

# A Two-sample Approach for State Estimates of a Chronic Condition Outcome

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# Objective

- To produce state estimates of health information in the NHIS (chronic condition, pre-existing condition, etc.)
  - NHIS does not include state in its public use file
  - restricted access file provides some opportunity but sample design not intended for state-level estimates
- To calculate appropriate errors for the estimates for comparison between states or as inputs in other analyses
- Predict/impute an outcome measure (condition status) in a survey with state-level sample design (CPS, ACS) using NHIS data



#### Method

- Applying elements of method used in (Schenker, N., Raghunathan, T., Bondarenko, I., 2010) \*
  - imputed clinical values of hypertension, diabetes and obesity in NHIS with self-reported values and both clinical and self-reported values from NHANES
  - self-reported rates were lower than clinical values
  - requires multiple imputation techniques and propensity scores

\*Schenker, N., Raghunathan, T., Bondarenko, I., "Improving on analyses of self-reported data in a large-scale health survey by using information from an examination-based survey". Statistics in Medicine, Volume 29, Issue 5, pages 533–545, February 2010



### Method-Data

- National Health Interview Survey (NHIS) 1997-2001, 2004-2008
  - Minnesota Population Center and State Health Access Data Assistance Center, *Integrated Health Interview Series: Version* 2.0. Minneapolis: University of Minnesota. <u>http://www.ihis.us</u>
  - Harmonizes the data and documentation for the NHIS
  - 1,000's of vars, 38 years, linkable to NHIS data supplements
- Current Population Survey (CPS) 1999, 2006
  - Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. *Integrated Public Use Microdata Series, Current Population Survey: Version 3.0.* [Machine-readable database]. Minneapolis: University of Minnesota, 2010.



# Method-Primary Steps

- 1) Assemble Data
- 2) Identify outcome status in NHIS
- 3) Create identically coded covariates in NHIS and CPS
- 4) Predict survey of observation using covariates, create subgroups for model

4b) Predict key variable using covariates

- 5) Impute missing CPS values using predicted survey, covariates (or predicted key variable) and interactions
- 6) Produce estimates of outcome using imputed data



## Method- Data Assembly

<u>CPS obs</u>	<u>CPS</u>	<u>1997</u>	<u>1998</u>	<u>1999</u>	<u>2000</u>	<u>2001</u>	<u>2002</u>	<u>2003</u>	<u>2004</u>	<u>2005</u>	<u>2006</u>	<u>2007</u>	<u>2008</u>
133,710	1999	103,477	98,785	97,059	100,618	100,759							
	2000		1	1	1	1	1						
	2001			1	1	1	1	1					
	2002				1	1	1	1	1				
	2003					1	1	1	1	1			
	2004						1	1	1	1	1		
	2005							1	1	1	1	1	
206,639	2006								94,460	98,649	75,716	75,764	74,236
	2007									1	1	1	1
	2008										1	1	1
	2009											1	1



\*Reference period of survey not the year it was conducted

### Method-Data Assembly

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					Со	ndition in	dicato	or	
Data	State	Chronic	Covariates	Pr(survey)	imp1	imp2		imp10	
NHIS 2004		х	х	х	Х	х		x	
		х	х	х	x	х		x	
		Х	x	х	x	х		x	
NHIS 2005		х	х	х	х	х		х	
		х	х	х	x	х		x	
		Х	x	х	x	х		x	
NHIS 2006		Х	х	х	х	х		х	Same as
		х	х	х	x	х		x	original
		х	x	х	x	х		x	onginai
NHIS 2007		Х	х	х	х	х		х	
		х	x	х	x	х		x	
		Х	х	х	x	х		x	
NHIS 2008		Х	х	х	х	х		х	
		х	х	х	x	х		x	
		Х	x	х	x	x		×	
CPS 2006	х		х	х	X	X		X	
	х		х	х	( x	X		x	
	х		x	х	X	X		X	
									Impute thes values

# Method-Identify Outcome status

- Chronic condition
  - Limitation of activity due to chronic condition
  - asked of all persons
  - ~12% of population nationally



