Measurement Error Properties in an Accelerometer Sample of U.S. Elementary School Children

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Abstract
Measurement error modeling approaches have been used extensively in nutrition studies to estimate distributions of usual dietary intakes by accounting for and adjusting for day-to-day variability and measurement errors in observed intakes. Similar procedures have recently been developed for studies of physical activity and energy expenditure, but applications usually focus on study data obtained from adult populations. In this paper, we use measurement error modeling procedures to estimate the distributions of usual physical activity and the sources of variation in physical activity data collected via accelerometers from a sample of 4th- and 5th-grade U. S. students. The students were part of the Randomized Experiment of Playworks study. We found that most of the variability in the physical activity data was due to intra-individual (day-to-day) variations in measured activity. Conversely, in studies of adult populations, the majority of variability in physical activity was inter-individual variability; intra-individual sources of variations in activity were fairly minimal. Adjustments for measurement errors and other sources of intra-individual variations should be made when estimating usual physical activity outcomes, especially in populations of children.

Key Words: Children, physical activity, measurement error model, intra-individual variation, Playworks

1. Introduction and Review of the Literature

Using measurement error models to account for and adjust for sources of errors and biases in dietary intake outcomes, such as energy intake and intake of food and nutrients, has become a staple of nutritional epidemiology. In 1986, the U.S. National Research Council proposed a simple approach for distinguishing inter-individual and intra-individual variability in dietary intake data (NRC 1986). Subsequently, more advanced statistical adjustment procedures for estimating usual intake outcomes were developed at Iowa State University (Nusser, Carriquiry, Dodd, & Fuller et al. 1996; Nusser, Fuller, & Guenther 1997; Carriquiry 2003), the National Cancer Institute (Kipnis et al. 2003; Tooze et al. 2006; Kipnis et al. 2009; Tooze et al. 2010; Zhang et al. 2011), and elsewhere (Spiegelman, Zhao, & Kim 2005; Rosner, Michels, Chen, & Day 2008). Such methods are commonly utilized for estimating dietary intake outcomes in large-scale studies of foods and nutrients. See, for example, Subar et al. (2003), Thompson et al. (2005), Bailey et al. (2010), Marriot, Cole, & Lee (2009), Krebs-Smith, Guenther, Subar, Kirkpatrick, & Dodd (2010), and Cogswell et al. (2012).

In Figure 1, which is taken from Carriquiry (2003), we illustrate why it is important to adjust for measurement errors and biases in dietary intake data. The solid line in the figure is the estimated distribution for usual daily vitamin B6 intake after adjusting for measurement error. The dashed line is the estimated distribution based on one day of observed measurements. The vertical EAR (estimated average requirement) at 1.1 parallel to the y-axis represents the EAR of vitamin B6 intake. By adjusting for measurement errors, a more accurate assessment of the distribution of vitamin B6 can be made. In this particular example, the adjusted distribution differs from the unadjusted distribution in terms of scale and shape, which leads to different inferences. According to the adjusted distribution, 20 percent of the sample is below the EAR, whereas, according to the unadjusted distribution, 37 percent is estimated to be below the EAR.

