

# SEARCH TECHNICAL REPORT

## Estimation of Completeness of Case Ascertainment Using Capture-Recapture

Richard F. Hamman, MD DrPH<sup>1</sup>

Dana Dabelea, MD, PhD<sup>1</sup>

Angela D. Liese, PhD<sup>2</sup>

Lenna L. Liu, MD, MPH<sup>3</sup>

Jennifer W. Talton, MS<sup>4</sup>

Andrea Anderson, MS<sup>4</sup>

Mark A. Espeland, PhD<sup>4</sup>

Kristi Reynolds, PhD<sup>5</sup>

Scott Isom, MS<sup>4</sup>

Jasmin Divers, PHD<sup>4</sup>

July, 2015

based on prior reports from 2005, 2007 and 2013

<sup>1</sup> University of Colorado Denver, Colorado School of Public Health, Department of Epidemiology

<sup>2</sup> Arnold School of Public Health, University of South Carolina, Department of Epidemiology and Biostatistics

<sup>3</sup> University of Washington School of Medicine, Department of Pediatrics

<sup>4</sup> SEARCH Coordinating Center, Wake Forest University School of Medicine, Department of Biostatistical Sciences

<sup>5</sup> Kaiser Permanente Southern California

## Background

The purpose of this technical report is to summarize SEARCH activities to estimate the completeness of case ascertainment using the capture-recapture (C-R) method. The goal is to estimate the total size of the population of youth with diabetes aged 0-19 in a population, when the size of that population is not known. Case ascertainment through multiple sources provides a count of the number of cases found, but the number not identified remains unknown and must be estimated. The C-R method<sup>1</sup> was developed from animal biology to estimate the size of rodent populations, but it has been applied extensively to human disease situations<sup>2-7</sup>. The unknown total population size is estimated based on the number of cases found in more than one source (e.g., duplicate records from multiple hospitals, health care offices, and other sources). The approach is shown in Figure 1. Since two or more sources are required for C-R, it was not possible to use it in the SEARCH sites primarily utilizing one data source. These include the Kaiser Permanente Southern California site and participating Native American Tribes. The Kaiser Permanente site uses information from multiple health databases (laboratory, pharmacy, inpatient and outpatient encounters) and direct case reports from pediatric endocrinologists but these sources are not independent. Native American tribes used a single source, the Indian Health Service RPMS record system. This report further explores the use of two mode or multiple-mode sources in a systematic way for all four geographic sites.

**Figure 1.** Estimation of the total (unknown) population size.

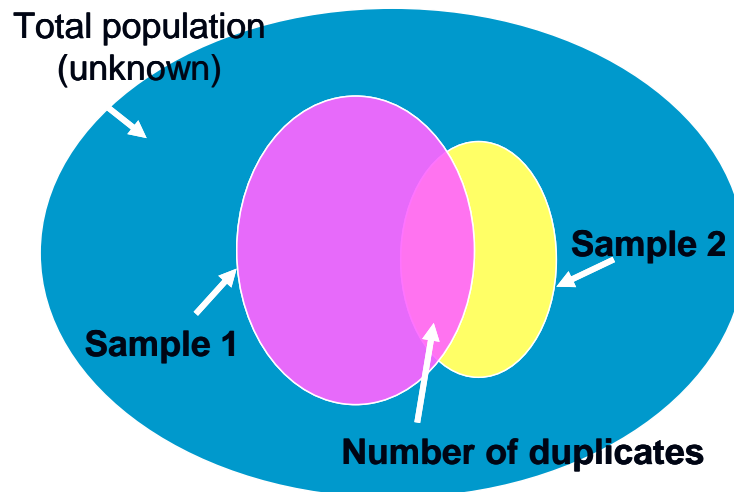


Table 1 summarizes the data display for a simple two source situation, where  $N$  can be estimated algebraically as shown in the formula if it is assumed that the two sources identify cases independently (this assumption cannot be verified without additional data).

