 | 78.62 |

Our selected approach to MICE produced out-of-sample AUC of 75.51, compared with AUC of 70.79 in complete-case analysis.

**Bayesian meta-regression model**

We represent our model with a stochastic component and a systematic component, where the stochastic component is a negative binomial model of count data:

\[
(3) \quad Y_i \sim \text{NegativeBinomial}(N_{eff}^l, \pi_i, \eta),
\]
where \( i \) indexes the specific measurement, \( Y_i \) is the prevalence count of those with visual acuity loss (or blindness) in measurement \( i \), \( N_{\text{eff}}^i \) is the effective sample size from which the count was taken (and so \( p_i = \frac{Y_i}{N_{\text{eff}}^i} \) is the prevalence rate typically reported in a PBS), \( \pi_i \) is the prevalence rate predicted by the model, \( \eta \) is the over-dispersion parameter of the negative binomial distribution (assumed to be the same for all measurements). DisMod-MR 1.1.1 uses the Python PyMC2 package to implement this Bayesian computation, and follows the formulation of the negative binomial model provided by PyMC2, where
\[
\Pr(Y = x | \mu, \alpha) = \frac{\Gamma(x + \alpha)}{x! \Gamma(\alpha)} \left( \frac{\alpha}{\mu + \alpha} \right)^\alpha \left( \frac{\mu}{\mu + \alpha} \right)^x,
\]
which in terms of the equation above has \( x = p_i \cdot N_{\text{eff}}^i, \mu = \pi_i, \) and \( \alpha = \eta \).

In the systematic component of the model, we included fixed effects for sex \( (\alpha_{\text{sex}}) \), age \( (\beta_k \) \) for \( k = 0, \ldots, K \), race \( (\gamma_j \) \) for \( j = \text{white, Black, Hispanic, and other races} \), and data source \( (\delta_j \) \) for \( j = \text{EDPRG, CHES, LALES, ACS, BPEDS, MESA, and NSCH; we coded NHANES as the reference category} \), as well as sex/race and race/age interaction fixed effects. We also include random effects for state \( (50 \text{ states and Washington, D.C.;} \eta_j \) \) for \( j = 1, \ldots, 51 \). Our formulation includes a piece-wise linear spline model on age, with spline knots \( (\text{knot}_1, \text{knot}_2, \ldots) \) indexed by \( k \) for \( k = 1, \ldots, K \), as well as intercept shifts for additional key covariates to account for differential sex ratios and age patterns by race as follows:
\[
\pi_i = \exp[a_{\text{sex}}[\text{sex}_i = \text{female}]] \times \left( \int_{x = \text{age}^i_b}^{\text{age}^i_t} \left( \beta_0 + \sum_{k=1}^{K} \beta_k (x - \text{knot}_k)^+ \right) dx \right) \times \exp \left\{ \sum_{j=1}^{4} \gamma_j [\text{race}_i = j] + \sum_{j=1}^{7} \delta_j [\text{source}_i = j] + \sum_{j=1}^{51} \eta_j [\text{location}_i = j] + \text{interaction_terms} \right\},
\]
where $\text{sex}_i$ is the sex measured in measurement $i$; $\text{age}_{0i}$ and $\text{age}_{1i}$ are the start and end of the age group measured in measurement $i$; $\text{race}_i$ is the race/ethnicity group measured in measurement $i$; $\text{source}_i$ is the data source for measurement $i$; $\text{location}_i$ is the state location of measurement $i$; and notation $[\text{variable} = \text{value}]$ represents an indicator function which takes value 1.0 if the variable is equal to the value and 0.0 otherwise and notation $(\text{value})^+$ represents the value in the parenthesis if it is positive, and takes value zero, otherwise. We used evenly spaced spline knots at ages (0, 20, 40, 60, 80, 100).

