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Covariate Measurement Error in Life History Data

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Abstract

In practice it often happens that some collected data are subject to measurement error. Sometimes covariates (or risk factors) of interest may be difficult to observe precisely due to physical location or cost. Sometimes it is impossible to measure covariates accurately due to their nature. In other situations, a covariate may represent an average of a certain quantity over time, and any practical way of measuring such a quantity necessarily features measurement error. When carrying out statistical inference in such settings, it is important to account for the effects of mismeasured covariates; otherwise, erroneous or even misleading results may be produced. In this paper, I discuss measurement error models and review some analysis methods handling covariate measurement error for life history data.

Keywords and Phrases: Binary Data, Case-control Studies, Clustered Data, Longitudinal Data, Measurement Error, Survey Data, Survival Data.

AMS Classification: Primary 62H12; Secondary 62F10.

1 Introduction

Measurement error has long been a concern in medical, health and epidemiological studies. It arises commonly in a variety of settings including longitudinal studies, case-control studies, survival data analysis and survey sampling. In nutrition studies, for instance, food frequency questionnaires are commonly used to measure diet, and it is known that this instrument involves a large degree of variation and measurement error (e.g., Rosner, Willett and Spiegelman 1989). Measurement error is often present with various reasons. Sometimes covariates of interest may be difficult to observe precisely due to physical location or cost. For example, the degree of narrowing of coronary arteries may reflect risk of heart failure, but physicians may measure the degree of narrowing in carotid arteries instead due to the less invasive nature of this method of assessment. Sometimes it is impossible to measure covariates accurately due to the nature of the covariates. For example, the level of exposure to potential risk factors for cancer such as radiation can not be measured accurately (Pierce et al. 1992). In other situations, a covariate may represent an average of a certain quantity over time, and any practical way of measuring such a quantity necessarily features measurement error. It is known that ignoring measurement error in variables often leads to biased results. For example, in simple linear regression with an error-contaminated covariate that is characterized by a classical additive error model, the estimate of the slope can be attenuated if ignoring error in the covariate. Measurement error effects could be complex, generally depending on the form of the error model and the relationship between the response and covariates as well as distributions of covariates. There is an enormous literature on this subject. A textbook treatment of measurement error problems is given by Fuller (1987) for linear regression and by Carroll et al. (2006) for nonlinear models.

In this article I discuss certain analysis methods of measurement error problems concerning life history data. The intention here is to give readers a flavor of research on measurement error models. I do not attempt to give a complete list of research work in this area. Instead, I focus the discussion on methods concerning survival data and longitudinal/clustered data as well as binary data related to case-control studies. The discussion begins with a number of measurement error models that are often used in the literature, followed by several inference methods accounting for error effects. A brief survey of some recent advances is provided, along with a short discussion on measurement error in survey sampling.

2 Measurement Error Models

2.1 An Illustration of Measurement Error Effects

For $i = 1, 2, \ldots, n$, let Y_i be a response variable, X_i be a covariate that is subject to measurement error, and W_i be its observed measurement. To quickly illustrate measurement error effects, we consider a simple regression model with

$$Y_i = \beta_0 + \beta_x X_i + \varepsilon_i \tag{1}$$

where β_0 and β_x are regression parameters, and ε_i is independent of X_i and W_i. If we ignore error in X_i, i.e., use W_i to replace X_i in (1) to fit the model, then the (naive) least squares estimator for the slope is given by

$$\hat{\beta}_x^* = \frac{\sum_i (W_i - \bar{W})(Y_i - \bar{Y})}{\sum_i (W_i - \bar{W})^2},$$

where the bar on a variable represents the corresponding sample average.

