Correcting for Measurement Error in Reporting of Episodically Consumed Foods When Estimating Diet-Disease Relationships

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OUTLINE

- Introduction: impact of dietary measurement error
- Regression calibration correction
- Challenges to analysis of episodically consumed foods
- Regression calibration model
- Simulation study:
 - whole grains vs colorectal cancer in men
 - fish vs colorectal cancer in men
- Example: red/processed meat vs lung cancer in NIH-AARP Diet & Health Study
- Discussion

Impact of Measurement Error

- Food Frequency Questionnaire (FFQ) is instrument of choice in most studies in nutritional epidemiology
- FFQ is known to contain substantial measurement error, random and systematic
- Typically measurement error causes two things:
 - bias in the estimated exposure effect (often leading to flattened or attenuated true slope in disease model)
 - loss of statistical power to detect exposure effect

Impact of Measurement Error

• <u>Disease model</u>: for disease outcome D, vector $\mathbf{T} = (T_1, ..., T_K)^t$ of true usual intakes, and vector $\mathbf{Z} = (Z_1, ..., Z_L)^t$ of covariates

$$\mathbb{E}(D|\boldsymbol{T},\boldsymbol{Z}) = m(\alpha_0 + \boldsymbol{\alpha}_T^t \boldsymbol{T} + \boldsymbol{\alpha}_Z^t \boldsymbol{Z})$$

where $m^{-1}(.)$ is link function (e.g., logit)

• Main assumption: errors in reported intakes Q are non-differential with respect to outcome D, i.e.

$$\mathcal{F}(D|T,Q,Z) = \mathcal{F}(D|T,Z)$$

 Example: conditional distribution of reported intakes given true intakes is the same among cases and controls

Regression Calibration

• Disease model

$$\mathbb{E}(D|T,Z) = m(\alpha_0 + \boldsymbol{\alpha}_T^t T + \boldsymbol{\alpha}_Z^t Z)$$

• Regression calibration: to a very good approximation

$$\mathbb{E}(D|\boldsymbol{Q},\boldsymbol{Z}) = m(\alpha_0 + \boldsymbol{\alpha}_T^t \mathbb{E}(\boldsymbol{T}|\boldsymbol{Q},\boldsymbol{Z}) + \boldsymbol{\alpha}_Z^t \boldsymbol{Z})$$

• Intuition: substitution for unknown vector T its best prediction given the reported intakes Q and covariates Z

Regression Calibration

- In absence of gold standard, regression calibration predictors $\mathbb{E}(T_k|\boldsymbol{Q},\boldsymbol{Z}),\ k=1,...,K$ are estimated using short-term reference measurements
- For continuous intake, reference measurements are required to satisfy classical error model

$$R_{ij} = T_i + \epsilon_{ij}$$

where errors ϵ_{ij} are additive, independent of true intake, errors in FFQ, and each other

• Then regression calibration predictor can be estimated as

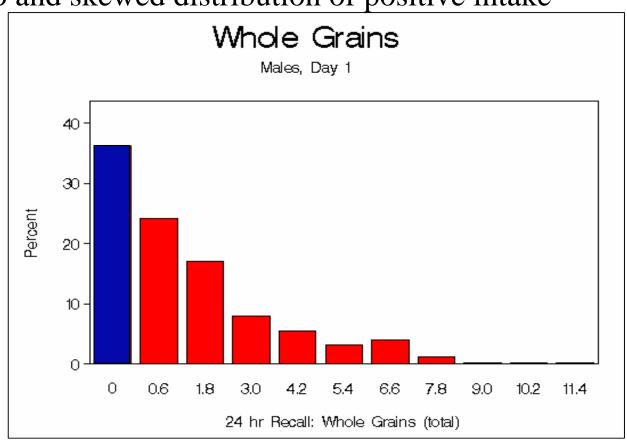
$$\mathbb{E}(R_{ij}|\boldsymbol{Q}_i,\boldsymbol{Z}_i) = \mathbb{E}(T_i|\boldsymbol{Q}_i,\boldsymbol{Z}_i)$$

Regression Calibration

- Ideal reference measure
 - short-term 'recovery' biomarker
- Reference measure in reality
 - more extensive short-term dietary-assessment method such as 24HR or diary
- 24HR is of special interest because it is used in 2 largest cohorts, AARP and EPIC
- Distributions of nutrient intakes are typically rather skewed: classical error model for reference measure may not hold
- Remedy: transformation to a scale where classical error model holds

Intake of Episodically Consumed Foods

• <u>Problem</u>: short-term reference measure (e.g., 24HR) has spike at zero and skewed distribution of positive intake



Statistical Model: true usual intake

• For person i, day j, and intake T_{ij} of interest, let

$$p_i = \mathbb{P}(T_{ij} > 0|i)$$

denote probability to consume on any given day

• Let

$$A_i = \mathbb{E}(T_{ij}|i; T_{ij} > 0)$$

denote usual consumption amount

• Then usual intake, defined as $T_i = \mathbb{E}(T_{ij}|i)$, is given by

$$T_i = \mathbb{E}(T_{ij}|i; T_{ij} > 0) \times \mathbb{P}(T_{ij} > 0|i) = p_i A_i$$