We also included interaction terms to capture the possibility that the sex and age effects were different by race/ethnicity and group quarters status:

$$\text{interaction_terms} = \sum_{j=1}^{4} \gamma_j' \left[ \text{race}_i = j \text{ and } \text{sex}_i = \text{female} \right]$$

$$+ \gamma_j'' \left[ \text{race}_i = j \right] (\text{age}_{0mid}^{i} + \text{age}_{1mid}^{i})$$

$$+ \gamma_j''' \left[ \text{race}_i = j \right] \left[ \text{age}_{mid}^{i} > 50 \right] (\text{age}_{mid}^{i} - 50)$$

$$+ \gamma_j'''' \left[ \text{g. quarters}_i = \text{inst} \right] (\text{age}_{0}^{i} + \text{age}_{1}^{i})$$

where $\gamma_j'$ is the effect coefficient for race $j$ interacted with sex (for $j = 1, \ldots, 4$), $\gamma_j''$ is the effect coefficient for race $j$ interacted with age, $\gamma_j'''$ is the effect coefficient for race $j$ interacted with age $> 50$, and $\gamma_j''''$ is the effect coefficient for race $j$ interacted with age $> 50$, and $\text{age}_{mid}^{i} = \frac{\text{age}_{0}^{i} + \text{age}_{1}^{i}}{2}$ is the midpoint of the age group measured in measurement $i$.

Together $\gamma_j'''$ and $\gamma_j''''$ constitute an age-dependent spline for the group quarters population with knots at 0 and 50. We used a Bayesian framework for inference with weakly informative priors for model parameters other than state to assist in regularization, which primarily allowed the data to inform the model estimates. Prior distributions for $\alpha_{\text{sex}}$, $\beta_k$, $\gamma_j$, $\gamma_j'$, $\gamma_j''$, $\gamma_j'''$, $\gamma_j''''$, and $\delta_j$ were all set to independent normal distributions with mean 0.0 and
standard deviation 1.0. To capture state variation in prevalence, we used informative priors for state random effects, which were informed by the state-to-state variation in age-/sex-/race-standardized endorsement rates of the respondent-reported visual acuity loss question in ACS. This prior took the form

\[ u_j \sim \text{Normal}(\mu_j, \sigma_j^2), \]

where, in short, \( \mu_j \) is the log of the ratio of the standardized state prevalence to the national prevalence, and \( \sigma_j^2 \) is the standard deviation of the log-ratio of the crude state prevalence to the national prevalence for all strata with at least 500 individuals, and \( u_j \) is normal distribution with mean \( \mu_j \) and standard deviation \( \sigma_j \). To be precise, to estimate \( \mu_j \) and \( \sigma_j^2 \), we first estimated the crude prevalence rate of respondent-reported visual acuity loss in the US in 2017 as observed in ACS data. We next estimated the prevalence rate of respondent-reported visual acuity loss for each state \( j \) from the same data source, stratified by age-group, sex, race/ethnicity, and group quarters status. We then used the state-specific stratified estimates to calculate a standardized prevalence rate, standardizing with the age group, sex, race/ethnicity, and group-quarters weights at the national level, to control for demographic difference between states. We then used these data to estimate the ratio of the standardized state prevalence to the national prevalence. For each state \( j \), we set the prior on \( u_j \) to be normally distributed with mean \( \mu_j = \log(\text{ratio}_j) \), where \( \text{ratio}_j \) is the ratio of standardized prevalence in state \( j \) to the national prevalence. We obtained an informative standard deviation \( \sigma_j \) for this prior as follows: analogous to the ratio use used for the mean, we constructed a ratio of the national prevalence rate to the state-specific prevalence rate for each strata (stratified by age-group, sex, race/ethnicity, and group quarters status) and calculated the standard deviation of the log-ratio for all strata with at least 500 individuals in the
state, age, sex, and race/ethnicity-specific strata. We put a cap on the predicted prevalence at 0.25 to ensure that we are not over estimating our results.

Only data from ACS was available to inform the group-quarters effect coefficients, but unlike the state-to-state variation, we used this ACS data in the likelihood instead of constructing an informative prior. To guard against inferring with more confidence than appropriate from the ACS group quarters data, we used aggregate measurements for broad age groups (25-year intervals) and did not stratify them by sex or by race/ethnicity. We also included fixed effects for each age group, which effectively treated each comparison of the prevalence in the institutional group quarters population and the free-living population as a separate study in the meta-regression.