Depending on the relationship between W_i and X_i , $\hat{\beta}_x^*$ may or may not be consistent for the slope β_x . For example, if W_i and X_i are linked by:

$$W_i = X_i + e_i \tag{2}$$

where e_i has mean 0 and variance σ_e^2 , and is independent of ε_i, then the naive estimator $\hat{\beta}_x^*$ can be written as

$$\begin{aligned}
\hat{\beta}_i^* &= \frac{\sum_i (W_i - \bar{W}) \left[\beta_x (X_i - \bar{X}) + (\varepsilon_i - \bar{\varepsilon})\right]}{\sum_i (W_i - \bar{W})^2} \qquad (3) \\
&= \frac{\sum_i (W_i - \bar{W}) \beta_x (X_i - \bar{X})}{\sum_i (W_i - \bar{W})^2} + \frac{\sum_i (W_i - \bar{W})(\varepsilon_i - \bar{\varepsilon})}{\sum_i (W_i - \bar{W})^2} \\
&= \beta_x \frac{\sum_i (X_i - \bar{X})^2 + \sum_i (X_i - \bar{X})(e_i - \bar{e})}{\sum_i (X_i - \bar{X})^2 + 2\sum_i (X_i - \bar{X})(e_i - \bar{e}) + \sum_i (e_i - \bar{e})^2} + \frac{\sum_i (W_i - \bar{W})(\varepsilon_i - \bar{\varepsilon})}{\sum_i (W_i - \bar{W})^2}
\end{aligned}$$

By the independence between W_i and ε_i , the second term converges in probability to 0 as $n \to \infty$. It is easily seen that the first term converges in probability to

$$\beta_x \left(\frac{\sigma_x^2 + \sigma_{xe}}{\sigma_x^2 + 2\sigma_{xe} + \sigma_e^2} \right), \qquad \text{as } n \to \infty \tag{4}$$

where σ_{xe} is the covariance between X_i and e_i, and σ_x^2 is the variance of X_i. Depending on the strength of the correlation between X_i and e_i, limit (4) may attenuate or inflate the covariate effect β_x . If X_i and e_i are independent, then (4) is an attenuation of β_x since the factor $\sigma_x^2/(\sigma_x^2 + \sigma_e^2)$ is no more than 1; otherwise, (4) may inflate the slope β_x when $\sigma_{xe} < -\sigma_e^2$. Therefore, the naive estimator $\hat{\beta}_x^*$ is not a consistent estimator for β_x under model (2). In other situations, for example, if W_i and X_i is related by X_i = W_i+e_i with e_i having zero mean and being independent of W_i, then it is easily seen, by the expression of (3), that the limit of $\hat{\beta}_x^*$ is identical to β_x. That is, the naive estimator $\hat{\beta}_x^*$ is still a consistent estimator for β_x for this scenario.

This example illustrates that attenuation is a typical phenomenon for simple linear regression when the error model is characterized by (2) with the true covariate X_i being independent of e_i. However, the impact of error in X_i may be dramatically changed if the association strength between X_i and e_i varies, or if the relationship between X_i and W_i changes. In the same spirit we can discuss the impact of covariate measurement error on estimation of the variance of the estimators. There has been extensive research on investigating measurement error effects in various situations. For example, Kim and Saleh (2003a) provided a detailed study of measurement error problems for both conditional and unconditional models. A short review of error-in-variable can be found in Huffel et al. (2007).

In summary, measurement error may have varying effects in different situations. The effects could be complex and they generally depend on the forms of the response model and the error model and the extent of error as well. In principle, if covariate error is present, we should not simply ignore that. Instead, a careful examination should be taken in order to carry out valid inference.

2.2 Measurement Error Models

A number of measurement error models have been investigated in the literature. Many of those are rooted in the following two basic models. The first one is the so-called classical additive model which assumes the form

$$W_i = X_i + e_i, \tag{5}$$

or more generally,

$$W_i = \alpha_0 + \alpha_1 X_i + e_i,$$

where error term e_i has mean 0 and is independent of X_i, and α_0 and α_1 are parameters. Alternatively, a Berkson model assumes the form

$$X_i = W_i + e_i, \tag{6}$$

or more generally,

$$X_i = \alpha_0 + \alpha_1 W_i + e_i,$$

where error term e_i has mean 0 and is independent of W_i, and α_0 and α_1 are parameters.

