Title Page

Title: Improving Implementation and QI Research with Regression Risk Analysis

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Final Report

Structured Abstract. (233 Words)

Purpose: Extend and validate methods for estimating risk measures (ratios and differences) and standard errors from logistic regression to account for complex designs, including weighted samples and clustered data, interactions, and multinomial regression. Develop and share computer code to make these techniques accessible to typical health services and quality improvement researchers.

Scope: We primarily used mathematical methods to develop and Monte Carlo simulations to validate. Logistic regression is the most common multivariable method used in medical research. Regression risk analysis was developed by Kleinman and Norton (2009); it enhances interpretation of logistic models.

Methods: We extended regression risk analysis to explore issues described above. We used Monte Carlo simulations to validate our approaches and developed STATA code for all and SAS code for many circumstances.

Results: Regression risk analysis was successfully extended to account for issues of complex survey design (weighted samples, clustered data, and stratification) and also for multinomial outcomes, making it more accessible for QI researchers. We have confirmed it successfully handles interactions. We have developed working code. In the course of our work, we described the novel construct of rank reversal and received NIH funding to help us to develop that work. We have presented at national meetings, have manuscripts accepted and under review, and have emailed our computer code to researchers around the world. In March 2012, we launched a dissemination website, www.Whatstherisk.org, that we developed.

Key Words: Logistic regression, Regression risk analysis, Odds ratio, Risk Ratio, Risk Difference, Comparative effectiveness research, Multivariable regression, Rank reversal

Purpose (Objectives of Study).

The objectives of our study are to:

1. Refine the method of estimating risk ratios and risk differences and their standard errors from logistic regression to account for i) complex designs, including weighted samples, stratification, and clustered data; ii) interactions (effect modification) between variables; and iii) multinomial regression.
2. Validate the estimates using Monte Carlo simulations.
3. Develop and share SAS and Stata code to make these techniques accessible to typical health services/quality improvement researchers.

Scope (Background, Context, Settings, Participants, Incidence, Prevalence).

Background and Context

For more than two decades, researchers have used logistic regression to isolate the effect of a specified factor on a dichotomous outcome, controlling for an unlimited variety of confounders (Hosmer and Lemeshow 1989; Lee 1981). The ability to interpret a logistic model with an adjusted odds ratio (AOR) has made the method popular (Hosmer and Lemeshow, 1989). However, odds ratios diverge from risk ratios, particularly when outcomes are common (Altman, Deeks, and Sackett 1998; Beaudeau and Fourichon 1998; Cummings 2004; Deddens and Petersen 2004; Greenland 2004; Lee 1994; McNutt et al 2003; Rothman and Greenland 1998; Savitz 1992; Zhang and Yu 1998). Accordingly, the frequent use of AOR to describe impact has led to significant miscommunications about the meaning of research findings (Schwartz, Woloshin,and Welch, 1999), and the inability to translate the AOR into the more intuitive risk ratio has vexed researchers and consumers of research alike (Altman, Deeks and Sackett 1998; Bier 2001; Beaudeau and Fourichon 1998; Cummings 2004; Deddens and Petersen 2004; Lee 1981; Lee 1994; McNutt et al. 2003; Robbins, Chao, and Fonseca 2002; Savitz 1992; Schwartz, Woloshin, and Welch 1999; Spiegelman and Hertzmark 2005; Teuber 1992; Wacholder 1986; Wilcosky 1985; Zhang and Yu 1998; Zou 2004; Ukoumunne et al 2008).

The appeal that generating an adjusted risk ratio from logistic regression has to researchers is evident in the frequent citation of a recent article that proposed a simple equation to transform an AOR into an adjusted risk ratio (Zhang and Yu 1998). Unfortunately, further analysis demonstrated serious flaws in this method (McNutt et al 2003, Kleinman and Norton 2009).

As a solution to this longstanding issue, Drs. Kleinman and Norton have developed regression risk analysis (RRA), an analytic approach that allows for the accurate and precise estimation of adjusted risk ratios and risk differences (and their standard errors) directly from nonlinear models, including logistic regression.