## Method- Create Identical Covariates

	<u>CPS</u>	NHIS*		<u>CPS</u>	<u>NHIS*</u>		<u>CPS</u>	NHIS*
Age			Education			Health Status		
0-17	25.0	25.0	No HS Diploma	11.4	12.1	Excellent	33.1	35.5
18-34	23.0	23.1	HS Diploma	23.6	22.3	Very good	32.0	30.8
35-54	29.0	29.1	Some college/associates	20.4	21.3	Good	23.6	24.2
55-64	10.8	10.6	Bachelors or more	19.6	19.3	Fair	7.9	7.2
65-74	6.4	6.4	NIU	25.0	25.0	Poor	3.4	2.4
75+	5.7	5.7	Wages			Insurance Status		
Sex			0-10K	8.0	9.0	Uninsured	15.8	14.8
Male	49.1	48.9	10k-25K	12.6	13.3	Insured	84.2	85.2
Female	50.9	51.1	25k-50K	16.1	17.5	Region		
Marital Status			50K+	13.2	12.3	Northeast	18.2	18.1
Married	42.0	43.3	0/NIU	50.1	47.8	Midwest	22.1	23.4
Not married	33.0	31.7	Poverty			South	36.4	36.1
NIU	25.0	25.0	0-99	13.7	13.4	West	23.3	22.3
Race/Ethnicity			100-199	18.1	19.3	Birthplace		
White-NH	66.1	67.5	200-299	17.1	16.9	US born	86.1	86.7
Black-NH	12.1	12.5	300-399	13.4	13.8	Born outside US	13.9	13.3
Hispanic	15.1	14.9	400-499	10.5	10.2			
Other-NH	6.6	5.1	500+	27.3	26.5			

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\*NHIS missing values imputed using sequential hotdeck

# Method-Predict Survey Propensity

- Survey propensity: this predicts which survey an observation is from based on its covariates.
  - Ideally, you would have very similar distributions implying observations are similarly likely in either dataset.
  - This strengthens the case for using NHIS observations to impute CPS observations

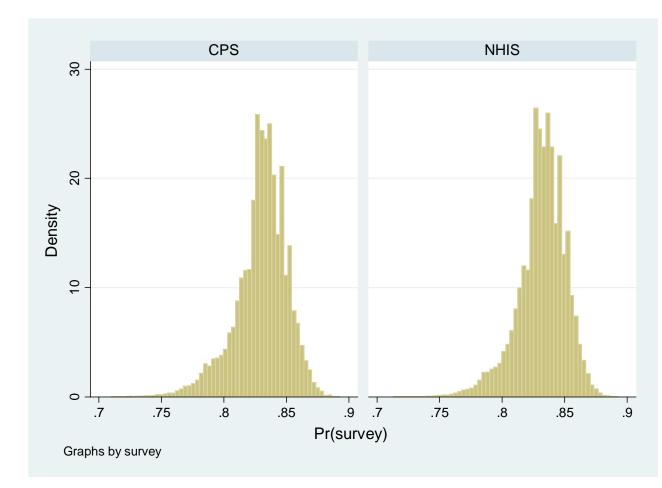


# Method-Predict Survey Propensity

- Why do you predict the survey?
  - although the values of covariates are coded the same, the responses in two surveys may not truly be identical.
  - Therefore, by predicting the survey there is a single dimension to assess how likely the observations are to be similar.
- Why predict propensities? Isn't that used for matching studies?
  - for the imputation we are looking for similar observations in different surveys to predict a likely values
- Survey propensity model: age, sex, race, education, marital status, birthplace insurance status, wages, poverty, region



# Method-Predict Survey Propensity



1= NHIS, 0=CPS

mean>50% because there are more NHIS obs than CPS obs in the imputation sample

Similar and narrow shape indicates coding is similar between surveys.



# **Results- Imputation Models**

- Full Imputation Model
  - All covariates interacted by propensity group
  - Possible due to large sample size
- Parsimonious Imputation Model
  - predicted health status interacted by propensity group
  - very similar results due to strength of common health status variable
- Two-Step Model
  - Fit all covariates on NHIS, predict on CPS
  - Standard errors of state means too small