These models, especially the first one, have been commonly adopted in the literature. The use of different model forms is typically driven by the nature of individual data set. If measurement W_i is thought to fluctuate around the true covariate X_i, using a classical additive model might be a reasonable assumption. In other situations, the actual measurement W_i determines the true value of X_i, using a Berkson type model may be preferable. For example, in pesticide studies, the drug amount applied to a plant is measureable, but the actual amount absorbed by a plant is not measurable, and it basically depends on how much pesticide is applied. In this circumstance, a Berkson model is more feasible than a classical additive model. As commented in Carroll et al. (2006), there are no universal guidelines to decide which model is more reasonable for an individual problem. This could be a subjective matter, although different specifications of error models may, in principal, lead to different inference results. One mathematical judgment is based on the essential difference between (5) and (6). Both (5) and (6) imply that $E(X_i) = E(W_i)$. However, the variability is different. (5) gives $\text{var}(X_i) \leq \text{var}(W_i)$, while (6) leads to $\text{var}(X_i) \geq \text{var}(W_i)$. So knowing the variability of data may help us choose a plausible model to feature measurement error in X_i.

Related to models (5) and (6), a number of different formats have been developed. For example, for a survey data set Hwang (1986) employed a multiplicative form given by $W_i = X_i e_i$. To preserve the identity of participants, when collecting the data, some predictors X_i that may be used to identify the subject's information have been manipulated by multiplying a random variable e_i, hence, the actual reported measurement is W_i but not X_i. It is easily seen that this multiplicative form can be transformed to an additive form by applying the logarithm. More generally, Eckert, Carroll and Wang (1997) proposed a transformed additive error model

$$h(W_i) = h(X_i) + e_i$$

where $h(.)$ is a monotone transformation function. Taking $h(t) = \log(t)$ gives a multiplicative error model, while setting $h(t) = t$ recovers an additive error model. To accommodate complex error structures, $h(.)$ can assume a form from the Box-Cox transformations, or a form of piecewise polynomial spline function.

Some other models have also been developed to feature complicated characteristics of various error processes. For instance, Li, Shao and Palta (2005) considered a latent model to analyze data arising from a Sleep Cohort Study. Specifically, they assumed

$$W_i = \max(0, L_i + e_i)$$

and

$$X_i = \max(0, L_i),$$

where L_i is a continuous latent variable which links X_i and W_i, and e_i is the measurement error on the latent scale having a certain distribution. Mallick, Hoffman and Carroll (2002) analyzed the data from a study of thyroid disease in relation to fallout from the Nevada test site, and they employed a mixture of the additive error model and the Berkson model to characterize the measurement error process. Specifically, they specified

$$\log(W_i) = \log(L_i) + e_{ic},$$

and

$$\log(X_i) = \log(L_i) + e_{ib},$$

where L_i is a latent variable, and e_{ib} is the Berkson error, independent of e_{ic} that is regarded as a classical error. Other mixture models such as a Berkson type model written as a mixture of additive and multiplicative errors were employed by Stram and Kopecky (2003).

More generally, to address the concern that the measurement error process is subject to possible misspecification, Carroll and Wand (1990) considered a kernel density estimate of the measurement error model. Carroll, Roeder and Wasserman (1999) proposed mixtures of normal distributions to accommodate departures from standard parametric models.

3 Inference Methods

In principle, to analyze data with covariate measurement error we need to jointly model the response variable Y_i and the true covariates X_i and Z_i in combination with the observed version

W_i. Here Z_i denotes precisely observed covariates, such as gender, age and treatment indicator. We may base inference on different factorizations of the joint distribution $f(y_i, x_i, w_i, z_i)$ in the light of inference objectives and the nature of measurement error processes. Often, the central theme of the study is to understand the relationship between the response and the true covariates, i.e., to study $f(y_i|x_i, z_i)$. Distinct measurement error mechanisms can be classified according to the connection between Y_i and W_i. Given the true covariates X_i and Z_i, if Y_i and W_i are independent, then the resulting error mechanism is called a nondifferential error mechanism; otherwise, a differential error mechanism.