Their 2009 *Health Services Research* paper describes the method, validates its accuracy, and demonstrates its tangible benefits over existing alternative methodologies. This study extends RRA, demonstrating its utility and validity in non-standard circumstances that may commonly occur in QI and implementation research, such as analysis of national data sets with complex sampling schemes, interaction effects between variables, and multinomial outcomes.

Settings, Participants, Incidence, Prevalence

Our work required use of simulated data sets, the creation of which is described below in the methods section. Accordingly, our project did not involve participant recruitment and was not focused on specific diseases and conditions.

Methods (Study Design, Data Sources/Collection, Interventions, Measures, Limitations)

Study Design

Objectives 1 and 2:

We developed data sets using Monte Carlo simulations to demonstrate that our methods yield precise and unbiased estimates of the true risk ratio and risk differences, even for data with the common challenges described above. Each simulation was designed to simulate aspects of the data that might be studied in real-world evaluations of implementation of QI research. For complex survey and sample design, we generated an extremely large data set and assigned demographic information, treatment status, and disease status to each individual in this set. We also created correlations within clusters and stratifying variables. For interaction effects, we systematically varied the relationship of the dependent variable, based on the values of two or more predictor variables. To analyze RRA in multinomial logit models, we created categorical outcome variables within the simulations.

After generating the data sets, we drew samples from each simulation population and calculated adjusted risk ratio (ARR) estimates. In the case of complex survey design, two ARR estimates were calculated: one that accounted for the complex survey characteristics, and one that did not. In addition, because we knew the characteristics of all of the cases in the data set we created, we were able to compute an ARR estimate for the population as a whole.

To assess accuracy and validity, the ARR estimates produced for each simulation were compared to the corresponding population estimates as well as the effective risk ratios (ERR). The ERR is a statistic developed by Drs. Kleinman and Norton, calculated as the raw risk ratio in a data set in which predictor variables are all constructed identically to the simulation data set but are not related to the outcome variable (as the simulation set requires); hence, they do not confound the estimates.

Objective 3:
We have used the new margins command in Stata to develop user-friendly code. The margins command is highly versatile and accurately estimates marginal effects for complex, nonlinear models, including those with interactions and survey data. We have utilized the estimating power of this command to create the "adjrr" command, which computes adjusted risk ratios and adjusted risk differences following multinomial logistic regressions, as well as regular logistic and probit and ordered logit and probit. We also have used the margins command to create code that adjusts for complex survey design for all of those models. Additionally, we revised the SAS code for computing adjusted risk ratios and adjusted risk differences after logistic regression.

Data Sources/Collection

In addition to the Monte Carlo simulations, we have also made use of publicly available data sets to demonstrate our methods and code with real-world data. For our work with multinomial outcomes, we utilized the Household Component of the 2004 Medical Expenditure Panel Survey (MEPS). This component contained data on a sample of families and individuals, drawn from a nationally representative subsample of households that participated in the prior year's National Health Interview Survey. We also used data from the National Survey of Children's Health (NSCH). For our complex survey work, we used data from the National Health and Nutrition Examination Survey (NHANES).

Interventions and Measures

Our study did not involve an intervention or specific measures.

Limitations

As with any study, ours has limitations. When we demonstrate our code using the public-use files of real data, we do not know the true value of the parameters. Therefore, analysis of Monte Carlo data focused on demonstrating that our approach is unbiased, but with the real data we demonstrated ease of use and interpretation.

One known limitation of RRA is that it is not appropriate to be used when the data result from a case-control study. Other information must be added. Specifically, that information is a measure of the prevalence (mean of the dependent variable). Adding this information for case-control designs was beyond the scope of our study. RRA can be used, however, for population-based (nested) case-control studies for which the prevalence is available.

Results (Principal Findings, Outcomes, Discussion, Conclusions, Significance, Implications).

Principal Findings and Outcomes

We successfully extended regression risk analysis to account for issues of complex design. Comparisons of the sample adjusted risk ratios to the population estimates and ERR estimates indicate that our models successfully accommodate for issues of weighted samples, stratification, and clustered data.