We included all other data sources (NHANES, PBS, NSCH) in the likelihood with the assumption that they applied to a nation-level estimate, which we assumed to be constant over time. This includes data from NSCH, NHANES, and BPEDS for children under the age of 18, and also ACS data on free-living adults over the age of 85.

Validation and Verification

We assessed the cross-model validation of our model by setting its population parameters to those of the VPUS study (persons 40 and older in household settings), estimating the number of cases it generated when using only PBS data, and then sequentially estimating the number of cases it generated using the new data sources and model specifications that we included in our final model. See eMethods supplementary materials for full details.

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**eFigure 1:** Crude prevalence rate of blindness increases with age for all race and ethnic groups, starting around age 60 years.
**eTable 1:** Estimated prevalence count of people living with visual acuity loss or blindness, stratified by state, as well as prevalence rates (in percent).

| State | Prevalence Count | Prevalence Rate (%) |
|-------|------------------|---------------------|
|       | Mean | 2.5<sup>th</sup> percentile | 97.5<sup>th</sup> percentile | Mean | 2.5<sup>th</sup> percentile | 97.5<sup>th</sup> percentile |
| AK    | 12,300 | 10,600 | 14,400 | 1.66 | 1.43 | 1.95 |
| AL    | 131,200 | 112,400 | 151,100 | 2.69 | 2.31 | 3.10 |
| AR    | 160,300 | 135,000 | 184,300 | 2.28 | 1.92 | 2.63 |
| AZ    | 89,300 | 75,800 | 104,100 | 2.97 | 2.52 | 3.46 |
| CA    | 810,900 | 709,900 | 935,100 | 2.05 | 1.80 | 2.37 |
| CO    | 99,000 | 84,200 | 115,600 | 1.76 | 1.50 | 2.06 |
| CT    | 62,300 | 51,500 | 73,000 | 1.74 | 1.44 | 2.03 |
| DC    | 22,400 | 19,400 | 25,300 | 3.22 | 2.80 | 3.65 |
| DE    | 18,100 | 15,400 | 21,300 | 1.88 | 1.60 | 2.21 |
| FL    | 558,600 | 475,700 | 641,500 | 2.66 | 2.27 | 3.06 |
| GA    | 221,300 | 190,900 | 255,700 | 2.12 | 1.83 | 2.45 |
| HI    | 30,200 | 24,500 | 35,600 | 2.12 | 1.71 | 2.50 |
| IA    | 48,000 | 38,800 | 56,400 | 1.52 | 1.24 | 1.79 |
| ID    | 37,000 | 30,600 | 43,500 | 2.15 | 1.78 | 2.53 |
| IL    | 244,900 | 211,600 | 282,000 | 1.91 | 1.65 | 2.20 |
| IN    | 141,900 | 120,400 | 166,400 | 2.13 | 1.81 | 2.50 |
| State | 2005   | 2010   | 2015   | 2005-2010 | 2010-2015 | 2005-2015 |
|-------|--------|--------|--------|-----------|-----------|-----------|
| KS    | 63,000 | 52,600 | 73,200 | 2.16      | 1.80      | 2.51      |
| KY    | 125,300| 103,600| 145,200| 2.81      | 2.33      | 3.26      |
| LA    | 123,000| 104,600| 141,100| 2.63      | 2.23      | 3.01      |
| MA    | 129,600| 107,200| 152,400| 1.89      | 1.56      | 2.22      |
| MD    | 102,800| 86,900 | 118,900| 1.70      | 1.44      | 1.97      |