A nondifferential error mechanism gives $f(y_i|x_i, w_i, z_i)$=$f(y_i|x_i, z_i)$. Intuitively, it implies that the observed version W_i does not contribute additional information on inference as long as X_i and Z_i are given. Therefore, it would be natural to conduct inference with the factorization

$$\begin{aligned} f(y_i, x_i, w_i, z_i) &= f(y_i|x_i, w_i, z_i)f(x_i, w_i, z_i) \\ &= f(y_i|x_i, z_i)f(x_i, w_i, z_i) \end{aligned} \tag{7}$$

If further decomposing $f(x_i, w_i, z_i)$ in (7), we can write

$$f(x_i, w_i, z_i) = f(w_i|x_i, z_i)f(x_i|z_i)$$

or

$$f(x_i, w_i, z_i) = f(x_i|w_i, z_i)f(w_i|z_i)$$

which facilitates different measurement error models that are discussed in Section 2.2. Sometimes, we base inference on conditioning on X_i, which in a sense X_i is treated as fixed, and thus the distribution of X_i may be left unspecified. This strategy is called a functional method. If X_i is regarded as a random variable or vector whose distribution is specified, then this leads to the so-called structural modeling strategy.

Under a differential error mechanism, the true covariates are not sufficient to explain response variable Y_i. The information carried by the observed measurement W_i can not be ignored. Instead of using factorization (7), we may proceed with

$$f(y_i, x_i, w_i, z_i) = f(w_i|x_i, y_i, z_i)f(y_i|x_i, z_i)f(x_i, z_i)$$

to spell out the response process $f(y_i|x_i, z_i)$ that is of prime interest. This strategy requires modeling the distributions $f(w_i|y_i, x_i, z_i)$, $f(y_i|x_i, z_i)$, and $f(x_i, z_i)$. The model $f(y_i|x_i, z_i)$ can be characterized by standard statistical modeling techniques. $f(x_i, z_i)$ again can be treated by either functional or structural modeling approach based on the inference objectives and the features of data. The difficulty here is to describe the distribution $f(w_i|y_i, x_i, z_i)$ which is often impossible in practice unless there is a validation subsample consisting of measurements for all the variables X_i, Y_i, W_i, and Z_i.

Nondifferential error is often the main theme in the subject of measurement error problems. It is commonly adopted in observational studies or cohort studies where the response variables are often measured after a time point that covariates are already collected. However, in certain situations like retrospective case-control studies, differential error mechanisms often make more sense. For example, in food intake studies, women who have been diagnosed with breast cancer may tend to exaggerate their fat intake, resulting a measurement W_i that is different from the true fat intake X_i, hence the distribution of W_i depends on the disease status Y_i.

There is a large body of inference methods that are devoted to address measurement error problems. These methods mainly differ in the modeling strategy and inference objectives. They also depend on measurement error mechanisms and the availability of data sources that may be used to determine the parameters associated with measurement error processes (e.g., Kim and Saleh 2003b; 2005). In the sequel, I outline several inference strategies that are commonly employed in the literature. For general strategies see Carroll et al. (2006) for a comprehensive discussion.

3.1 Likelihood-based Methods

A likelihood-based method may be viewed as a structural modeling strategy which requires the specification of the distribution of the true covariates X_i. For illustrations, here I discuss the case with nondifferential error when the true covariates X_i not available. If a classical additive error model (5) is assumed, then the likelihood of the observed data can be formulated as

$$f(y_i|w_i, z_i; \beta) \propto \int f(y_i|x_i, z_i; \beta) f(w_i|x_i, z_i) f(x_i|z_i) dx_i;$$

if a Berkson error model is used, we may proceed with

$$f(y_i|w_i, z_i; \beta) \propto \int f(y_i|x_i, z_i; \beta) f(x_i|w_i, z_i) dx_i,$$

where β denotes the parameter vector indexed the response process. Parameter vector β is of prime interest and is often assumed to be distinct from the parameters associated with the measurement error or covariate process which are suppressed in the notation.

These methods are flexible and efficient in dealing with problems concerning covariate measurement error (e.g., Stefanski and Carroll 1990; Schafer and Purdy 1996). However, model robustness is a major concern in this context. Typically, the specification of the distribution of X_i is generally difficult since X_i is often not observable. Furthermore, likelihood methods are often computationally demanding because of the integrals involved.