We have shown that RRA successfully handles interactions. We have also developed and validated working Stata code that can accommodate for multinomial outcomes and for complex survey design. We are preparing a paper to demonstrate these findings, and the editors of HSR have expressed interest in the paper. Findings also are illustrated in our work that was presented at the 2012 Federal Conference on Statistical Methodologies, for which a proceedings paper has been published.

As excerpted from that paper:

3.1 NSCH data

The National Survey of Children's Health (NSCH) is sponsored by the Child and Maternal Health Bureau of the U.S. Department of Health and Human Services. This telephone survey is administered nationwide by the National Center for Health Statistics using the State and Local Area Integrated Telephone Survey (SLAITS) and collects health and health care information about children under 18 years old. First administered in 2003, this survey is conducted every 4 years.

We use the 2007 NSCH to illustrate the calculation and interpretation of adjusted risk ratios (ARR) and adjusted risk differences (ARD) in a multinomial logistic regression. In our model the outcome of interest is the primary location where the sampled child receives healthcare ("usc" in our model, representing usual source of care). We modified this variable such that the four most prevalent locations were maintained as separate locations, and we dropped all other locations (consisting of less than one percent of the responses). The primary explanatory variable of interest is the child's type of health insurance. In the NSCH, insurance status is divided into private insurance, public insurance, and no insurance. Approximately 66 percent of the sample has private insurance, 26.8 percent of the sample has public insurance, and 7.2 percent are uninsured.

The set of explanatory variables in our model includes the health insurance variables and a basic set of demographic variables. We construct age categories to correspond to children in different developmental and educational phases. Children up to age four consist of one category, children ages five to eleven create the second age category, and children ages twelve to seventeen make up the final category. Individuals report their race as being White, Black, multi-racial, or other. Due to a sizeable number of individuals not reporting their race, a separate variable is constructed that denotes the race variable is missing for those observations. The race and ethnicity variables are constructed similarly; these variables equal one if the child is identified as part of a particular race or ethnicity and equals zero otherwise. The resulting sample size of variables with non-missing values on the variables of interest is 86,913 observations.

The NSCH was administered with a complex sampling structure. Observations were stratified at the state level, and the primary sampling unit is the household. Probability weights are used in the analysis to generate a sample that is nationally representative (Blumberg et al., 2007). The following tables show summary statistics for the explanatory variables and then for the dependent variable.

```
-------------------------------------------------------
             |       Mean        Min        Max
-------------+-----------------------------------------
     ins_pub |   .2862582          0          1
     ins_uni |   .0808009          0          1
     age5_11 |   .3813833          0          1
    age12_17 |   .3422308          0          1
      female |   .4902354          0          1
     race_bl |   .1440758          0          1
  race_multi |   .0494847          0          1
    race_oth |   .0522108          0          1
race_missing |    .092276          0          1
    hispanic |   .1873219          0          1
-------------------------------------------------------

. tab usc
            Place of health care |      Freq.     Percent        Cum.
---------------------------------+-----------------------------------
               1 Doctor's office |     68,219       78.49       78.49
      2 Hospital emergency room |      1,184        1.36       79.85
3 Hospital outpatient department |      1,880        2.16       82.02
       4 Clinic or health center |     15,630       17.98      100.00
---------------------------------+-----------------------------------
                          Total |     86,913      100.00
```

3.2 Multinomial logit model

We estimate a multinomial logistic model to predict the probability of each of four types of usual sources of care as a function of the insurance status and demographics. Because there are four categorical outcomes, the model estimates three parameters for each explanatory variable.

```
. svy: mlogit usc i.ins_pub i.ins_uni age5_11 age12_17 i.female race_bl race_multi
race_oth race_missing hispanic
(running mlogit on estimation sample)
```