**Table 1: Summary of capture-recapture calculations**

Source 1	Source 2		
	Yes	No	Total
Yes	A	B	A+B
No	C	X=?	?
Total	A+C	?	N=?

$$\hat{N} = \frac{(A + B + 1)(A + C + 1)}{A + 1}$$

The addition of 1 to each cell counts prevents the estimated totals from taking nonsensical values like 0 and infinity.

## Assumptions

Traditional C-R methods, such as we have adopted, make the following assumptions<sup>1</sup>: Cases are:

- From the same space and time. This means that geographic and temporal residence is the same for all members of the population and can be determined similarly in all cases.
- Identical with respect to how likely they are to be identified. This assumption means that every case has the same probability of being identified by a given source, i.e., that some cases are not inherently easier or less difficult to identify than others. This is rarely met in health care studies.
- Independently ascertained by separate modes. The assumption of independence of sources is rarely met in disease ascertainment but can be dealt with using log-linear models with interaction terms to estimate and model the source dependence when more than two modes of ascertainment are involved. When only two ascertainment modes are available, the assumption of independence cannot be assessed.
- Matched between modes of ascertainment. The assumption of equal matching between modes of ascertainment assumes that sufficient data are available on personal identifiers from each source to be ‘certain’ that cases identified in multiple sources are, or are not, the same person. This may vary across sites and within sites across sources, depending on the amount of personal information provided by a source.
- Cases have been validated. This assumes that cases truly have diabetes and that this can be determined in each source.
- Cases are from a closed population. This assumption means that cases in the total population are not moving in or out of the population during the time interval.

## Methods

In each of the geographic sites (Colorado, Ohio, South Carolina, and Washington) cases were identified from multiple sources (CO: 13+; Ohio: 20; SC: 41; WA: 26). A “source” was defined as any location where cases were reported. Sources were then aggregated. First, all individual small practices were usually grouped into ‘practices’, but these were initially maintained distinctly from larger pediatric endocrine practices, HMOs providing larger numbers of cases, etc. Individual hospitals were also maintained separately. Matching across sources was done on a regular basis as cases were reported to identify potential duplicate records. Initial computerized listings were generated, sorted and compared using available personal health identifiers (PHI), and then manual matching was completed. The amount of PHI available to conduct the matching across sites differed by site, with some sites unable to identify names at the first receipt of data. Once matching was accomplished across sources, the sources were further grouped into ‘modes’ of ascertainment. After exploratory analyses, all provider sources were aggregated, as were all hospital system records and modes were defined for all sites as ‘provider’ and ‘hospital’. Several sources were large health care systems that included both ambulatory and inpatient facilities (e.g., Children’s Hospital, Seattle). In these cases, manual review of records categorized youth by whether they had been cared for in either one or both portions of the system to allow better classification of the mode of ascertainment. As of January 2015, the 2 modes of ascertainment in SEARCH will be defined as “inpatient” and “outpatient”. A SEARCH study participant is considered to be inpatient if the participant was ascertained during a hospital visit that included at least one overnight stay. Cases ascertained during a visit that did not involve an overnight stay will be classified as outpatient. For example, a participant identified during an emergency room visit will be classified as inpatient if the visit went from 6:00 PM to 6:00 AM the next day, or outpatient if the visit started at 6:00 AM and ended at 6:00 PM the same day. The inpatient mode will include most of the sources that were initially classified as ‘hospital’. Similarly, the outpatient mode will consist of the majority of sources previously included in the ‘provider/other’ source. The list of sources and corresponding mode of ascertainment is provided in the appendix.