3.2 Regression Calibration and Simulation-Extrapolation

Functional modeling is appealing in a sense that the distribution of X_i is not needed. Regression calibration and simulation-extrapolation are two methods that are used widely in practice. The idea of regression calibration is to replace the true but unavailable covariates X_i with their conditional expectation given the observed version W_i and error free covariates Z_i. It is expected that, for some models, this replacement resembles the initial model structure. The algorithm is comprised of the following steps. First, regress X_i on (W_i, Z_i) with $E(X_i|W_i, Z_i)=m(W_i, Z_i; \gamma)$, and obtain the estimate $\hat{\gamma}$ of the associated parameter γ. Then replace X_i with $m(W_i, Z_i; \hat{\gamma})$, and run a standard analysis to obtain the estimates for the response parameters β that are of primary interest. Finally, we need to adjust the resulting standard errors to account for the variation induced by estimation of γ, using either the bootstrap or a sandwich method. This algorithm is simple to implement and it turns out to work well for linear and generalized linear models. But it could perform poorly for some nonlinear models (e.g., Carroll and Stefanski 1990, Pierce and Kellerer 2004).

Another useful functional method is the simulation-extrapolation (SIMEX) approach proposed by Cook and Stefanski (1994) for classical error models (5) with e_i following a $N(0, \sigma_e^2)$ distribution, for instant. The SIMEX method consists of two steps - a simulation step and a subsequent extrapolation step. The simulation step establishes the naive estimates for the cases when the variance of the error term for each measurement W_i is inflated by adding additional noise term $\sqrt{\lambda}\sigma_e U$, where λ is a certain nonnegative number, and U is a standard normal variable. The extrapolation step leads to the ideal situation of no measurement error by setting $\lambda = -1$.

The asymptotic properties of the SIMEX estimators are established in Carroll et al. (1996) under the assumption that the exact extrapolation function is known. The idea of the SIMEX method may be illustrated with simple linear regression (1). If replacing X_i with its observed measurement W_i, which is modeled by (2) with the independence assumed between X_i and e_i, then the resulting least squares estimator $\hat{\beta}_x^*$ converges in probability to the limit $\beta_x[\sigma_x^2/(\sigma_x^2 + \sigma_e^2)]$. Intuitively, if replacing X_i with $W_i + \sqrt{\lambda}\sigma_e U$, then the resultant estimator $\hat{\beta}_x^*(b, \lambda)$ converges in probability to $\beta_x[\sigma_x^2/(\sigma_x^2 + (1 + \lambda)\sigma_e^2)]$. If $\lambda = 0$, $\hat{\beta}_x^*(b, 0)$ is just the naive estimator $\hat{\beta}_x^*$. However, if setting $\lambda = -1$, then the correponding limit is identical to the true parameter β_x.

The SIMEX approach is attractive because it does not require modeling the covariate process, and hence the resultant estimators are robust to a possible misspecification of the distribution of covariates. Although computationally time consuming, implementation of the SIMEX method can be readily realized by adapting existing statistical software. A major disadvantage of this method is that in general this method can only yield approximately consistent estimators, as in the actual implementation, only an approximate (rather than exact) extrapolation function can be used in the extrapolation step.

3.3 Estimating Function Methods

Other functional methods include estimating functions approaches such as conditional score functions methods, "corrected" score functions and moment construction methods. Stefanski and Carroll (1987) discussed the conditional score method, where the estimating functions are obtained by conditioning on sufficient statistics for some important models such as linear, logistic, loglinear, and the inverse-gamma. The performance of various estimators, including those obtained from the quasi-score and "corrected" score functions, is investigated by authors such as Kukush, Schneeweiss and Wolf (2004), Kukush and Schneeweiss (2004), and Shklyar, Schneeweiss, and Kukush (2007).

Nakamura (1990) proposed the use of "corrected" score functions, illustrating the method with applications to several practical models (e.g., Gaussian and Poisson), when the measure ment error is additive with a distribution. A "corrected" score function is a function of the observed data (Y_i, W_i, Z_i) such that its expectation with respect to the conditional distribution of W_i given (X_i, Z_i) is equal to the score function based on the distribution of (Y_i, X_i, Z_i). More specifically, if $S(\beta; Y_i, X_i, Z_i)$ is the score function from the true model of Y_i and (X_i, Z_i), and β is the parameter of interest, then any function $S^*(\beta; Y_i, W_i, Z_i)$ of the observed data and parameter β is called a "corrected" score function if $E_{W|(Y,X,Z)}\left[S^*(\beta; Y_i, W_i, Z_i)\right]$=$S(\beta; Y_i, X_i, Z_i)$. Estimation of β may be conducted by solving the equation $\sum_i S^*(\beta; Y_i, W_i, Z_i) = 0$.