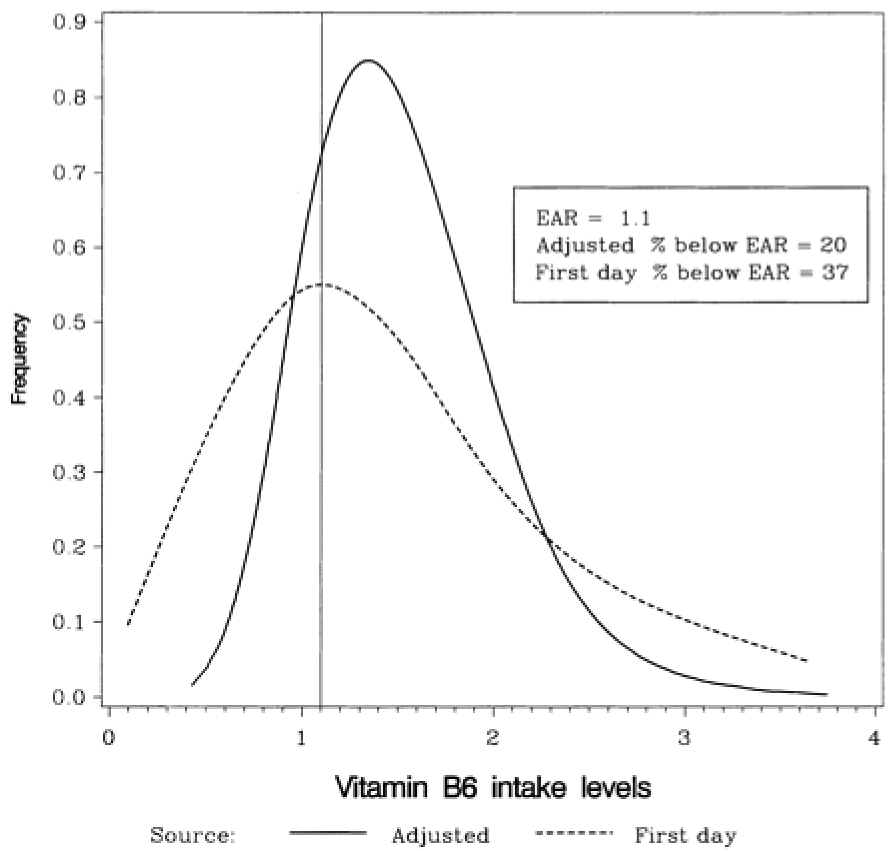

Figure 1: Plot of Adjusted and Unadjusted Vitamin B6 Intakes from Carriquiry (2003)

Recently, measurement error modeling procedures have been proposed for studies of physical activity (Ferrari, Friedenreich, & Matthews 2007; Nusser et al. 2012; Tooze, Troiano, Carroll, Moshfegh, & Freedman 2013). Ferrari and colleagues developed a three-equation measurement error model to estimate validity coefficients and attenuation factors for three instruments used to measure physical activity: accelerometers (which are monitoring devices that measure intensity of activity), physical activity logs, and physical activity questionnaires. The models were fit to physical activity data from a sample of 154 adults from the Alberta Cancer Board Validation Study (Friedenreich et al. 2006). The validity coefficient was highest for the accelerometers (0.81) and smallest for the questionnaires (0.26). The estimated attenuation factor for the questionnaires was also relatively low (0.13), which suggests that associations between physical activity, as measured by questionnaire, and health outcomes would be attenuated by measurement errors. That is, the true associations between physical activity and health outcomes would not be very observable without proper measurement error adjustments.

Nusser et al. (2012) developed a method for estimating distributions of usual daily energy expenditure and illustrated its utility from a sample of 171 women who were part of the Physical Activity Measurement Survey. The women were measured for energy expenditure using 24-hour self-report recalls and SenseWear Pro 3 armband monitors. A two-equation measurement error model was developed to account for and adjust for the measurement errors and other day-to-day variations in energy expenditure measured from these instruments. Estimated distributions functions of usual daily energy expenditure were then compared to distributions based on the observed measurements (without any adjustments). The findings, although illustrative in nature, showed considerable error variation in the 24-hour recall data, and, as with the findings from Ferrari and colleagues, stress the need for statistical adjustments to avoid potential biases in estimated physical activity outcomes. In terms of the objectively measured activity, based on the armband monitors, there was much more inter-individual variability in physical activity than there was intra-individual variability, which is contrary to what is typically observed in nutritional studies, where estimates of intra-individual variability are typically larger than estimates of inter-individual variability.

Like Ferrari and colleagues, Tooze et al. (2013) developed a measurement error model to evaluate physical activity self-report instruments, namely the physical activity questionnaire used in the National Health and Nutrition Examination Survey (NHANES). The authors used data from NHANES and the Observing Protein and Energy Nutrition (OPEN) Study to conduct their analyses. They found modest correlations between questionnaire-based physical activity measurements and true physical activity levels: estimated correlation coefficients ranged from 0.32 to 0.42. They also estimated attenuation factors of 0.43 and 0.73 for women and men, respectively, which were larger than the attenuation factor of 0.13 estimated by Ferrari and colleagues. Just as Nusser et al. (2012) observed, Tooze and colleagues found that most of the variability in the measurements of physical activity was due to inter-individual variation and not intra-individual variations.