Once two modes were identified and their duplicates noted, log linear models<sup>8,24,25</sup> were fitted to the data to estimate the total (unknown) population. These estimates were computed separately for prevalent 2001, prevalent 2009 and incident 2002 to 2009 youth. The models were fitted using all the data that was available in each subset adjusting for relevant covariates including and site. Multiple mode interaction models were evaluated systematically for each of the four geographic sites. For models with more than two modes, an estimate of the ‘best’ model was based on identifying the minimum value (best fit) of an information criterion statistic<sup>16</sup> defined as:

$$IC = G^2 - c \times df$$

Where:

$G^2$ : Likelihood ratio statistic (-2 logarithm of the ratio of the likelihood of the fitted model to the likelihood of the saturated model);

*df*: Number of degrees of freedom for the comparison of any fitted model with the saturated model;

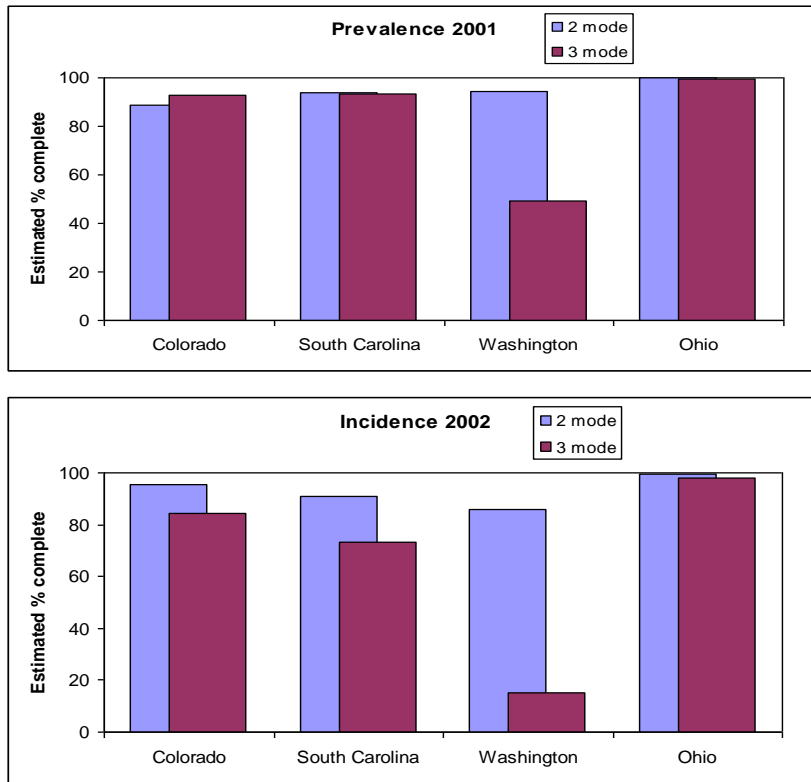
*c*: A constant that varies with the method used to estimate the information criterion. For the minimum Akaike information criterion (AIC),  $c = 2$ .

The percent completeness of ascertainment for any group was estimated as the number of observed cases divided by the total number estimated from C-R. Estimates of the ascertainment rates pooled across clinical sites were produced from a global log-linear model<sup>8</sup>, which allowed for separate intra-site performance. The rates were estimated using maximum likelihood and the standard errors were estimated using the delta method<sup>9</sup>.

## Results

Four different ascertainment modes were initially defined for the analysis. In the “provider” mode, practices were split into “endocrine” and “other”, and “hospitals” were divided into “hospitals only” and “integrated practices”. There were too few cases in some locations in each of the four modes to successfully use this approach, so “hospitals” was used as a single mode, and there were two practice modes (endocrine and other) to allow a three mode model. Three mode models were explored allowing all possible 3-way interactions, and the ‘best’ model was chosen with the lowest IC value. The overall estimate of completeness of ascertainment was then compared to the 2 mode model (from which no IC value can be calculated). As shown in Figure 2 below, there was wide variability in the 3 mode estimates across centers, ranging (for prevalence) from 44 to 99% complete. This 3 mode estimate can be compared to the range of the 2 mode estimates from 89 to ~100% across sites. For incidence estimates, the 3 mode models ranged from 15 to 98%, whereas the 2 mode model was much more consistent – from 86% to ~100%. Results of the different models within site also showed substantial heterogeneity. Across sites, there were several different patterns of interactions between sites – that is, there were not consistent types of modes that interacted across centers. In Ohio, the 2 and 3- mode approaches gave almost identical results, since all estimates were > 97%. The widest changes within a single site occurred in Washington, where for prevalence, the 2 mode estimate was 94% and the 3 mode was 49%; for incidence it was 86% for 2 mode and 15% for the “best” 3 mode model.