# Results-Chronic Prevalence by Survey and Covariates

	<u>CPS</u>	<u>NHIS</u>		CPS	<u>NHIS</u>		<u>CPS</u>	NHIS
Overall	13.3	12.0	Overall	13.3	12.0	Overall	13.3	12.0
Age			Education			Health Status		
0-17	7.2	7.1	No HS Diploma	25.1	23.7	Excellent	3.1	2.9
18-34	5.1	4.6	HS Diploma	18.2	15.3	Very good	5.5	5.7
35-54	11.5	10.2	Some college/associates	13.4	11.8	Good	16.0	15.6
55-64	22.2	20.0	Bachelors or more	8.5	7.2	Fair	49.6	48.2
65-74	28.7	25.5	NIU	7.2	7.1	Poor	82.6	81.7
75+	48.2	42.3	Wages			Insurance Status		
Sex			0-10K	9.9	9.9	Uninsured	11.7	7.8
Male	12.9	11.5	10k-25K	6.3	6.2	Insured	13.6	12.7
Female	13.7	12.4	25k-50K	4.6	4.4	Region		
Marital Status			50K+	3.2	3.2	Northeast	13.1	11.7
Married	12.5	11.0	0/NIU	21.1	19.0	Midwest	13.7	12.6
Not married	19.1	17.2	Poverty			South	13.7	12.4
NIU	7.2	7.1	0-99	21.5	19.6	West	12.5	11.0
Race/Ethnicity			100-199	19.4	17.0	Birthplace		
White-NH	14.7	13.2	200-299	14.3	13.1	US born	14.1	12.7
Black-NH	14.5	13.0	300-399	11.7	10.2	Born outside US	8.4	7.4
Hispanic	8.1	7.3	400-499	8.7	8.4			
Other-NH	8.9	7.3	500+	7.2	6.1			



#### **Results- Chronic Prevalence by State**

State	Mean	<u>SE</u>	<u>State</u>	<u>Mean</u>	<u>SE</u>	<u>State</u>	<u>Mean</u>	<u>SE</u>
Alabama	17.4	1.14	Kentucky	18.6	0.98	North Dakota	13.2	1.18
Alaska	12.4	0.82	Louisiana	15.3	1.26	Ohio	14.8	0.74
Arizona	12.6	0.95	Maine	15.4	1.01	Oklahoma	15.1	1.08
Arkansas	16.3	1.01	Maryland	11.4	0.63	Oregon	15.4	1.01
California	11.9	0.39	Massachusetts	12.5	0.89	Pennsylvania	15.9	0.82
Colorado	11.2	0.83	Michigan	14.2	0.65	Rhode Island	13.0	1.01
Connecticut	11.4	0.72	Minnesota	11.4	0.63	South Carolina	16.0	1.15
Delaware	12.6	0.88	Mississippi	17.5	1.40	South Dakota	14.0	1.05
District of Columbia	11.4	0.85	Missouri	15.5	0.91	Tennessee	16.2	1.14
Florida	12.6	0.60	Montana	15.5	1.08	Texas	12.0	0.47
Georgia	11.6	0.72	Nebraska	11.6	0.91	Utah	11.1	0.85
Hawaii	11.3	0.72	Nevada	11.9	0.90	Vermont	13.1	1.10
Idaho	12.9	1.10	New Hampshire	11.4	0.73	Virginia	11.6	0.71
Illinois	12.8	0.70	New Jersey	10.8	0.77	Washington	13.0	0.86
Indiana	14.2	1.06	New Mexico	14.0	1.20	West Virginia	21.3	1.28
lowa	13.0	0.76	New York	13.1	0.48	Wisconsin	12.8	0.77
Kansas	13.1	0.89	North Carolina	14.2	0.87	Wyoming	14.2	1.11

# Results-Selected State Means of Chronic by Model

		Fu	III	Parsim	onious	Two-	Step	
	State	Mean	SE	Mean	SE	Mean	SE	
]	West Virginia	21.3	1.28	20.7	1.34	21.4	0.80	
	Kentucky	18.6	0.98	17.5	1.08	18.3	0.68	
	Mississippi	17.5	1.40	18.0	1.31	17.4	0.76	
Highest	Alabama	17.4	1.14	17.3	1.14	17.0	0.76	
10 7	Arkansas	16.3	1.01	16.3	1.09	16.1	0.65	
	Tennessee	16.2	1.14	16.2	1.44	16.2	0.59	
States	South Carolina	16.0	1.15	16.4	1.07	16.1	0.62	
	Pennsylvania	15.9	0.82	14.4	0.74	15.6	0.40	
	Missouri	15.5	0.91	13.8	0.91	15.2	0.52	
Ĺ	– Montana	15.5	1.08	12.6	1.02	15.0	0.65	
ſ	– Nebraska	11.6	0.91	10.7	0.85	11.8	0.45	
	District of Columbia	11.4	0.85	12.9	1.14	11.3	0.50	
Lowoot	New Hampshire	11.4	0.73	10.0	0.76	11.2	0.36	
Lowest	Minnesota	11.4	0.63	10.2	0.66	11.4	0.37	
10	Connecticut	11.4	0.72	11.0	0.77	11.5	0.36	
States	Maryland	11.4	0.63	12.2	0.88	11.3	0.36	
	Hawaii	11.3	0.72	12.4	0.74	11.1	0.37	
	Colorado	11.2	0.83	10.5	0.65	11.3	0.38	
	Utah	11.1	0.85	10.2	0.96	11.0	0.50	. –
www.shadac.org	– New Jersey	10.8	0.77	11.5	0.64	10.9	0.38	17