The limited literature available on measurement error modeling of physical activity suggests that (a) systematic and random measurement errors do exist, especially in data obtained from self-report instruments; and (b) the majority of variation in physical activity data may be attributed to inter-individual variation in activity, and not so much to intra-individual variations, which include instrument measurement errors and day-to-day deviations in physical activity. These findings, however, are based on data collected from U.S. adult populations. To the best of our knowledge, no study to date has used a measurement error model framework to estimate sources of errors and biases in physical activity data or to estimate usual physical activity distributions from physical activity data measured from populations of U.S. children and adolescents.

In this paper, we use a measurement error modeling approach to estimate sources of errors and variation in physical activity data obtained using accelerometers from a sample of 4th- and 5th-grade students from six U.S. cities who participated in a randomized evaluation study of Playworks. We also use the estimated model parameters to simulate distributions of usual physical activity and compare the distributions to those based on the observed physical activity data. In what follows, we first present the measurement error model for physical activity and describe how we will estimate parameters from the model. We also give a summary of the steps used for estimating usual physical activity distributions (more technical details about the approach are presented in Beyler [2010]). Second, we describe the Playworks study design and provide descriptive statistics of the accelerometer sample used for analyses. Third, we present the key findings based on our measurement error modeling approach. We end with a brief discussion of the findings and how they differ from those of adult samples.

2. A Measurement Error Model for Physical Activity

To estimate sources of measurement error and variations we consider the following measurement error model:

$$X_{ij} = x_i + u_{ij}.$$

In the model, X_{ij} is the observed measurement of physical activity for student *i* on day *j*, where *j* is either 1 or 2 (each child has two days of measurements). The term x_i represents the true, unobserved usual daily physical activity for student *i*. The term u_{ij} is the unobserved measurement error for child *i* on day *j*. This term accounts for any sources of error or variation that would result in the observed measurement (X_{ij}) being different than the usual daily physical activity level (x_i). Differences could exist because of day-to-day variation in physical activity because students are often more (or less) active on some days than others, and because of instrument measurement error. In our analyses, we assume that the x_i terms are independent and normally distributed with a common mean μ_x and common variance σ_x^2. We also assume that the u_{ij} terms are independent and normally distributed with mean 0 and variance σ_u^2. Finally, we assume that the covariance between x_i and u_{ij} is 0 for all *i* and *j*.

To estimate the model parameters μ_x, σ_x^2, and σ_u^2 we consider method of moments estimation. Let

$$\boldsymbol{Z}_i = \binom{\bar{X}_{i.}}{X_{i1} - X_{i2}},$$

where $\bar{X}_{i.}$ is the average of X_{i1} and X_{i2}, and let

$$\boldsymbol{m}_1 = \binom{m_{1,1}}{m_{1,2}}$$

and

$$\boldsymbol{m}_2 = \begin{pmatrix} m_{2,11} & m_{2,12} \\ m_{2,21} & m_{2,22} \end{pmatrix}$$

be the sample mean and variance of the $\boldsymbol{Z}_i$ terms, respectively. Based on the model assumptions described above, it follows that

$$E\{\boldsymbol{m}_1\} = \binom{\mu_x}{0}$$

and

$$E\{\boldsymbol{m}_2\} = \begin{pmatrix} \sigma_x^2 + 0.5\sigma_u^2 & 0 \\ 0 & 2\sigma_u^2 \end{pmatrix}.$$

By equating the sample moments to their expectations, we obtain the method of moments estimators for μ_x, σ_x^2, and σ_u^2:

$$\hat{\mu}_x = m_{1,1},$$

$$\hat{\sigma}_x^2 = m_{2,11} - 0.25m_{2,22}$$

and

$$\hat{\sigma}_u^2 = 0.5m_{2,22},$$

respectively. To estimate the variances for these estimators, we use a Taylor series approximation described in Beyler (2010).