Survey: Multinomial logistic regression

Number of strata	= 51	Number of obs	=	86913
Number of PSUs	= 86913	Population size	=	68905676
		Design df	=	86862
		F(30, 86833)	=	47.33
		Prob > F	=	0.0000

usc	Coef.	Linearized Std. Err.	t	P>|t|	[95% Conf.	Interval]
1_Dr's office	(base outcome)					
2_Hosp ER						
1.ins_pub	1.142589	.2066544	5.53	0.000	.737548	1.54763
1.ins_uni	1.992841	.2199382	9.06	0.000	1.561764	2.423918
age5_11	.1875998	.1922636	0.98	0.329	-.1892351	.5644347
age12_17	.3488113	.1748101	2.00	0.046	.0061851	.6914375
1.female	.0495236	.1536241	0.32	0.747	-.2515783	.3506254
race_bl	1.433909	.1779922	8.06	0.000	1.085045	1.782772
race_multi	-.0516816	.2692711	-0.19	0.848	-.5794506	.4760875
race_oth	1.031731	.4342249	2.38	0.018	.180654	1.882808
race_missing	.6750487	.3171608	2.13	0.033	.0534164	1.296681
hispanic	.9825168	.2229067	4.41	0.000	.5456216	1.419412
_cons	-5.313072	.1761959	-30.15	0.000	-5.658414	-4.96773
3_Hosp OPD						
1.ins_pub	.5343329	.1416113	3.77	0.000	.256776	.8118898
1.ins_uni	.8920434	.2027603	4.40	0.000	.4946349	1.289452
age5_11	.035345	.1694218	0.21	0.835	-.2967202	.3674103
age12_17	.2538672	.1727587	1.47	0.142	-.0847384	.5924727
1.female	.0106483	.1328544	0.08	0.936	-.2497452	.2710418
race_bl	1.184395	.1304534	9.08	0.000	.9287077	1.440083
race_multi	1.142207	.3137291	3.64	0.000	.5273005	1.757113
race_oth	1.727319	.2241178	7.71	0.000	1.28805	2.166588
race_missing	1.220938	.2280895	5.35	0.000	.7738846	1.667992
hispanic	.261648	.1345126	1.95	0.052	-.0019954	.5252915
_cons	-4.514257	.1871833	-24.12	0.000	-4.881134	-4.147379
4_Clinic/Cntr						
1.ins_pub	1.017277	.0571559	17.80	0.000	.9052515	1.129301
1.ins_uni	1.296523	.0825516	15.71	0.000	1.134722	1.458323
age5_11	-.0454325	.0642795	-0.71	0.480	-.1714198	.0805548
age12_17	.130426	.0649003	2.01	0.044	.0032219	.25763
1.female	.1138293	.0513247	2.22	0.027	.0132332	.2144253
race_bl	.31956	.0660122	4.84	0.000	.1901767	.4489433
race_multi	.0091794	.1241035	0.07	0.941	-.2340624	.2524213
race_oth	.4852826	.1148665	4.22	0.000	.2601453	.7104199
race_missing	.6239109	.1039805	6.00	0.000	.4201101	.8277117
hispanic	1.005137	.0758997	13.24	0.000	.8563738	1.153899
_cons	-2.463513	.0593282	-41.52	0.000	-2.579796	-2.34723

The coefficients from a multinomial model are hard to interpret directly. Instead, we calculate ARRs and ARDs for three covariates for children: public insurance, uninsured, and female. For each covariate, we calculate an ARR and ARD for each outcome. The delta-method standard errors are shown in parentheses. For the following output, the usual source of care for outcome 1 is the Doctor's Office; for outcome 2, it is the Hospital Emergency Room; for outcome 3, it is a Hospital Outpatient Department; and for outcome 4, it is a Clinic or Community Health Center.

```
. adjrr ins_pub
ARR(outcome 1) = 0.8067  (0.0108)
ARD(outcome 1) = -0.1605 (0.0094)
ARR(outcome 2) = 2.1979  (0.4253)
ARD(outcome 2) = 0.0170  (0.0047)
ARR(outcome 3) = 1.2918  (0.1721)
ARD(outcome 3) = 0.0061  (0.0032)
ARR(outcome 4) = 2.0180  (0.0837)
ARD(outcome 4) = 0.1373  (0.0091)

. adjrr ins_uni
ARR(outcome 1) = 0.6935  (0.0195)
ARD(outcome 1) = -0.2455 (0.0159)
ARR(outcome 2) = 4.1614  (0.8167)
ARD(outcome 2) = 0.0497  (0.0108)
ARR(outcome 3) = 1.5064  (0.2887)
ARD(outcome 3) = 0.0112  (0.0060)
ARR(outcome 4) = 2.1451  (0.1102)
ARD(outcome 4) = 0.1846  (0.0163)

. adjrr female
ARR(outcome 1) = 0.9817  (0.0090)
ARD(outcome 1) = -0.0144 (0.0072)
ARR(outcome 2) = 1.0163  (0.1491)
ARD(outcome 2) = 0.0003  (0.0029)
ARR(outcome 3) = 0.9845  (0.1259)
ARD(outcome 3) = -0.0004 (0.0029)
ARR(outcome 4) = 1.0853  (0.0406)
ARD(outcome 4) = 0.0145  (0.0066)
```