**Figure 2.** Estimates of case ascertainment completeness for prevalence (2001) and incidence (2002) using a 2 mode (blue bar) and 3 mode (red bar) capture-recapture model, by geographic site.



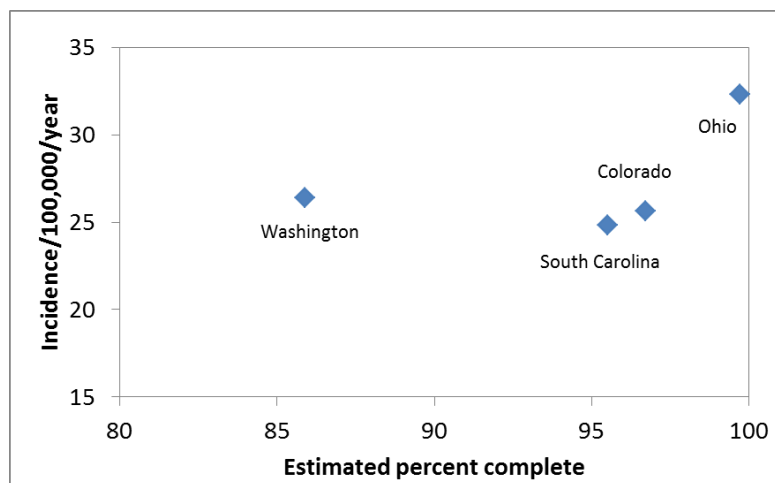
Based on the heterogeneity of results from the 3 mode (interaction) models, which appeared to be due largely to site specific differences in patterns of care, reporting, location of duplicate cases, and statistical variability, it was decided that the 2 mode model provided more consistent results with better face validity. For example, the 3 mode model suggested that Washington missed over 1500 cases in 2002, more than 3 times the number actually identified. Another rationale for choosing the 2 mode estimate comes from the consistency of the incidence rates by site. This consistency is shown for total incidence (all types) in 2002 in Table 2. If the 3 mode model were correct, it would suggest that rates in Washington and South Carolina would be substantially lower than actually observed.

**Table 2.** Total incidence rates of diabetes (all types) by geographic sites, 2002.

Center	Youth with DM	Population Denominator (Person-years)	Incidence Rates (per 100,000/year)	95% CI (per 100,000/year)
Ohio	355	1,097,960	32.3	29.1-35.9
South Carolina	539	2,170,362	24.8	22.9-27.0
Washington	509	1,927,958	26.4	24.2-28.8
Colorado	655	2,553,884	25.7	23.8-27.8

The incidence rate in Ohio was ~ 25% higher than rates in the other three geographic sites and Ohio also had the highest estimated completeness. However, rates for South Carolina, Washington and Colorado were quite similar (24.8-26.4) while estimates of completeness ranged from 86% (Washington) to 97% (Colorado) (Figure 3). It cannot be ruled out that higher rates in Ohio were due in part to slightly higher estimated completeness, however, over this narrow range, it did not appear to influence rates in the other three sites.

**Figure 3.** Incidence rates (per 100,000/yr.) by estimated completeness from capture-recapture (2 mode) by site, SEARCH 2002 incidence



For these capture-recapture analyses, we therefore chose a 2 mode model to estimate completeness by site and overall. Table 3 shows the results using C-R for the four geographic sites using a two mode ascertainment model ('hospital' vs. 'provider sources' combined) for prevalent and incident cases, by site and age group.