If the estimated inter-individual variance parameter, $\hat{\sigma}_x^2$, is larger than the estimated intra-individual variance parameter, $\hat{\sigma}_u^2$, that would suggest there is more inter-individual variation in the physical activity data than there is intra-individual variation. This was true in the studies conducted on adult samples (Nusser et al. 2012; Tooze et al. 2013). If, instead, $\hat{\sigma}_u^2 > \hat{\sigma}_x^2$, that would suggest there is more intra-individual variation, which is typically the case in dietary intake studies (Carriquiry 2003).

Using the estimated measurement error model parameters, we can also simulate distributions of usual daily physical activity. In the normal scale, we assume that usual daily physical activity values are independently distributed as $x_i \sim N(\mu_x, \sigma_x^2)$. To estimate a distribution of usual daily physical activity, in the original scale (assuming a transformation was made to approximate normality for model fitting), we can simply simulate x_i values from a normal distribution with mean $\hat{\mu}_x$ and variance $\hat{\sigma}_x^2$. Then we can back-transform the simulated value into the original scale to obtain the estimated distribution function in the original scale. More technical details about such an approach are discussed in Beyler (2010) and also in Nusser et al. (1996) and Dodd et al. (2006).

Before fitting the measurement error model to physical activity data (which are described in the next section), we took additional steps to ensure that the modeling assumptions would be met. First, we checked for "nuisance effects" in data to make sure that variation in the data was not a function of the study design. We checked to make sure that the observation day (day 1 or 2) and the amount of time the student wore the accelerometer were not related to their physical activity levels. Simple regression modeling results suggested that neither nuisance effect was correlated with students' physical activity. Second, we determined, based on preliminary model fittings, that we should fit the measurement error model separately to four subgroups of the student sample based on gender and treatment status (that is, whether the student was in a Playworks school or control school). Preliminary analyses suggested that the model error variances were constant within these four subgroups, which is appropriate because we assume that the u_{ij} terms all have a constant error variance, σ_u^2 within these subgroups. Third, we transformed the data to approximate normality because the physical activity data, in the original scale, were not normally distributed. A power transformation of 0.62 was used to approximate normality. In other studies, a log transformation is typically used to approximate normality (Nusser et al. 2012; Ferrari et al. 2007), but in this case a power transformation was more appropriate.

3. Study Design and Characteristics of the Student Accelerometer Sample

Twenty-nine schools from low-income areas across the U.S. were recruited for the Randomized Experiment of Playworks study, which was conducted by Mathematica Policy Research and John W. Gardner Center at Stanford University. Schools were randomly assigned to implement Playworks or to be part of a control condition. In each school, classrooms were randomly selected to participate in both student and teacher data collection activities. Students from selected 4th- and 5th-grade classrooms (ages 9 to 11) wore accelerometers during recess periods. A sample of 365 students wore accelerometers during recess on two days for at least 10 minutes each day. This sample serves as the basis of our measurement error modeling analyses.

Approximately 51 percent of the 365 students were in treatment schools; the other 49 percent were in control schools. The sample was split evenly across gender (50 percent girls and 50 percent boys). There were more 4th-grade students (58 percent) than 5th-grade students (42 percent). The sample was racially and ethnically diverse. Of the 365 students, about 41 percent identified themselves as Hispanic, 30 percent identified themselves as black, and 22 percent identified themselves as white.

The accelerometers worn by students during recess measured the intensity of the students' movement second by second. The intensity counts were then used to determine the percentage of time students spent in moderate to vigorous activity (MVPA) during recess. Cut points used to distinguish moderate to vigorous activity from all other activity (sedentary and light-intensity activity) came from Edwardson and Gorely (2010). The outcome—the percentage of time spent in MVPA during recess—is the physical activity outcome used in the measurement error modeling analyses.

4. Results

The methods described in Section 2 were used to estimate sources of measurement errors and variations in the accelerometer data. The estimated model parameters for the four sample subgroups are presented in the first section of Table 1. The estimated usual MVPA means (in the transformed scale) vary across subgroups. MVPA tends to be larger in treatment students, compared to control students, and boys, compared to girls. The estimated inter-individual variance components range from 1.46 to 2.96. The estimated intra-individual variance components are much larger, ranging from 5.51 to 10.43. In the bottom portion of Table 1, we estimate the percentage of the total variance that is attributed to inter-individual variation and intra-individual variation based on the estimated variance components. In all subgroups except one (control group girls), 80 percent or more of the total variability is due to intra-individual variations. For control group girls, the percentage of total variability due to intra-individual variations was still well more than 50 percent.