To interpret the insurance variables, we must remember that the omitted insurance variable in the multinomial model is private insurance; the results for the other insurance variables are understood with respect to this reference category. The results for the publicly insured and the uninsured have similar patterns as to where individuals receive care, with a larger effect size observed among the uninsured compared to the publicly insured children.

The interpretation of the ARRs for outcome 1 (care typically received at a doctor's office) by insurance status is straightforward. Those publicly insured are 19.33% less likely (1 – 0.8067 = 0.1933) to receive care at a doctor's office than those with private insurance (ARR = exposed risk/baseline risk = 0.6694/0.8299 = 0.8067). *[This result, as well as the other ARR and ARD calculations, reflects rounding.] On average among all children, those who are uninsured are 30.65% less likely (1 – 0.6935 = 0.3065) to receive care in this setting than the privately insured, holding all else equal (ARR = 0.5555/0.8010 = 0.6935). In terms of absolute differences, those who are publicly insured receive care from doctor's offices 16.05 percentage points less often than those privately insured (ARD = exposed risk – baseline risk = 0.6694 – 0.8299 = -0.1605). In comparison, the uninsured receive care from doctor's offices 24.55 percentage points less often than those privately insured (ARD = 0.5555 – 0.8010 = -0.2455). One can readily estimate that the uninsured receive care at private doctor's offices 8.5 percentage points (16.05 – 24.55) less often than those with public insurance.*

The uninsured and the publicly insured receive care far more frequently in hospital emergency rooms and clinics and health centers than the privately insured. On average, uninsured children receive care in hospital emergency rooms approximately 316% more often (4.1614 – 1 = 3.1614) than privately insured children (ARR = 0.0654/0.0157 = 4.1614). In comparison, publicly insured children receive care in this setting approximately 120% more often (2.1979 – 1 = 1.1979) than privately insured children (ARR = 0.0312/0.0142 = 2.1979).