**Table 3.** Summary of percent completeness of ascertainment by capture-recapture analysis by year, site and age-group.  
SEARCH 2001-2002

Year	Site	Age group at diagnosis				Total	95% CI	
		0 - 4	5 - 9	10 - 14	15 - 19		LL	UL
2001	Colorado <sup>(1)</sup>	95.3	91.6	92.0	83.9	88.8		
Prevalent	Washington	95.9	92.5	89.8	87.3	89.3		
	Ohio	100.0	100.0	99.9	99.4	99.8		
	South Carolina <sup>(1)</sup>	94.4	96.6	99.6	94.9	97.0		
	All sites <sup>(2)</sup>	96.3	94.1	93.3	90.9	92.2	91.1	93.3
2002	Colorado <sup>(3)</sup>	99.0	98.8	93.7	91.9	96.9		
Incident	Washington	94.4	87.3	83.7	79.6	85.9		
	Ohio	-- <sup>(4)</sup>	99.9	100.0	97.9	99.7		
	South Carolina <sup>(3)</sup>	97.2	98.3	96.2	86.0	95.5		
	All sites <sup>(2)</sup>	97.5	95.1	92.8	87.9	93.8	91.9	95.6

(1) Prevalence sub-areas of state (2) Weighted average using observed cases at each site as weight (3) Entire state  
(4) Too few cases to estimate

The C-R analyses suggest that over all four sites, both prevalent and incident cases are at least 91% ascertained. Ascertainment appeared somewhat lower in the older than younger age groups, reflecting clinic experience at the difficulty of identifying and recruiting older youth. Analyses will be updated periodically and reported in relevant manuscripts.

### Limitations

These analyses have a number of limitations, and while the C-R method is often touted as the best way to estimate completeness of ascertainment <sup>2,10</sup>, several authors have identified significant problems with the method <sup>1,11-23</sup>. In the context of the current US healthcare system and HIPAA regulations, several of the limitations of the method were encountered. These include: a) possible incomplete matching across sources due to restrictions on access to names for matching in some states (thus violating the assumption that cases can be matched in all sources); b) uncertainty about the residence location of some cases (thus violating the assumption that cases were from the study area); and c) design of the ascertainment system for efficiency (thus avoiding sources of likely duplicate cases). Each of these problems is known to inflate the estimated number of total cases in the C-R analysis, leading to an underestimate of the percent completeness. In addition, given the multiple sources of information used to identify cases, it was possible to arbitrarily combine these sources into two modes in many alternate ways instead of the one chosen: ‘hospital’ vs. ‘provider’. If this was done on the identical dataset, it was possible to drive the estimates of completeness from 72.7% to 86.5% completeness (in South Carolina as an example). An example of another problem came from Colorado. Preliminary analyses conducted in December 2003 suggested that prevalent cases were 87%



complete, and that there were approximately 1246 estimated cases if all cases had been identified. By December of 2004, Colorado had identified a total of 1366 prevalent cases; however, the C-R estimate dropped to 81.5% complete. Addition of duplicates changed this to 88.8% complete. We, therefore, believe that the C-R estimates shown in Table 2 are a 'lower bound' on the completeness of ascertainment in these four sites. While some redesign of the case ascertainment system might provide better estimates of completeness, inherent limitations of access to records in all sources with incomplete personal identifiers make the use of C-R in the US difficult. Nonetheless, given the large geographic areas covered, and the multiple providers and hospitals contacted and used during case ascertainment, SEARCH achieved at least 90% ascertainment of prevalent and incident cases across all four geographic sites.

Systematic evaluation of models allowing interaction terms between 3 ascertainment modes did not improve estimates of ascertainment completeness, and were inconsistent with the observed rate consistency. Given the limitations noted above, the 2-mode model will continue to be used.