Motivated by the EM algorithm for dealing with missing data problems, Wang and Pepe (2000) proposed the expected estimating equation (EEE) and pseudo-EEE methods to handle covariate measurement error when repeated measurements or surrogate variables are available. A key step in the EM algorithm is to solve the equation

$$E\{S(\beta; \text{complete data})|\text{observed data}\} = 0$$

where $S(\beta; \text{complete data})$ denotes the likelihood score function for the entire data, i.e., it is $\sum_i S(\beta; Y_i, X_i, Z_i)$ under the nondifferential error mechanism. Instead of requiring $S(\beta; Y_i, X_i, Z_i)$ be the score function from the true model of Y_i and (X_i, Z_i) , Wang and Pepe (2000) worked on an unbiased estimating function $S(\beta; Y_i, X_i, Z_i)$ constructed from the true model. They defined the EEE estimator as the solution of

$$\sum_i E\left[S(\beta; Y_i, X_i, Z_i)|(Y_i, W_i, Z_i)\right] = 0.$$

This approach is different from that in Carroll and Stefanski (1990) where quasi-likelihood methods are used in conjunction with the regression calibration algorithm.

3.4 Semiparametric and Nonparametric Methods

Sometimes, inference methods are termed semiparametric or nonparametric approaches because of their flavor of semiparametric or nonparametric modeling for a process of response, covariate or measurement error. For instance, Pepe and Fleming (1991) used the empirical estimation of the likelihood to deal with the mismeasured covariate problem with validation data where measurement error is described nonparametrically. Stefanski, Knickerbocker and Carroll (1994) proposed a semiparametric correction for bias caused by measurement error. For recurrent event data with error-contaminated covariates Jiang, Turnbull and Clark (1999) proposed bias correction methods under a semiparametric Poisson process. With validation data Wang (1999) discussed a least squares estimation procedure for partial linear models where the error model is not specified. Kulich and Lin (2000) developed a class of estimating functions for the regression parameters for the additive hazards models with covariates subject to measurement error. Schafer (2001) proposed a semiparametric likelihood analysis for a class of regression models including linear, generalized linear and nonlinear regression models with error-prone covariates. Structural modeling is invoked in which probability distributions are assumed for the response and measurement error processes. The exact distribution form of the error-prone covariates is left unspecified, rather it is estimated by the nonparametric maximum likelihood. For nonparametric regression in the presence of covariate measurement error, Studenmayer and Ruppert (2004) developed a local polynomial estimator with the SIMEX algorithm. For nonlinear regression with predictors subject to Berkson type error Wang (2004) proposed a minimum distance estimation method by using the first two conditional moments of the response variable given the observed predictors. Carroll, Delaigle and Hall (2007) explored nonparametric estimation of regression functions with covariates subject to a mixture of classical and Berkson errors. Other discussions can be found, for instance, in Liang and Wang (2005) and Liang, Wang and Carroll (2007) among others.

4 A Brief Survey of Some Recent Work

4.1 Survival Data

Survival data analysis is often challenged by the presence of measurement error in covariates. Biomarkers such as blood pressure, cholesterol level, and CD4 counts are subject to measurement error. There has been a large number of research papers devoted to handle covariate measurement error for survival data since Prentice (1982) proposed a regression calibration approach for proportional hazards models. Methods for dealing with measurement error can be distinguished according to whether they assume the availability of a validation sample for which both true and mismeasured covariates are observed. When there is no validation sample it is necessary to make assumptions about the measurement error process. In some cases there may be repeat measurements for mismeasured covariates, which allows estimation of measurement error variability.