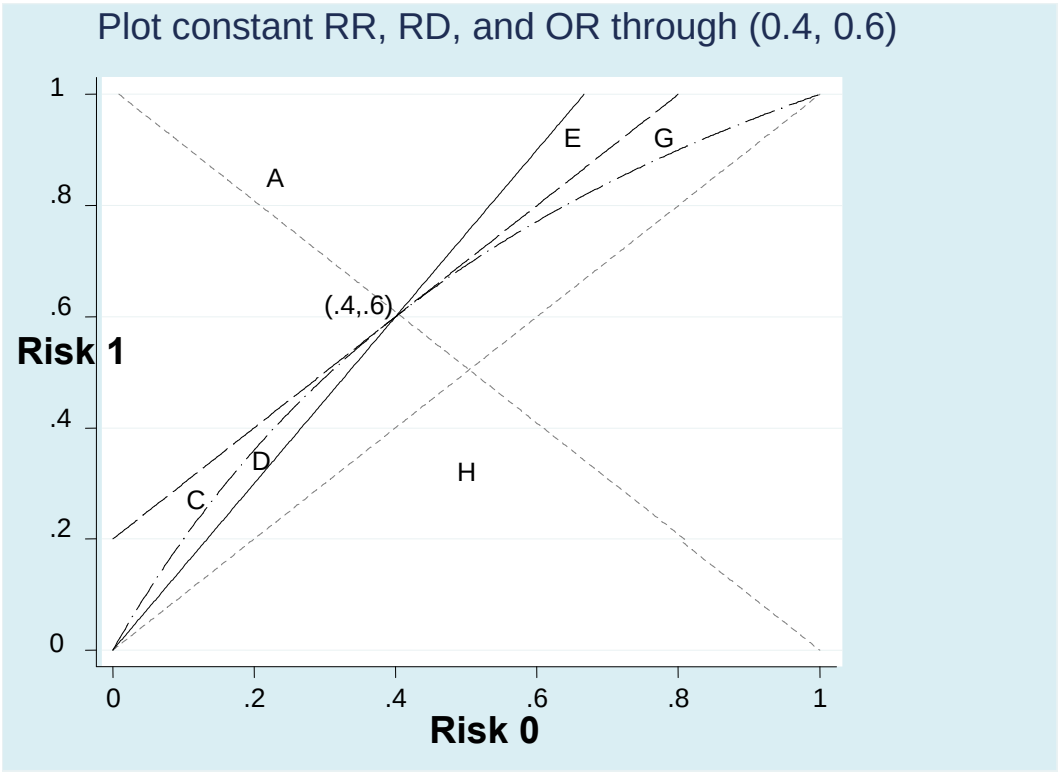
In examining the results from the variable female, girls and boys receive care at similar rates in hospital settings. Differences in location of care by sex emerge at doctor's offices (outcome 1) and clinics and health centers (outcome 4). Girls receive care from clinics and health centers 8.53% more than boys, on average (ARR = 0.1841/0.1697 = 1.0853). In comparison, boys receive care from doctor's offices 1.83% more than girls (ARR = 0.7734/0.7879 = 0.9817). In terms of absolute differences, girls are 1.45 percentage points more likely to go to clinics and health centers (ARD = 0.1841 – 0.1697 = 0.0145) and they are 1.44 percentage points less likely to go to doctor's offices than boys, on average (ARD = 0.7734 – 0.7879 = -0.0144).

3.3 Complex survey design

In the above model, we specified the complex survey design of the NSCH before estimating the results. Identifying the stratification, sampling structure, and weighting of observations affects the model's results. If we had run the previous model without the survey commands, we would have estimated the following results for the ARRs and ARDs for the public insurance variable.

```
. adjrr ins_pub
ARR(outcome 1) = 0.8412  (0.0046)
ARD(outcome 1) = -0.1292 (0.0038)
ARR(outcome 2) = 2.6797  (0.1773)
ARD(outcome 2) = 0.0165  (0.0014)
ARR(outcome 3) = 1.4690  (0.0763)
ARD(outcome 3) = 0.0090  (0.0013)
ARR(outcome 4) = 1.6600  (0.0265)
ARD(outcome 4) = 0.1037  (0.0037)
```

Figure 1.



As you can see, these lines carve the plane into several distinct areas. Each area is defined by the level of agreement between the ranks as determined by a comparison of the rank of (0.4, 0.6) and the points in that area using the various measures, RR, OR, and RD.

When summing the areas on the unit square, we find that 90.5 % of the area has no rank reversal, but the OR is the exception for 2.4%, the RR for 4.3%, and the RD for 2.4%.

Table 1.

Area	RR	RD	OR	Agree?
A	R1	R1	R1	Yes
B	R1	R1	R0	OR different
C	R1	R0	R1	RD different
D	R1	R0	R0	RR different
E	R0	R1	R1	RR different
F	R0	R1	R0	RD different
G	R0	R0	R1	OR different
H	R0	R0	R0	Yes

In the course of our work, we have identified and described the construct of rank reversal, in wihch the ranking of different treatments varies depending on which measure of effect size (ARR or AOR) is used. We also have determined certain conditions under which rank reversal may occur, namely in studies using indirect comparisons, in which two treatments are each separately compared to their own control. Additionally, we have developed graphic representations of patterns in which rank reversal occurs and the relative magnitudes of risk ratios, risk differences, and odds ratios (Figure 1 and Table 1, above). These are demonstrated in a paper that will be published in *Value in Health* in November 2013.