Table 1: Measurement Error Model Parameter Estimates

Status	Control	Treatment	Control	Treatment
Gender	Girls	Girls	Boys	Boys
μ_x Est (SE)	7.72 (0.25)	8.71 (0.25)	8.12 (0.28)	9.28 (0.27)
σ_x^2 Est (SE)	2.96 (0.94)	1.46 (1.02)	2.14 (1.21)	1.62 (1.25)
σ_u^2 Est (SE)	5.51 (0.81)	8.12 (1.21)	8.78 (1.35)	10.43 (1.51)
Inter-Individual Variation	35%	15%	20%	13%
Intra-Individual Variation	65%	85%	80%	87%

A series of estimated distribution functions for MVPA are presented in Figures 2–4. In each figure, the x-axis represents the percentage of time spent in MVPA at recess, and the y-axis gives the probability densities of the distributions. In Figure 2, we present the estimated usual MVPA distributions (after accounting for measurement errors) for the girls in the treatment group and the girls in the control group. The estimated distribution for treatment group girls is shifted to the right, relative to the distribution for control group girls, and there is also less variability in the distribution for treatment group girls. In Figure 3, we present the estimated usual MVPA distributions for the two other subgroups—boys in the treatment and control groups. The distribution functions are similar in terms of their variability, but the treatment group distribution is shifted to the right, relative to the control group distribution, which is expected, given the estimated model parameters in Table 1 where we see that the mean MVPA is larger for treatment group boys than for control group boys.

