Disclosure Treatment of Sparsely Populated Geographic Areas

Josh Borton NORC at the University of
Chicago
June 23, 2016



Common challenge

- Demand for reports at sub-state geographies, such as county
 - Presents *disclosure issues* if the county is sparsely populated, or has very small sub populations



Reporting Problems Caused by Sparse Geographies

CDC EPH tracking

- Different disclosure limitation standards and methods used by different states
- Lack of standard rules and delivery causes problems with data harmonization
- State published data
 - Unable to report of some parts of the population
 - Geographic and/or demographic
 - Analytic utility may be limited



Best Practices for Dealing with Small Geographies

- Is the population sparse or is the data sparse?
 - Small counts for larger populations may meet disclosure standards
- Combine regions to meet disclosure standards
 - Recoding
- Suppress statistics that don't meet disclosure standards
 - Lose ability to analyze some areas
- Consider using estimation to protect sensitive values



Options for Protecting Sparse Geographies

- De-Identify Underlying Micro-Data
 - Everything is an estimate
- De-Identify Tabular Data
 - Cells determined to be disclosive require attention
 - Frequency defined by the number of observations in the cell
- Suppress disclosive cells
 - Loss of information from suppression
- Aggregate disclosive cells
 - Information becomes more general
- Estimate disclosive cells
 - Information is less precise but remains available



Common Tabular Methods

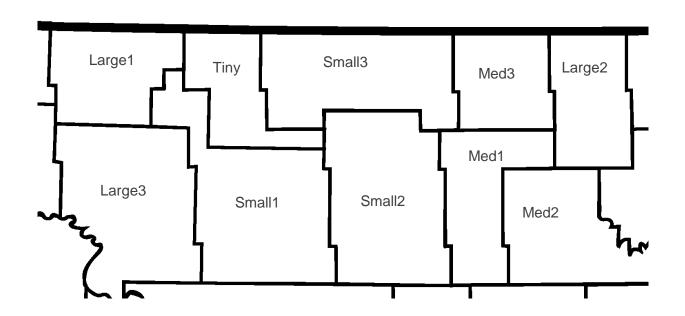
General Comments

- Generally use suppression and recoding
 - Leads to loss of information due to missing values
 - 'Holes' in a table
- Inter-table disclosure can be difficult to manage
- Traditionally risk is not measured
 - NORC has developed methods to quantify the risk of suppressed tables, including risk from inter-table dependencies



Geography for Tabular Examples

- Example of 10 fake counties
- Create tables showing counts of disease by age range



Tabular Method 1:

Suppress Disclosive Cells

- Suppression of disclosive cells allows for clear explanation of treatment to the user
- Requires the suppression of complementary, often nondisclosive cells, in order to ensure protection

Raw Data										
		A	ge							
County	<55	55-64	65-74	75+	TOT					
large1	25	32	103	99	259					
large2	64	50	114	116	344					
large3	32	30	200	175	437					
med1	9	16	88	82	195					
med2	15	9	72	65	161					
med3	19	25	99	41	184					
small1	19	15	16	12	56					
small2	13	16	14	20	63					
small3	7	11	25	13	62					
tiny	3	9	8	3	23					
тот	206	213	739	626	1784					



	S	Supress	sion		
		Ą	ge		
County	<55	55-64	65-74	75+	TOT
large1	25	32	103	99	259
large2	64	50	114	116	344
large3	32	30	200	175	437
med1	4	16	88	82	195
med2	4	9	72	65	161
med3	19	25	99	41	184
small1	19	15	16	12	62
small2	13	16	14	20	63
small3	7	11	25	13	56
tiny	3	9	8	3	23
тот	206	213	739	626	1784

Tabular Method 2:

Aggregate Disclosive Cells

- Aggregation, or recoding, of cells can be used in place of suppression
- Prevents 'holes' in the table at the cost of less specific table dimensions
- Tables are complete, but may not be useful to those interested in values of a dimension that has been recoded

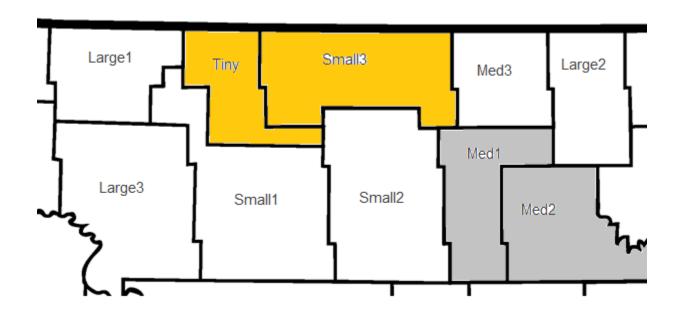
		Raw Da	ata			
		Ą	ge			
County	<55	55-64	65-74	75+	TOT	
large1	25	32	103	99	259	
large2	64	50	114	116	344	
large3	32	30	200	175	437	
med1	9	16	88	82	195	
med2	15	9	72	65	161	
med3	19	25	99	41	184	
small1	19	15	16	12	56	
small2	13	16	14	20	63	
small3	7	11	25	13	62	
tiny	3	9	8	3	23	
тот	206	213	739	626	1784	