Statistical Model: assumptions for reference instrument

ullet Conditional on (transformed) $oldsymbol{X}_i = (oldsymbol{Q}_i^t, oldsymbol{Z}_i^t)^t$

$$\mathbb{P}(R_{ij} > 0 | \boldsymbol{X}_i) = \mathbb{P}(T_{ij} > 0 | \boldsymbol{X}_i)$$

• For a monotone transformation g(.) reference amount on transformed scale has classical measurement error

$$g(R_{ij}|R_{ij}>0)=\mu_{R_i}+\epsilon_{ij},\ \epsilon_{ij}\sim N(o,\sigma_{\epsilon}^2)$$

• Reference amount is unbiased on transformed scale:

$$\mathbb{E}\{g(R_{ij})|i,R_{ij}>0\}=g(A_i)$$

Statistical Model: part I

Part I – Probability to consume

Logistic regression (mixed model)

$$\mathbb{P}(R_{ij} > 0 | \boldsymbol{X}_i) = \mathbb{P}(T_{ij} > 0 | \boldsymbol{X}_i)$$

$$=H(\beta_{01}+\boldsymbol{\beta}_{X1}^{t}\boldsymbol{X}_{i}+u_{1i})$$

where

 $H(v) = (1 + e^{-v})^{-1}$ is logistic function

 $u_{1i} \sim N(0, \sigma_{u_1}^2)$ is person-specific random effect allowing person's value to differ from that defined by covariates

Statistical Model: part II

• Part II – Amount on consumption day

Linear regression (mixed model) on transformed scale

$$g(R_{ij}|R_{ij} > 0; \boldsymbol{X}_i) = \mu_{R_i} + \epsilon_{ij}$$

$$= \beta_{02} + \boldsymbol{\beta}_{X2}^t \boldsymbol{X}_i + u_{2i} + \epsilon_{ij}$$

where

$$g(v) = (v^{\theta} - 1)/\theta - \text{Box-Cox transformation}$$

$$u_{2i} \sim N(o, \sigma_{u_2}^2)$$
 – person-specific random effect

$$\epsilon_{ij} \sim N(o, \sigma_{\epsilon}^2)$$
 — within-person random error

Statistical Model

• Two-part model

$$\mathbb{P}(R_{ij} > 0 | \boldsymbol{X}_i) = H(\beta_{01} + \boldsymbol{\beta}_{X1}^t \boldsymbol{X}_i + u_{1i})$$
$$g(R_{ij} | R_{ij} > 0; \boldsymbol{X}_i) = \beta_{02} + \boldsymbol{\beta}_{X2}^t \boldsymbol{X}_i + u_{2i} + \epsilon_{ij}$$

Link

$$(u_{1i}, u_{2i})^t \sim N(\mathbf{0}, \mathbf{\Sigma}), \, \mathbf{\Sigma} = \begin{pmatrix} \sigma_{u_1}^2 & \rho_{u_1, u_2} \sigma_{u_1} \sigma_{u_2} \\ & \sigma_{u_2}^2 \end{pmatrix}$$

- person-specific random effects are correlated
- covariates can be (partially) shared

Regression Calibration Model

• True usual intake

$$T_i = H(eta_{01} + oldsymbol{eta}_{X1}^t oldsymbol{X}_i + u_{1i}) imes g^{^{-1}}(eta_{02} + oldsymbol{eta}_{X2}^t oldsymbol{X}_i + u_{2i})$$

• Regression-calibration predictor for transformed $h(T_i)$

$$\mathbb{E}[h\{H(\beta_{01} + \boldsymbol{\beta}_{X1}^{t}\boldsymbol{X}_{i} + u_{1i})g^{^{-1}}(\beta_{02} + \boldsymbol{\beta}_{X2}^{t}\boldsymbol{X}_{i} + u_{2i})\}|\boldsymbol{X}_{i}]$$

- Linear regression calibration:
 - Monte Carlo estimation of regression calibration predictors by generating $\hat{\boldsymbol{u}} = (\hat{u}_{1i}, \hat{u}_{2i})^t \sim N(\mathbf{0}, \hat{\boldsymbol{\Sigma}})$, using estimated parameters $(\hat{\beta}_{01}, \hat{\beta}_{02}, \hat{\boldsymbol{\beta}}_{X1}, \hat{\boldsymbol{\beta}}_{X2})$ to calculate $h(\hat{T}_i)$ and regressing $h(\hat{T}_i)$ on \boldsymbol{X}_i

EATS: Design

- Men and women 20-70 years
- Nationally representative sampling of 12,615 telephone numbers
- Approximately 1600 recruited
- Four 24HRs, one in each season
- After one year: DHQ about past year
- 886 respondents completed four 24HRs and DHQ