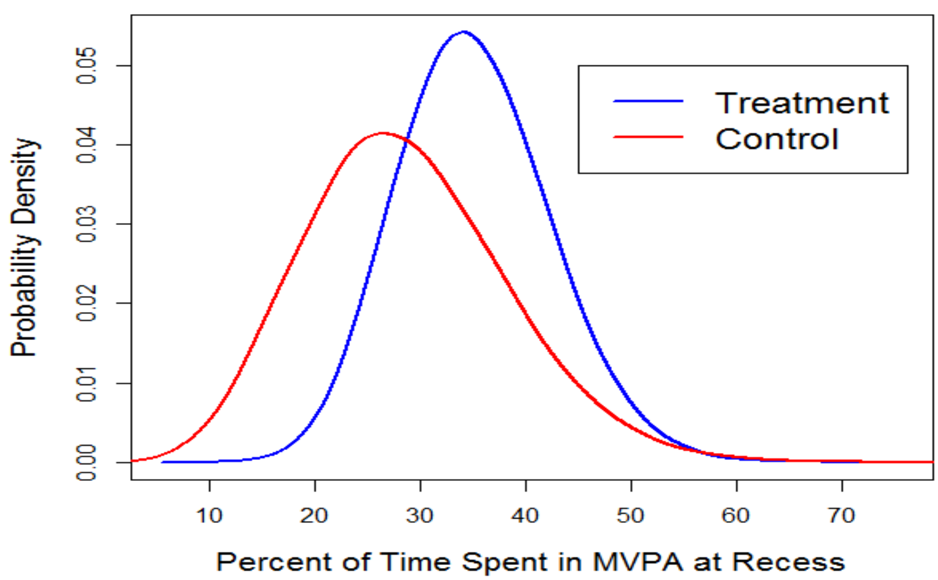

Figure 2: Estimated Usual MVPA Distributions for Girls

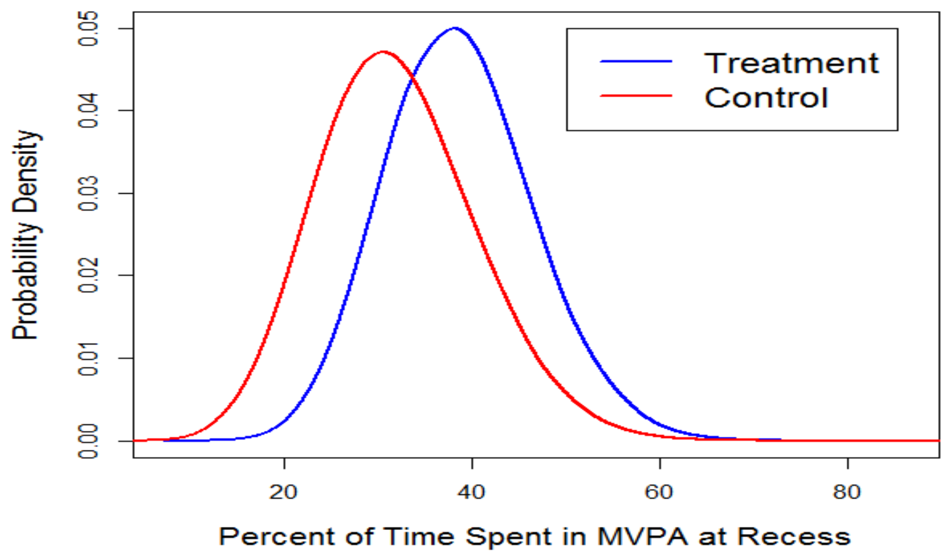

Figure 3: Estimated Usual MVPA Distributions for Boys

In Figure 4, we compare the estimated usual MVPA distribution for treatment group girls to the distribution based on observed (unadjusted) MVPA values for the treatment group girls. The distributions are strikingly different. The vast majority of the density for the usual MVPA distribution, which is adjusted for measurement error, lies between 20 and 50 percent, which would suggest that the vast majority of treatment group girls spend between 20 and 50 percent of their time during recess engaged in moderate to vigorous activity. However, the unadjusted distribution, based on the observed MVPA values, is much more variable and would suggest that the vast majority of treatment group girls spend 0 to 70 percent of their recess time engaged in moderate to vigorous activity.

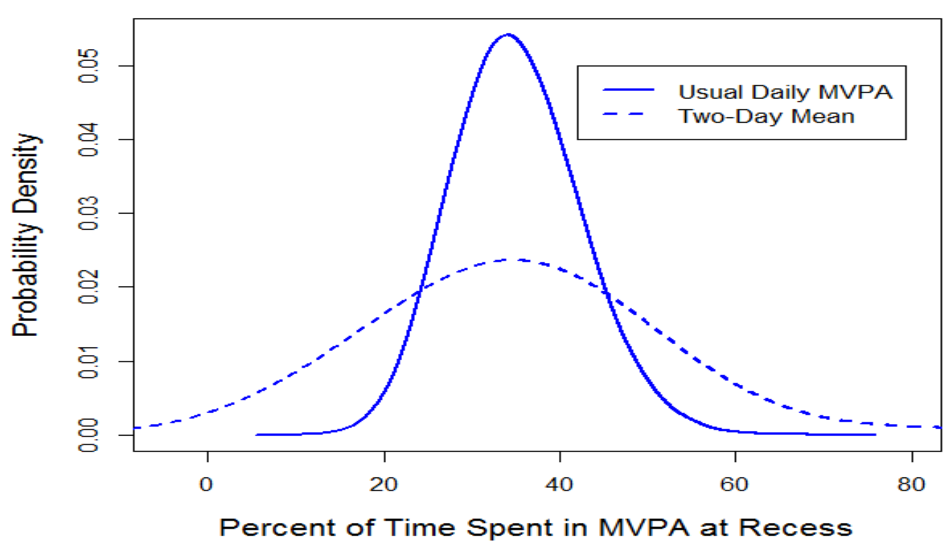

Figure 4: Estimated Distributions for Treatment Group Girls (Adjusted and Unadjusted)

5. Discussion of Findings

The findings presented in Section 4 collectively show how using measurement error modeling can impact estimates of MVPA in an accelerometer sample of 4th- and 5th-grade students (ages 9 to 11). In summary, the results show there is considerably more intra-individual variability—due to day-to-day variations in MVPA and instrument measurement errors—than there is inter-individual variability. This was reflected in the model parameter estimates in Table 1 and Figure 4, which compared a distribution adjusted for intra-individual variations to one that was not. To the best of our knowledge, this is the first set of published findings that uses measurement error modeling approaches to investigate sources of errors and biases in objective physical activity measured from U.S. children and estimate distribution functions for usual physical activity in U.S. children. More research is needed to understand the error and variance properties of physical activity measurement in children so accurate and reliable inferences can be made.