	Α	ggrega	tion		
Race	<55	55-64	65-74	75+	TOT
large1	25	32	103	99	259
large2	64	50	114	116	344
large3	32	30	200	175	437
med1	24	25	88	82	195
med2	24		72	65	161
med3	19	25	99	41	184
small1	19	15	16	12	62
small2	13	16	14	20	63
small3	10	20	22	16	56
tiny	10	20	33	10	23
TOT	206	213	739	626	1784



Recoded Geography



Tabular Method 3:

Estimate Disclosive Cells

- It is possible to present estimates for cells that are deemed to be disclosive
 - Includes complementary suppressions
- Estimates do not increase disclosure risk of table
 - Same values a sophisticated intruder could calculate themselves
- Allows user to see a table without 'holes'
 - User is aware which cells are true values and which are estimates

		Raw Da	ata						
		Age							
County	<55	<55 55-64 65-74 75+							
large1	25	32	103	99	259				
large2	64	50	114	116	344				
large3	32	30	200	175	437				
med1	9	16	88	82	195				
med2	15	9	72	65	161				
med3	19	25	99	41	184				
small1	19	15	16	12	56				
small2	13	16	14	20	63				
small3	7	11	25	13	62				
tiny	3	9	8	3	23				
тот	206	213	739	626	1784				



	E	stimat	ion		
		Αį	ge		
Race	<55	75+	TOT		
large1	25	32	103	99	259
large2	64	50	114	116	344
large3	32	30	200	175	437
med1	9.1	15.9	88	82	195
med2	12.3	11.7	72	65	161
med3	19	25	99	41	184
small1	19	15	16	12	62
small2	13	16	14	20	63
small3	8.2	13.1	22.8	11.9	56
tiny	4.4	4.3	10.2	4.1	23
тот	206	213	739	626	1784



Footer Information Here

De-Identify Underlying Micro-Data

- Many commonly used micro-data methods introduce bias
- NORC X-ID methods avoid bias by using aggregation and sampling
 - Restructure data into small aggregates of size 10 to 20
 - Termed micro-groups
 - Produce summary statistics at the micro-group level
 - Add protection through intelligent sub-sampling of the data
- All outputs are estimates
 - Provides estimates with little error for adequately sized analysis questions
 - Provides estimates with large amount for error for individuals or very small groups



Micro Group Formation

Observation Level Data (all of these records are assigned to one microgroup)

mg num	n3	SETTING	Age Group	New	Race	Trans Vol	Trans Amount
mg_num			Age Group	INCW	Nace	Trails voi	
1	1	R	6	0	1	2	\$1,576.30
1	1	R	6	0	4	55	\$2,675.24
1	1	R	6	0	2	6	\$638.62
1	1	R	6	0	2	9	\$1,836.86
1	1	R	6	0	6	6	\$1,654.05
1	1	R	6	0	1	2	\$887.35
1	1	R	6	0	1	2	\$1,354.50
1	1	R	6	0	1	1	\$1,054.10
1	1	R	6	0	1	4	\$2,885.25
1	1	R	6	0	1	1	\$1,899.77
1	1	R	6	0	1	1	\$717.04
1	1	R	6	0	1	2	\$806.36
1	1	R	6	0	1	2	\$917.66
1	1	R	6	0	3	2	\$875.75

Micro Group Record

		Group Variables		Create Dummies	Micro Means		Micro Proportions						
mg_num	n3	SETTING	Age Group	New	Race	Trans Vol	Trans Amount	race1	race2	race3	race4	race5	race6
1	14	R	6	0	Micro Proportion	6.79	\$1,412.78	0.643	0.143	0.071	0.071	0.000	0.071



Treating Micro-Data vs Tabular Data

Treated Micro-Data

- More versatile and allows the production of nearly any table that is desired
- All cells are estimates
 - Large cells are good (very good) estimates
 - Small cells will have more error, for protection

Treated Tabular Data

- Requires that all tables be known at the time of treatment
- Presents the real value where the data allows
 - Non-disclosive cells that are not needed for complementary suppression
- Estimation of suppressed cells can improve user experience



Josh Borton borton-joshua@norc.org

Thank You!



Introducing Uncertainty via Sub-Sampling

Observation Level Data (all of these records are assigned to one microgroup)

mg_num	n3	SETTING	Age Group	New	Race	Trans Vol	Trans Amount
1	0.00	R	6	θ	1	2	\$1,576.30
1	0.00	R	6	θ	4	55	\$2,675.24
1	0.00	R	6	θ	2	6	\$638.62
1	0.00	R	6	θ	2	9	\$1,836.86
1	0.00	R	6	θ	6	6	\$1,654.05
1	4.65	R	6	0	1	2	\$887.35
1	0.00	R	6	θ	1	2	\$1,354.50
1	0.00	R	6	θ	1	1	\$1,054.10
1	0.00	R	6	θ	1	4	\$2,885.25
1	4.66	R	6	0	1	1	\$1,899.77
1	4.66	R	6	0	1	1	\$717.04
1	0.00	R	6	θ	1	2	\$806.36
1	0.00	R	6	θ	1	2	\$917.66
1	0.00	R	6	θ	3	2	\$875.75

Micro Group Record

			Group Variables		Create Dummies	Micro Means		Micro Propotions						
m	g_num	n3	SETTING	Age Group	New	Race	Trans Vol	Trans Amount	race1	race2	race3	race4	race5	race6
	1	13.98	R	6	0	Micro Proportion	3.07	\$1,315.21	0.628	0.246	0.000	0.000	0.000	0.127