A few recent references pertaining to these different settings are as follows. Wang et al. (1997) considered regression calibration for the case where there is a validation data set. Hu, Tsiatis and Davidian (1998) developed a likelihood based method that requires the specification of the distribution of the true covariates, but no validation set. Zhou and Wang (2000) used kernel smoothing to estimate the induced hazard function when a validation data set is available, but their approach is not feasible when the dimension of the covariates is large. Huang and Wang (2000) avoided distributional assumption for the error process and proposed a nonparametric approach to deal with the Cox model when repeated measurements on error-prone covariates are available for each subject. Xie, Wang and Prentice (2001) used a least squares estimation method to calibrate the induced hazard function, when repeat measurements are available.

Another often discussed approach is to "correct" estimating functions that apply when there is no measurement error, so as to make them exactly or approximately unbiased in the presence of measurement error with a specified family of distributions. Nakamura (1992) considered an approximate corrected partial likelihood score function to obtain estimators of regression coefficients in the Cox model. Buzas (1998) proposed a similar unbiased score function for regression coefficients. Hu and Lin (2002) extended the work of Nakamura (1992) and Buzas (1998) to obtain consistent estimators for the regression parameters and the baseline cumulative hazard function of the Cox proportional hazards model. Song and Huang (2005) gave a conditional score method for estimating the parameters in the response model. Other discussions include Augustin and Schwarz (2002), Augustin (2004), Li and Ryan (2004, 2006), Yi and Lawless (2007), Küchenhoff, Bender and Langner (2007), Song and Wang (2008), and the references therein.

For multivariate survival models Li and Lin (2000, 2003) discussed clustered survival data with mismeasured covariates using frailty models where the conditional models are specified as the proportional hazards models, given the random effects. Hu and Lin (2004) proposed semiparametric regression methods for multivariate failure times. Greene and Cai (2004) explored the use of the SIMEX procedure to correct bias induced by covariate measurement error.

The emphasis of the most research work above is on the Cox proportional hazards models. Using generalized estimating equations, Cheng and Wang (2001) developed inference procedures for failure time data that are modulated by a general class of linear transformation models. With accelerated failure time models, Yi and He (2006) and He, Yi and Xiong (2007) investigated structural and functional inference methods to account for measurement error effects. Tseng, Hsieh and Wang (2005) explored the joint modelling approach under the accelerated failure time assumption when covariates are assumed to follow a linear mixed effects model with measurement errors.

4.2 Clustered/Longitudinal Data

Covariate measurement error is a common source of bias in analysis of epidemiologic data which are often correlated. These data include clustered data, longitudinal data and multivariate data. There has been substantial research dealing with covariate measurement error in longitudinal studies. With generalized linear models with normal additive covariate measurement errors, Stefanski and Carroll (1987) constructed unbiased estimating functions by conditioning on certain sufficient statistics. Tsiatis and Davidian (2001) adapted this method to jointly model survival and longitudinal data. This idea was also applied by Li, Zhang and Davidian (2004) to analyze longitudinal data with generalized random effects models in which there is no need to make distributional assumptions on random effects.

Within generalized linear mixed models Wang et al. (1998) conducted bias analysis to investigate the impact of ignoring measurement error in covariates, and applied the SIMEX method to correct the resulting bias. Assuming covariates are the regression parameters of random effects models, Wang, Wang and Wang (2000) compared estimators obtained from the pseudo-expected estimating equations, the regression calibration and the refined regression calibration approaches. Buonaccorsi, Demidenko and Tosteson (2000) discussed likelihood based methods for estimation of both the regression parameters and variance components in linear mixed models when a time-dependent covariate is subject to measurement error.

Under nonlinear mixed models, Wang and Davidian (1996) and Tosteson, Buonaccorsi, and Demidenko (1998), among others, explored the effects of measurement error in covariates. Zidek et al.(1998) discussed a nonlinear regression analysis method for clustered data.

Lin and Carroll (2000) considered using the SIMEX approach to correct for measurement error effects in covariates under nonparametric regression models. Wu (2002) developed inference methods to address censored data and error-prone covariates that are postulated by nonlinear mixed models. Recently, Pan, Lin and Zeng (2006) described a structural method using transitional models to modulate the response and covariate processes. Other discussions may be found, for instance, in Higgins, Davidian and Giltinan (1997), Ko and Davidian (2000), Liu and Wu (2007), Yi (2008), and the references therein.