In January of 2013, capture-recapture estimates were updated to reflect on-going case ascertainment and inclusion of later registered cases. In order to estimate completeness by race/ethnicity and type of diabetes, the approach taken for fitting the log-linear model was revised. The current approach relies on adjusted models instead of the stratified models that were used previously. As the number of stratification variables increased, the cell counts observed in some cases were too small, which prevented the maximum likelihood estimation routines from converging. The adjusted models do not suffer from this limitation since they use all the available data<sup>24-25</sup>.

## Conclusions and use of results in SEARCH

Capture-recapture methods in the four geographic sites resulted in an overall estimate of completeness of at least 90% for both prevalence and incidence. No estimates are possible in the California and Native American sites. Given the closed nature of these data systems and the comparable methods used to identify cases in these health systems, it seems likely (though untested) that ascertainment rates were at least as good, if not better, than in the geographic sites. It is likely, given the limitations of the use of C-R methods as implemented in SEARCH, the estimates of completeness of ascertainment are a lower bound on the actual completeness.

## References

1. Hook EB, Regal RR. Capture-recapture methods in epidemiology: methods and limitations. *Epidemiol Rev.* 1995;17:243-264.
2. LaPorte RE, McCarty DJ, Tull ES. Counting birds, bees, and NCDs. *Lancet.* 1992;339:494-495.
3. Cormack RM, Chang YF, Smith GS. Estimating deaths from industrial injury by capture-recapture: a cautionary tale. *Int J Epidemiol.* 2000;29:1053-1059.

4. Corrao G, Bagnardi V, Vittadini G, Favilli S. Capture-recapture methods to size alcohol related problems in a population. *J Epidemiol Community Health*. 2000;54:603-610.
5. Ballivet S, Salmi LR, Dubourdieu D. Capture-recapture method to determine the best design of a surveillance system. Application to a thyroid cancer registry. *Eur J Epidemiol*. 2000;16:147-153.
6. Tilling K, Sterne JA, Wolfe CD. Estimation of the incidence of stroke using a capture-recapture model including covariates. *Int J Epidemiol*. 2001;30:1351-1359.
7. Verstraeten T, Baughman AL, Cadwell B, Zanardi L, Haber P, Chen RT. Enhancing vaccine safety surveillance: a capture-recapture analysis of intussusception after rotavirus vaccination. *Am J Epidemiol*. 2001;154:1006-1012.
8. Bishop YMM, Fienberg SE, Holland PW. Chapter 6. *Discrete multivariate analysis*. Cambridge, MA: MIT Press; 1975.
9. Espeland MA. A general class of models for discrete multivariate data. *Communications in Statistics: Simulation and Computation*. 1986;15:405-424.
10. LaPorte RE, McCarty D, Bruno G, Tajima N, Baba S. Counting diabetes in the next millennium. Application of capture-recapture technology. *Diab Care*. 1993;16:528-534.
11. Hook EB, Regal RR. The value of capture-recapture methods even for apparent exhaustive surveys. The need for adjustment for source of ascertainment intersection in attempted complete prevalence studies. *Am J Epidemiol*. 1992;135:1060-1067.
12. Papoz L, Balkau B, Lellouch J. Case counting in epidemiology: limitations of methods based on multiple data sources. *Int J Epidemiol*. 1996;25:474-478.
13. Nanan DJ, White F. Capture-recapture: reconnaissance of a demographic technique in epidemiology. *Chronic Dis Can*. 1997;18:144-148.
14. Domingo-Salvany A, Hartnoll RL, Maguire A et al. Analytical considerations in the use of capture-recapture to estimate prevalence: case studies of the estimation of opiate use in the metropolitan area of Barcelona, Spain. *Am J Epidemiol*. 1998;148:732-740.
15. Hook EB, Regal RR. Recommendations for presentation and evaluation of capture-recapture estimates in epidemiology. *J Clin Epidemiol*. 1999;52:917-926.
16. Hook EB, Regal RR. Accuracy of alternative approaches to capture-recapture estimates of disease frequency: internal validity analysis of data from five sources. *Am J Epidemiol*. 2000;152:771-779.
17. Ismail AA, Beeching NJ, Gill GV, Bellis MA. How many data sources are needed to determine diabetes prevalence by capture-recapture? *Int J Epidemiol*. 2000;29:536-541.
18. Hook EB, Regal RR. On the need for a 16th and 17th recommendations for capture-recapture analysis. *J Clin Epidemiol*. 2000;53:1275-1277.
19. Chao A, Tsay PK, Lin SH, Shau WY, Chao DY. The applications of capture-recapture models to epidemiological data. *Stat Med*. 2001;20:3123-3157.
20. Tilling K. Capture-recapture methods--useful or misleading? *Int J Epidemiol*. 2001;30:12-14.