A key finding from this research is that there is considerable intra-individual variability in objective measurements of physical activity in children. This was consistent across subgroups based on gender and treatment status. Similar measurement error modeling approaches that focus on adult samples measured for physical activity found that the majority of variability was inter-individual variability (Nusser et al. 2012; Tooze et al. 2013). There could be a number of potential explanations for this finding. It could imply that children tend to be more sporadic in their physical activity engagement on a day-to-day basis. It could imply that there is more instrument measurement error involved with measuring activity in children than there is with adults. The discrepancies could also just be due, largely, to the fact that the accelerometer data from this study focused on physical activity during recess, and in other studies, the focus is on adult engagement in physical activity over 24-hour periods.

Studies of dietary intake that use measurement error modeling often report considerable intra-individual variability in the dietary intake outcomes (Carriquiry 2003; Tooze et al. 2013). More intra-individual variation often increases the necessity to account for and adjust for such variations in order to avoid inaccurate and unreliable inferences. As with dietary intake studies, we found evidence of considerable intra-individual variations in accelerometer data collected from 4th- and 5th-grade students. These findings should be a clear indication to researchers that it is necessary to account and adjust for measurement errors and intra-individual variability in physical activity data, especially when considering child populations.

References

Bailey, R. L., Dodd, K. W., Goldman, J. A., Gahche, J. J., Dwyer, J. T., Moshfegh, A. J., Sempos, C. T., & Picciano, M. F. (2010). Estimation of total usual calcium and vitamin D intakes in the United States. *The Journal of Nutrition*, 140(4), 817–822.

Beyler, N. K. (2010). *Statistical methods for analyzing physical activity data*. Unpublished doctoral dissertation. Ames, IA: Iowa State University.

Carriquiry, A. L. (2003). Estimation of usual intake distributions of nutrients and foods. *Journal of Nutrition*, 133, 601S–608S.

Cogswell, M. E., Zhang, Z., Carriquiry, A. L., Gunn, J. P., Kuklina, E. V., Saydah, S. H., Yang, Q., & Moshfegh, A. J. (2012). Sodium and potassium intakes among U. S. adults: NHANES 2003–2008. *The American Journal of Clinical Nutrition*, 96(3), 647–657.

Dodd, K. W., Guenther, P. M., Freedman, L. S., Subar, A. F., Kipnis, V., Midthune, D., Tooze, J. A., & Krebs-Smith, S. M. (2006). Statistical methods for estimating usual intake of nutrients and foods: a review of the theory. *Journal of the American Dietetic Association*, 106(10), 1640–1650.

Edwardson, C. L., & Gorely, T. (2010). Epoch length and its effect on physical activity intensity. *Medicine & Science in Sports & Exercise*, 42(5), 928–934.

Ferrari, P., Friedenreich, C., & Matthews, C. E. (2007). The role of measurement error in estimating levels of physical activity. *American Journal of Epidemiology*, 166(7), 832–840.

Friedenreich, C. M., Courneya, K. S., Neilson, H. K., Matthews, C. E., Willis, G., Irwin, M., Troiano R. P., & Ballard-Barbash, R. (2006). Reliability and validity of the past year total physical activity questionnaire. *American Journal of Epidemiology*, 163(10), 959–970.

Kipnis, V., Subar, A. F., Midthune, D., Freedman, L. S., Ballard-Barbash, R., Troiano, R. P., Bingham, S., Schoeller, D. A., Schatzkin, A., & Carroll, R. J. (2003). Structure of dietary measurement error: results of the OPEN Biomarker Study. *American Journal of Epidemiology*, 158, 14–21.