4.3 Binary Data Analysis

In medical research binary data arise commonly. For example, it is often of scientific interest to understand how a certain disease status is related to nutritional, environmental, genetic, and other risk factors. In particular, in epidemiological research case-control studies are typical tools that are used to identify factors contributing to a certain medical condition, represented by a binary variable, say, a disease status. Conditioning on the disease response (e.g., yes or no), we sample a number of subjects to measure the risk factors. Case-control studies enable us to study rare health outcomes without having to follow thousands of subjects, and are therefore generally quick and cheap to conduct. However, these studies are frequently challenged by measurement error or misclassification that is caused by, for instance, imperfect diagnosis instrument.

A number of analysis methods have been developed to address measurement error or misclassification problems arising from case-control studies. For example, Carroll, Gail and Lubin (1993) explored a likelihood method to account for misclassification of a binary covariate under a retrospective logistic model. Roeder, Carroll and Lindsay (1996) discussed a prospective logistic model with covariate measurement error using a semiparametric mixture approach. For matched case-control studies Forbes and Santner (1995) investigated conditional maximum likelihood methods for retrospective studies, while McShane et al. (2001) considered a conditional score procedure with a prospective likelihood formulation. Freedman et al. (2004) proposed the so-called moment reconstruction method and they found this method is superior to the regression calibration method for certain case-control studies. Other discussions may be found, for example, in Armstrong, Whittemore and Howe (1989) and Satten and Kupper (1993).

For ordinary binary response data, Stefanski and Carroll (1985) proposed an inference method for logistic regression with covariates measured with independent normal error. Spiegelman and Casella (1997) explored both parametric and semiparametric inference procedures when validation data are available. Spiegelman, Rosner and Logan (2000) presented efficient maximum likelihood methods to accommodate both measurement error in continuous covariates and misclassification in categorical ones. Huang and Wang (2001) proposed a functional method when replicate measurements for error-prone covariates are available. Typically, they invoked a nonparametric technique to relax the assumption on the error terms. With logistic regression Sugar, Wang and Prentice (2007) compared the strengths and weaknesses of the regression calibration, refined regression calibration and conditional score methods.

5 Discussion

Measurement error may degrade the quality of inference and should be avoided whenever possible. In designing questionnaire or sample survey, for example, properly addressing the questions or involving more experienced interviewers may allow us to collect more accurate measurements. But in many situations, it is inevitable that collected measurements contain error due to the nature of the variable, thereby investigators should be aware of the possible bias in the results. In this article we are mainly concerned about measurement error in covariates, especially focusing on life history data. In practice, however, measurement error may arise from response variables as well (e.g., Neuhaus 1999, 2002; Buonaccorsi 1996). This is typical for survey data. There are numerous sources that yield measurement error in variables. These include poor design of questionnaires, difficult and ambiguous concepts, inexperienced interviewers, recall bias, and issue of sensitivity. Biemer and Trewin (1997) gave an overview of the measurement error effects on survey data analysis.

Various methods have been proposed to correct the bias induced by the errors in variables arising from survey sampling. To name a few, Hwang (1986) considered a multiplicative error model to address error involved in some explanatory variables for an energy consumption survey from the United States. When both misclassification and error in variables are present, Sélen (1986) examined a method of adjusting subgroup means. Ekholm and Palmgren (1987) discussed an extension of the generalized linear model to account for misclassification for doubly sampled data. Chua and Fuller (1987) developed a model for the response error associated with reported categorical data. Biemer and Wiesen (2002) discussed latent class analysis for evaluating the error in self-reports of drug use from the US National Household Survey data. Other discussions on misclassification or measurement error for survey data may be found in Biemer et al.(1991), for instance.

As a final comment, there are a large number of research papers addressing measurement error problems under the Bayesian framework. Bayesian analysis of measurement error models has been rapidly developed since Clayton (1992) and Stephens and Dellaprotas (1992). For more detailed discussion see Müller and Roeder (1997), Richardson and Green (2002), and Gustafson (2004, 2005).

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