#### Results-Region vs. State

• Using state instead of region results in 21 states with significantly different rates

	Sta	te	Reg	ion	
Region	Mean	SE	Mean	SE	Difference
South	21.3	1.28	13.7	0.17	7.5*
South	18.6	0.98	13.7	0.17	4.9*
South	17.5	1.40	13.7	0.17	3.8*
South	17.4	1.14	13.7	0.17	3.7*
West	15.5	1.08	12.5	0.19	2.9*
Northeast	15.9	0.82	13.1	0.24	2.8*
Midwest	11.6	0.91	13.7	0.21	-2.1*
Northeast	10.8	0.77	13.1	0.24	-2.3*
South	11.4	0.85	13.7	0.17	-2.3*
Midwest	11.4	0.63	13.7	0.21	-2.3*
South	11.4	0.63	13.7	0.17	-2.4*
	South South South South West Northeast Midwest Northeast South Midwest	Region Mean   South 21.3   South 18.6   South 17.5   South 17.4   Vest 15.5   Northeast 15.9   Midwest 10.8   South 11.4   Midwest 11.4	RegionMeanSESouth21.31.28South18.60.98South17.51.40South17.41.14West15.51.08Northeast15.90.82Midwest11.60.91Northeast10.80.77South11.40.85Midwest11.40.63	RegionMeanSEMeanSouth21.31.2813.7South18.60.9813.7South17.51.4013.7South17.41.1413.7South15.51.0812.5Northeast15.90.8213.1Midwest11.60.9113.7Northeast10.80.7713.1South11.40.8513.7Midwest11.40.6313.7	RegionMeanSEMeanSESouth21.31.2813.70.17South18.60.9813.70.17South17.51.4013.70.17South17.41.1413.70.17South15.51.0812.50.19Northeast15.90.8213.10.24Midwest11.60.9113.70.21Northeast10.80.7713.10.24South11.40.8513.70.17Midwest11.40.6313.70.21



# Limitations/Future Research

- Limitations
  - Model selection not optimized, primarily an exercise
  - Testing effects would require common variables that should also be included in imputation model
- Future Research
  - Investigate why national means are different
  - Identify more commonly coded variables between surveys
  - Create outcomes that align with pre-existing condition definitions
  - Consider applications for other surveys (MEPS, BRFSS)





- Newer accessible methods allows for creative integration of data sources with appropriate uncertainty incorporated
- The ability to make valid state estimates is valuable for health policy
  - could be used to develop state estimates of those with pre-existing conditions eligible for the temporary high risk pool



#### Contact Info

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# Extra: Results-Potential Upper bound of Unexplained Error at State level

- From 1997-2001 NHIS released MSA names
- Data assembled for 1999 CPS with matching MSA and non-MSA (region) codes.
  - only MSAs with over 3,000 observations per year of NHIS were used. Others grouped into their region
- The MSA portion of the MSA/Non-MSA(Region) code have smaller populations than states
  - provides an approximate upper bound on the error in the state imputation



# Extra: Results-MSA/Region Comparison

	CF	S	NF	IIS
Name	Mean	SE	Mean	SE
Northeast-Non MSA	14.3	0.53	13.4	0.30
Midwest-Non MSA	14.3	0.39	12.8	0.33
South-Non MSA	14.5	0.33	13.0	0.20
West-Non MSA	12.7	0.34	11.4	0.26
Los Angeles-Long Beach, CA	12.0	0.61	9.8	0.36
New York, NY	13.9	0.76	9.6	0.32
Chicago-Gary-Kenosha, IL-IN-WI	11.6	0.76	9.9	0.50
Houston-Galveston-Brazoria, TX	10.6	1.20	7.8	0.47
Detroit-Ann Arbor-Flint, MI	13.7	1.08	12.3	0.39
Boston-Worcester-Lawrence, MA	12.0	1.12	11.5	0.31
Washington, DC-MD-VA-WV	8.7	0.89	8.2	0.49
Philadelphia, PA-NJ	14.5	1.02	10.9	0.54
Miami, FL	10.7	1.12	6.9	0.58
Phoenix-Mesa, AZ	11.0	1.21	9.6	1.38



# Extra: Results-Survey Correlation for MSA/Region

 Scatterplot of CPS vs NHIS MSA/Region observations