21. Laska EM, Meisner M, Wanderling J, Siegel C. Estimating population size and duplication rates when records cannot be linked. *Stat Med.* 2003;22:3403-3417.
22. Carle, F., Gesuita, R., and Gregorio, F. Effect of overlapping among sources on the validity of capture-recapture estimates of prevalence of diabetes. 39th Annual Meeting EDEG . 2004.
23. Verlato G, Muggeo M. Capture-recapture method in the epidemiology of type 2 diabetes: a contribution from the Verona Diabetes Study. *Diab Care.* 2000;23:759-764.
24. Chao A, Tsay PK, Lin SH et al.: The applications of capture-recapture models to epidemiological data. *Statist Med* 2001; 20:3123-3157.
25. Cormack RM. Loglinear models for capture-recapture. *Biometrics* 1989; 45:395–413.

**Supplementary Table 1: Sources included in each mode of ascertainment in South Carolina**

<b>South Carolina</b>	Old classification	New classification
Anderson Area Medical Center	Hospital	
Anmed Child Health Center	Hospital	
Beaufort Hospital	Hospital	
Carolinas Hospital - Florence	Hospital	
Greenville Hospital System	Hospital	
Greenville Memorial Hospital	Hospital	
Lexington Medical Center	Hospital	
Mauldin Medical Center	Hospital	
McLeod Hospital	Hospital	
McLeod Regional Medical Center	Hospital	
Orangeburg Hospital	Hospital	
Palmetto Baptist Medical Center Easley	Hospital	
Palmetto Baptist Medical Center Columbia	Hospital	
Palmetto Health Alliance/RMH	Hospital	
Palmetto Health Baptist	Hospital	
Palmetto Health Easley	Hospital	
Palmetto Health Richland	Hospital	
Roper St Francis Hospital	Hospital	
Spartanburg Regional Healthcare System	Hospital	
Spartanburg Regional Medical Center	Hospital	
The Regional Medical Center of Orangeburg and Calhoun Counties	Hospital	
Amrhein	Other	
Broome	Other	
Carolina Diabetes and Kidney Center	Other	
Coulter	Other	
GHS Pediatric Endocrinology	Other	
Heinze	Other	
Hoffman	Other	
Jackson	Other	
Jocelyn Myers	Other	
Laurel Endocrine-Brennan	Other	
McLeod Pediatric Subspecialists	Other	
McLeod/Woodberry	Other	
Mendes	Other	
MUSC	Other	
Parker	Other	
Raine	Other	