Simulation Study

- Idea: simulate data that are similar to reported intake of *whole* grains and fish in EATS
 - transform FFQ using best Box-Cox transformation to approximate normality
 - fit two-part model relating 4 24HRs to transformed FFQ, Q^* , and estimate model parameters
 - generate $\mathbf{u}_i = (u_{1i}, u_{2i}) \sim N(\mathbf{0}, \mathbf{\Sigma}), i = 1, ..., 20,000$
 - generate $Q_i^* \sim N(\mu_{Q^*}, \sigma_{Q^*}^2), i = 1, ..., 20,000$
 - generate two 24HRs for 1,000 subjects in calibration study

$$R_{ij} = \begin{cases} 0 \text{ with pr} = 1 - p_i, \ p_i = H(\beta_{01} + \beta_{Q1}Q_i^* + u_{1i}) \\ g^{-1}(\beta_{02} + \beta_{Q2}Q_i^* + u_{2i} + \epsilon_{ij}) \text{ with pr} = p_i \end{cases}$$

Simulation Study

- Generate $T_i = H(\beta_{01} + \beta_{Q1}Q_i^* + u_{1i})g^{-1}(\beta_{02} + \beta_{Q2}Q_i^* + u_{2i})$ i = 1, ..., 20, 000, and transform to $h(T_i)$ using best Box-Cox transformation to approximate normality
- Generate binary outcome variable for colorectal cancer in men

$$\mathbb{P}(D_i = 1|T_i) = H\{\alpha_0 + \alpha_1 h(T_i)\}\$$

where α_1 represents log RR = 0.5 for increasing exposure from 10 % to 90 % of the true exposure distribution and $\alpha_0 = -3.05$ which corresponds to probability of 3% for a 60 y old man to get disease in general population within 10 years

Simulation Study

- Comparison of 4 different methods:
 - true exposure on transformed scale
 - FFQ-reported exposure on transformed scale
 - "conventional" regression calibration approach by using mean of 2 24HRs on transformed scale as reference instrument
 - suggested regression calibration
- Since different methods lead to fitting risk model on different scales, RR is always calculated for the given increase in intake from a to $b=a+\Delta$, where a is equal to 10th percentile and b is equal to 90th percentile of true exposure on original scale

Simulation Study: Results

• True log RR for increase in *whole grain* intake from 0.25 to 2.85 pyramid servings/day is equal to -0.74

	Method			
log RR	True exposure	FFQ	Naive RC	New RC
Mean (s.e.)	-0.74 (.008)	-0.47 (.008)	-0.59 (.01)	-0.75 (.012)
St. dev.	0.110	0.107	0.134	0.174
RMSE	0.110	0.290	0.201	0.174

Simulation Study: Results

• True log RR for increase in *fish* intake from 0.064 to 1.39 oz/day is equal to -0.69

	Method			
log RR	True exposure	FFQ	Naive RC	New RC
Mean (s.e.)	-0.70 (.008)	-0.51 (.008)	-0.97 (.017)	-0.71 (.012)
St. dev.	0.105	0.106	0.234	0.166
RMSE	0.105	0.216	0.361	0.167

NIH-AARP Diet & Health Study

- Prospective cohort of 567,169 men & women aged 50-71 in 1995-96
- FFQ administered at baseline
- Calibration substudy of ~ 1000 men and ~1000 women with 2 24HRs and additional FFQ
- Analysis: association between red/processed meat and lung cancer for 349,148 men using Cox regression
- Confounders: age, BMI, smoking, physical activity, education, non-red/non-processed meat, fruit, total energy

NIH-AARP Diet & Health Study: Meat & Lung CA

	Method			
	FFQ	Naive RC	New RC	
Red Meat				
HR(10% - 90%)	1.22	1.29	1.38	
Bootstrap 95% CI	(1.10; 1.35)	(1.05; 1.61)	(1.06; 1.81)	
Processed meat				
HR(10% - 90%)	1.18	1.22	1.34	
Bootstrap 95% CI	(1.09; 1.28)	(1.11; 1.36)	(1.16; 1.56)	

Discussion

- New method addresses all of the challenges for modeling usual intake of foods and overcomes the limitations of conventional regression calibration
 - Models intake as the product of probability to consume and consumption amount
 - Allows for skewed distribution of reference consumption amount by transforming to a scale with classical error model
 - Allows probability and amount to be correlated
 - Uses rigorous regression calibration approach

Discussion

- Method is based on important assumptions that reference instrument correctly specifies probability of short-term fact of consumption and that, on appropriate scale, it follows classical measurement error for consumption amount
- Studies with unbiased biomarker (DLW) for energy expenditure have found bias in reporting of energy intake on 24HR
 - suggests systematic misreporting of at least some foods
- For foods reported with bias on 24HR, correction for measurement error using 24HR as reference instrument will be biased as well