To disseminate our work, we have presented at national meetings, such as the AcademyHealth annual research meeting, and have manuscripts that have been accepted and that are currently under review. We have shared our computer codes to other researchers, both nationally and internationally. We also launched a website, www.whatstherisk.org.

Discussion, Conclusions, Significance, Implications

Regression risk analysis makes adjusted risk ratios and adjusted risk differences more accessible to researchers in general, and its extensions accommodate the specific needs of quality improvement and implementation research. The large-scale surveys and data sets, often used in such research, are rarely completely random samples, but instead stratify, over- and under-sample certain groups and sample from clusters. Our work provides researchers with a way to accommodate these complex survey characteristics in their analyses, to report accurate, more intuitively understood measures of effect size, and to more effectively communicate their findings. Consumers of researchers, including policymakers, can thus more readily interpret research and make more well-informed decisions.

Our discovery of the rank reversal phenomenon has strong implications for researchers and consumers as well. It underscores the need for researchers to carefully consider their choice of measure of effect size, particularly when planning and analyzing a study using indirect comparisons. It also demonstrates the importance of researchers making explicit their conceptual model and detailing whether their results are sensitive to measure choice. Furthermore, it highlights the importance of consumers making note of the measure choice when using research to inform their decisions.

The products from this project, including the user-friendly SAS and Stata codes, conference proceedings, and manuscripts, provide researchers will clear guidance for using RRA in their analyses. We will circulated our work through development of our website, www.whatstherisk.org, with the goal of encouraging researchers to more effectively design and analyze their studies and disseminate their findings.

List of Publications and Products

Papers

1. Norton EC, Miller MM, Wang J, Coyne K, Kleinman LC. Rank Reversals in Indirect Comparisons. In Press, *Value in Health*. Accepted June, 2012.
2. Norton EC, Miller MM, Kleinman LC. Computing adjusted risk ratios and risk differences in STATA. *Submitted to STATA Journal.*
3. Norton EC, Carroll NW, Miller MM, Coyne K, Wang JJ, Kleinman LC. Computing risk ratios from Data with Complex Survey Design. Submitted to *HSR: Health Services Research.*

Conference Proceedings

Miller MM, Norton EC, Coyne K, Wang J, Kleinman LC. Besting the Odds: Optimal Reporting of Logistic Regression. *Proceedings of the 2012 Federal Conference on Statistical Methodology*. http://www.fcsm.gov/12papers/Miller_2012FCSM_IX-A.pdf. (accessed July 11, 2012).

Electronic Resources

www.whatstherisk.org (Live, with ongoing development, last accessed July 11, 2012)

Presentations

1. Kleinman LC, Wang J, Coyne K, Miller M, Norton EC. Comparative Effectiveness Disorder Caused by Rank Reversal. Presented at Academy Health Annual Research Meeting, Seattle, WA June 12-14, 2011.
2. Miller MM, Norton EC, Wang J, Coyne K, Kleinman LC. Understanding Regression Risk Analysis in Multinomial Logistic Regressions. Presented at Academy Health Annual Research Meeting, Seattle, WA June 12-14, 2011.
3. Norton EC, *Kleinman LC, Miller MM, Coyne K, and Wang JJ. Practitioner's Guide to Regression Risk Analysis Using SAS and Stata. Federal Committee on Statistical Methodology Research Conference, Washington, DC. January, 2012.
4. Miller MM, Norton EC, *Kleinman LC, Wang JJ, and Coyne K. Understanding Regression Risk Analysis in Multinomial and Ordered Logistic Regressions. Federal Committee on Statistical Methodology Research Conference, Washington, DC. January, 2012.
5. Wang JJ, Norton EC, Coyne K, Miller MM, and Kleinman LC. Estimating Variance for Regression Risk Analysis. Federal Committee on Statistical Methodology Research Conference, Washington, DC. January, 2012.
6. Kleinman LC, Norton EC, Coyne K, Miller MM, and Wang JJ. Rank Reversal in Comparative Effectiveness Research. Federal Committee on Statistical Methodology Research Conference, Washington, DC. January, 2012.

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