Schwartz	Other	
USC Pediatric Endocrinology	Other	
Willi	Other	
Benedict College	Other	
Black River Community Health Care	Other	
Brooks Health Center	Other	
C.S.R.A. Renal Services	Other	
Care-South Carolina	Other	
Carolina Health Greenwood	Other	
Carolina Peds	Other	
Catawba Longhouse	Other	
Children and Family HealthCare Center (USC College of Nursing)	Other	
CSRA Renal Services	Other	
Debbie Yoman	Other	
Diabetes Education Center in Lancaster	Other	
Doctors Care (statewide)	Other	
Eau Claire	Other	
Eau Claire Cooperative Health Center	Other	
Eau Claire Cooperative Health Centers	Other	
Family Health Care Center--Orangeburg	Other	
Family Health Centers, Inc.	Other	
Family Practice Center-Palmetto Health	Other	
Franklin Coulter	Other	
Grand Strand Ped	Other	
Grand Strand Pediatrics	Other	
Lexington Pediatrics	Other	
Longcreek Family Practice	Other	
Orangeburg Hospital Diabetes Educator	Other	
Orangeburg Hospital-Diabetes Educator	Other	
Pediatric Associates, P.A.	Other	
Pediatric Associates, PA	Other	
Richland Community Health Care Association	Other	
SandHills Pediatrics-Wessinger	Other	
Sea Island Pediatrics P.A.	Other	
Self Report	Other	
The Pediatric Clinic	Other	
Undefined	Other	
USC Central Billing	Other	
USC Department of Family & Preventive Medicine	Other	
USC OB/GYN clinic (1801 Sunset)	Other	
USC-Central Billing-Dr. Bryant	Other	
Yoman	Other	



**Supplementary Table 2: Sources included in each mode of ascertainment in Ohio**

<b>Ohio</b>	Old classification	New classification
FHH StLuke UniversityHosp Christ Mercy MRH Jewish CCHMC StElizabeth GoodSam/ Bethesda McCullough	Hospital Hospital Hospital Hospital Hospital Hospital Hospital Hospital Hospital Hospital Hospital	
EndoAdult EndoPeds PrimaryMDs CDEs Universities Other CintiHealthDept Anthem Aetna KYMedicaid BCMH CareSource	Other Other Other Other Other Other Other Other Other Other Other Other	

**Supplementary Table 3: Sources included in each mode of ascertainment in Colorado**

<b>Colorado</b>	Old classification	New classification
St Mary's in Grand Junction	Hospital	
Exempla Hospitals	Hospital	
The Children's Hospital/The Children's Hospital Colorado	Hospital	
Centura Hospitals	Hospital	
Boulder Community Hospital	Hospital	
Pueblo, CO Hospitals/Metro Community Hospital	Hospital	
Barbara Davis Center	Other	
Pediatric Endocrine Associates	Other	
San Luis Valley/Valley Wide Health System	Other	
Western Ped. in Grand Junction	Other	
Salud Family Health Centers	Other	
Denver Health	Other	
Kaiser Permanente	Other	
Providers/San Luis Valley Case Reports	Other	



**Supplementary Table 4: Sources included in each mode of ascertainment in Washington**

<b>Washington</b>	Old classification	New classification
Boldt	Hospital	
CHRMC	Hospital	
CHRMC inpatient	Hospital	
Harborview Medical Center	Hospital	
Madigan Medical Center	Hospital	
Mary Bridge	Hospital	
Mary Bridge inpatient	Hospital	
Providence St. Pete's	Hospital	
Seattle Children's inpatient	Hospital	
Swedish Medical Center	Hospital	
UW Medical Center	Hospital	
Valley Medical Center	Hospital	
Virginia Mason	Hospital	
	Hospital	
	Hospital	
	Hospital	
	Hospital	
	Hospital	
	Hospital	
CHCKC	Other	
CHRMC Endo Clinic	Other	
CHRMC outpatient	Other	
Diabetes Care Center	Other	
Dr McGowen	Other	
Green	Other	
Joslin	Other	
Mauseth	Other	
MB outpatient	Other	
Minor & James clinic	Other	
N Sea Pub Health	Other	
Neighborcare	Other	
Ped Asso Olympia	Other	
PSNHC	Other	
SeaMar	Other	
Seattle Children's outpatient	Other	
Summit View Clinic	Other	
Swedish Joslin	Other	
UW Physicians Network	Other	
ADA	Other	

Camp Leo	Other	
GHC	Other	
Newspaper Advertisements	Other	
Other	Other	
SKWIDDS	Other	
	Other	
	Other	
	Other	
	Other	