| ME    | 18,000 | 13,600 | 22,100 | 1.35      | 1.02      | 1.65      |
| MI    | 200,700| 168,100| 234,800| 2.02      | 1.69      | 2.36      |
| MN    | 92,500 | 74,900 | 108,600| 1.66      | 1.34      | 1.95      |
| MO    | 138,000| 115,500| 161,200| 2.26      | 1.89      | 2.64      |
| MS    | 98,300 | 84,100 | 113,200| 3.29      | 2.82      | 3.79      |
| MT    | 19,100 | 15,500 | 23,100 | 1.82      | 1.47      | 2.20      |
| NC    | 230,800| 194,000| 265,300| 2.25      | 1.89      | 2.58      |
| ND    | 12,100 | 10,000 | 14,500 | 1.60      | 1.32      | 1.92      |
| NE    | 40,600 | 34,400 | 48,200 | 2.12      | 1.79      | 2.51      |
| NH    | 23,500 | 18,900 | 28,000 | 1.75      | 1.41      | 2.09      |
| NJ    | 169,000| 143,300| 192,600| 1.88      | 1.59      | 2.14      |
| NM    | 62,300 | 54,000 | 71,000 | 2.98      | 2.58      | 3.40      |
| NV    | 80,300 | 69,300 | 91,700 | 2.68      | 2.31      | 3.06      |
| NY    | 393,200| 337,500| 449,900| 1.98      | 1.70      | 2.27      |
| OH    | 251,200| 214,200| 296,700| 2.15      | 1.84      | 2.54      |
| State | Life Expectancy | Male Life Expectancy | Female Life Expectancy | Male/Female Ratio |
|-------|----------------|----------------------|------------------------|-----------------|
| OK    | 116,400        | 99,900               | 135,200                | 2.96            |
| OR    | 78,900         | 65,500               | 93,300                 | 1.90            |
| PA    | 302,600        | 250,500              | 352,500                | 2.36            |
| RI    | 21,500         | 17,900               | 25,700                 | 2.03            |
| SC    | 129,800        | 111,100              | 149,800                | 2.58            |
| SD    | 16,000         | 13,000               | 18,700                 | 1.84            |
| TN    | 172,300        | 143,100              | 199,400                | 2.57            |
| TX    | 634,000        | 551,100              | 726,300                | 2.24            |
| UT    | 43,000         | 35,900               | 50,000                 | 1.39            |
| VA    | 168,100        | 143,100              | 191,300                | 1.98            |
| VT    | 13,900         | 11,500               | 16,500                 | 2.23            |
| WA    | 144,200        | 118,700              | 165,400                | 1.95            |
| WI    | 101,600        | 83,500               | 119,200                | 1.75            |
| WV    | 65,200         | 53,200               | 77,400                 | 3.59            |
| WY    | 10,200         | 8,400                | 12,100                 | 1.77            |
**eTable 2:** Estimated prevalence count of people living with blindness, stratified by location, as well as prevalence rates (in percent).