Kipnis, V., Midthune, D., Buckman, D. W., Dodd, K. W., Guenther, P. M., Krebs-Smith, S. M., Subar, A. F., Tooze, J. A., Carroll, R. J., & Freedman, L. S. (2009). Modeling data with excess zeros and measurement error: application to evaluating relationships between episodically consumed foods and health outcomes. *Biometrics*, 65(4), 1003–1010.

Krebs-Smith, S. M., Guenther, P. M., Subar, A. F., Kirkpatrick, S. I., & Dodd, K. W. (2010). Americans do not meet federal dietary recommendations. *The Journal of Nutrition*, 140(10), 1832–1838.

Marriott, B. P., Cole, N., & Lee, E. (2009). National estimates of dietary fructose intake increased from 1977 to 2004 in the United States. *The Journal of Nutrition*, 139(6), 1228S–1235S.

National Research Council (1986). *Nutrient Adequacy*, Washington, DC: National Academy Press.

Nusser, S. M., Carriquiry, A. L, Dodd, K. W., & Fuller, W. A. (1996). A semiparametric transformation approach to estimating usual daily intake distributions. *Journal of the American Statistical Association*, 91(436), 1440–1449.

Nusser, S. M., Fuller, W. A., & Guenther, P. M. (1997). Estimating usual dietary intake distributions: adjusting for measurement error and nonnormality in 24-hour food intake data (689–709). In *Survey Measurement and Data Quality*. New York: Wiley.

Nusser, S. M., Beyler, N. K., Welk, G. J., Carriquiry, A. L., Fuller, W. A., & King, B. M. (2012). Modeling errors in physical activity recall data. *Journal of Physical Activity and Health*, 9(1), S56–S67.

Rosner, B., Michels, K. B., Chen, Y. H., & Day, N. E. (2008). Measurement error for nutritional exposures with correlated measurement error: use of the method of triads in a longitudinal setting. *Statistics in Medicine*, 27, 3466–3489.

Spiegelman, D., Zhao, B., & Kim, J. (2005). Correlated errors in biased surrogates: study designs and methods for measurement error correction. *Statistics in Medicine*, 24, 1657–1682.

Subar, A. F., Kipnis, V., Troiano, R. P., Midthune, D., Schoeller, D. A., Bingham, S., Sharbaugh, C. O., Trabulsi, J., Runswick, S., Ballard-Barbash, R., Sunshine, J., & Schatzkin, A. (2003). Using intake biomarkers to evaluate the extent of dietary misreporting in a large sample of adults: the OPEN study. *American Journal of Epidemiology*, 158(1), 1–13.

Thompson, F. E., Midthune, D., Subar, A. F., McNeel, T., Berrigan, D., & Kipnis, V. (2005). Dietary intake estimates in the National Health Interview Survey, 2000: methodology, results, and interpretation. *Journal of the American Dietetic Association*, 105(3), 352–363.

Tooze, J. A., Midthune, D., Dodd, K. W., Freedman, L. S., Krebs-Smith, S. M., Subar, A. F., Guenther, P. M., Carroll, R. J., & Kipnis, V. (2006). A new statistical method for estimating the usual intake of episodically consumed foods with application to their distribution. *Journal of the American Dietetic Association*, 106(10), 1575–1587.

Tooze, J. A., Kipnis, V., Buckman, D. W., Carroll, R. J., Freedman, L. S., Guenther, P. M., Krebs-Smith S. M., Subar, A. F., & Dodd, K. W. (2010). A mixed-effects model approach for estimating the distribution of usual intake of nutrients: The NCI method. *Statistics in Medicine*, 29(27), 2857–2868.

Tooze, J. A., Troiano, R. P., Carroll, R. J., Moshfegh, A. J., & Freedman, L. S. (2013). A measurement error model for physical activity level as measured by a questionnaire with application to the 1999–2006 NHANES questionnaire. *American Journal of Epidemiology*, published online ahead of print.

Zhang, S., Midthune, D., Guenther, P. M., Krebs-Smith, S. M., Kipnis, V., Dodd, K. W., Buckman, D. W., Tooze, J. A., Freedman, L., & Carroll, R. J. (2011). A new multivariate measurement error model with zero-inflated dietary data, and its application to dietary assessment. *The Annals of Applied Statistics*, 5(2B), 1456.