| Location | Prevalence Count | Prevalence Rate (%) |
|----------|------------------|---------------------|
|          | Mean | 2.5th percentile | 97.5th percentile | Mean | 2.5th percentile | 97.5th percentile |
| AK       | 1,600 | 1,200 | 2,100 | 0.22 | 0.17 | 0.28 |
| AL       | 21,500 | 16,400 | 27,600 | 0.44 | 0.34 | 0.57 |
| AR       | 22,400 | 16,700 | 29,300 | 0.32 | 0.24 | 0.42 |
| AZ       | 15,300 | 11,200 | 19,300 | 0.51 | 0.37 | 0.64 |
| CA       | 106,200 | 83,600 | 131,000 | 0.27 | 0.21 | 0.33 |
| CO       | 14,000 | 9,900 | 17,600 | 0.25 | 0.18 | 0.31 |
| CT       | 10,200 | 7,300 | 13,600 | 0.28 | 0.20 | 0.38 |
| DC       | 3,700 | 2,800 | 4,600 | 0.53 | 0.40 | 0.66 |
| DE       | 2,900 | 2,100 | 3,600 | 0.30 | 0.22 | 0.38 |
| FL       | 84,800 | 64,600 | 108,800 | 0.40 | 0.31 | 0.52 |
| GA       | 33,300 | 25,500 | 41,400 | 0.32 | 0.24 | 0.40 |
| HI       | 3,800 | 2,500 | 5,100 | 0.27 | 0.18 | 0.36 |
| IA       | 8,100 | 5,300 | 10,900 | 0.26 | 0.17 | 0.35 |
| ID       | 5,600 | 4,000 | 7,200 | 0.33 | 0.23 | 0.42 |
| IL       | 38,200 | 27,900 | 48,700 | 0.30 | 0.22 | 0.38 |
| IN       | 23,400 | 16,800 | 30,500 | 0.35 | 0.25 | 0.46 |
| State | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|-------|------|------|------|------|------|------|
| KS    | 10,600 | 7,600 | 14,100 | 0.37 | 0.26 | 0.48 |
| KY    | 21,300 | 15,900 | 27,700 | 0.48 | 0.36 | 0.62 |
| LA    | 20,100 | 15,100 | 24,900 | 0.43 | 0.32 | 0.53 |
| MA    | 20,600 | 14,400 | 27,100 | 0.30 | 0.21 | 0.40 |
| MD    | 15,700 | 12,000 | 20,300 | 0.26 | 0.20 | 0.34 |
| ME    | 3,000  | 2,000  | 4,000  | 0.22 | 0.15 | 0.30 |
| MI    | 32,300 | 23,500 | 41,900 | 0.32 | 0.24 | 0.42 |
| MN    | 15,400 | 10,300 | 20,300 | 0.28 | 0.18 | 0.36 |
| MO    | 23,200 | 16,000 | 30,400 | 0.38 | 0.26 | 0.50 |
| MS    | 16,700 | 13,100 | 20,800 | 0.56 | 0.44 | 0.70 |
| MT    | 3,000  | 2,100  | 4,000  | 0.29 | 0.20 | 0.38 |
| NC    | 37,000 | 27,800 | 46,400 | 0.36 | 0.27 | 0.45 |
| ND    | 2,100  | 1,400  | 2,900  | 0.28 | 0.19 | 0.38 |
| NE    | 7,000  | 5,000  | 9,200  | 0.36 | 0.26 | 0.48 |
| NH    | 3,900  | 2,600  | 5,200  | 0.29 | 0.19 | 0.39 |
| NJ    | 25,400 | 19,000 | 31,900 | 0.28 | 0.21 | 0.35 |
| NM    | 8,300  | 6,500  | 10,600 | 0.40 | 0.31 | 0.51 |
| NV    | 10,900 | 8,200  | 13,400 | 0.36 | 0.28 | 0.45 |
| NY    | 59,800 | 45,800 | 75,900 | 0.30 | 0.23 | 0.38 |
| OH    | 42,500 | 31,500 | 55,600 | 0.36 | 0.27 | 0.48 |
| State | OK  | 13,900 | 24,100 | 0.48 | 0.35 | 0.61 |
|-------|-----|--------|--------|------|------|------|
| OR    | 11,800 | 8,300 | 15,100 | 0.28 | 0.20 | 0.36 |
| PA    | 52,300 | 35,700 | 68,500 | 0.41 | 0.28 | 0.54 |
| RI    | 3,400 | 2,400 | 4,500 | 0.33 | 0.22 | 0.43 |
| SC    | 20,900 | 15,900 | 26,300 | 0.42 | 0.32 | 0.52 |
| SD    | 2,700 | 1,900 | 3,600 | 0.31 | 0.22 | 0.42 |
| TN    | 28,500 | 21,400 | 35,800 | 0.42 | 0.32 | 0.53 |
| TX    | 86,100 | 66,200 | 106,200 | 0.30 | 0.23 | 0.38 |
| UT    | 5,900 | 4,500 | 7,700 | 0.19 | 0.14 | 0.25 |
| VA    | 25,800 | 19,700 | 32,700 | 0.30 | 0.23 | 0.39 |
| VT    | 2,400 | 1,600 | 3,100 | 0.38 | 0.26 | 0.49 |
| WA    | 21,300 | 16,000 | 27,200 | 0.29 | 0.22 | 0.37 |
| WI    | 16,600 | 11,800 | 21,800 | 0.29 | 0.20 | 0.38 |
| WV    | 11,700 | 8,300 | 15,100 | 0.65 | 0.46 | 0.83 |
| WY    | 1,600 | 1,100 | 2,000 | 0.27 | 0.20 | 0.35 |