doi:10.1111/j.2047-6310.2013.00161.x

Targeting childhood obesity in schools: an examination of the stability and utility of the Value Added Index

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Received 29 July 2012; revised 20 December 2012; accepted 15 February 2013

What is already known about this subject

- High rates of childhood obesity and overweight have promoted interest in school-based interventions.
- Procter's Value Added Index (VAI) identifies schools with higher-than-predicted rates of obesity.

What this study adds

- The VAI can be calculated with much simpler techniques than those proposed by Procter and associates.
- VAI data from a span of 4 years indicated that rank orderings of schools vary widely over time.
- This casts doubt on the utility of the VAI measure for targeting policy interventions, and we suggest that using a simpler method would be more effective, especially when obesity rates are high.

Summary

Background: High rates of childhood obesity and overweight have promoted interest in school-based interventions. As a way to identify schools with high unexpected prevalence of obesity and the greatest need, Procter and associates developed a 'Value Added Index' (VAI). It compares rates of obesity in entry level and advanced students in elementary schools, quantifying the extent to which rates for advanced students are higher than what would be expected given entry level rates and socio-demographic characteristics.

Methods: This paper replicates their analysis using data over a 4 year time span from 17 schools in the western United States. Our analysis compared results obtained with the relatively complicated mixed-model approach, which was used by Procter and associates, and a more simple linear regression, which could be easily used by local school officials. Results were also compared across the 4 years for which data were available.

Results: Identical results were found when the two methods were compared. There was little stability in the rank ordering of schools, based on the VAI, from 1 year to another.

Conclusions: Our results cast doubts on the utility of the VAI for policy makers and suggest policy makers consider a universalistic, rather than targeted, approach to interventions.

Keywords: BMI screening, childhood obesity, school policy, value added modelling.

Introduction

The prevalence of child overweight and obesity has increased dramatically over the last three decades across all sectors of the U.S. population, leading to one of the nation's greatest public health challenges. Recent data indicate approximately 17% (or 12.5 million) of children and adolescents aged 2–19 years are obese (1,2). According to Ogden *et al*. (3), 11.9% (95% CI, 9.8–13.9%) of children and adolescents

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aged 2–19 years were at or above the 97th percentile of the BMI-for-age growth charts; 16.9% (95% CI, 14.1–19.6%) were at or above the 95th percentile; and 31.7% (95% CI, 29.2–34.1%) were at or above the 85th percentile of body mass index (BMI) for age. Among school-age children, comparisons of data from NHANES surveys administered in 1976–1980 and 2007–2008 show that the prevalence of obesity has changed from 6.5 to 19.6% among children 6–11 years of age and from 5.0 to 18.1% for those aged 12–19 years (1). Overweight and obesity during childhood and adolescence are associated with the onset of a variety of serious health conditions including type 2 diabetes, hypertension, hyperlipidaemia, fatty liver disease, asthma, sleep apnea and certain types of cancer (4–7). Poor psychosocial adjustments also are associated with obesity among children and adolescents, including lower self-esteem, depression and behavioural problems (8–11).

The recognition of the growing prevalence of overweight and obesity among children led both the American Pediatric Society and the Institute of Medicine to urge schools to assess the BMI of their students and provide the information to parents (12,13). Increasingly schools are being identified as a key setting for public health strategies to lower or prevent the prevalence of overweight and obesity (14), and school-based BMI assessment, for both screening and surveillance, is often considered a potentially important part of a multifaceted strategy for reducing both child and adolescent overweight and obesity (15). According to recent reports, 20 states require BMI or body composition school-based screening of children (16–19). Linchey and Masden's report indicates another nine states recommend some form of BMI screening and found the states requiring BMI screening or fitness assessment had adolescent obesity rates that were higher than states without screening or assessment requirements (17).

In addition to BMI screening, an impressive range of health interventions and prevention programs have been developed and implemented in schools across the country (20). The belief in the importance of public health involvement in schools has also led to a changing academic landscape with a diverse set of staff and health-focused personnel (e.g. mental health workers, peer health advocates) and curriculum initiatives (14,21).

School-based BMI screening and health-related policies and programs have the potential for parental and child health education as well as addressing the increasing levels of disparities of child obesity (18,22–25). Additionally, BMI screening can provide information about school health (26,27) that can assist districts and schools in implementing policies and programs to promote healthy behaviours that are appropriate to districts or specific schools in a district. Policy makers and health organizations have called for states and school districts to enact policies to change the school nutrition and activity environment (27–29). Bethell *et al*. (30) suggest an examination of within and across-state variation in childhood obesity rates is critical to shaping effective national and state-level policy and program responses to prevent and reduce overweight and obesity among children. To date, there has been some evaluation of the effectiveness of these programs; however, research and evaluation design still needs to be strengthened (31–35).

Procter *et al*. (36) suggest that, in light of the current limited information on the efficacy of school-based interventions, it is important to develop a means for identifying schools with the highest unexpected prevalence. This identification could then facilitate resources being targeted to those schools with the greatest need. They describe such a modelling process using measures of demographic characteristics. The model results in a 'Value Added Index' (VAI) that can be used to identify 'hot spots', schools that are most in need of intervention. A higher value indicates that obesity increased relative to the expected value from first grade to the higher grade and suggests that something about the school environment may be involved in increasing obesity. This paper replicates the analysis of Procter *et al*. regarding the use of the VAI to examine the impact of school environments on child obesity and assesses its utility.

This paper also addresses two methodological issues. The first issue involves the way in which the VAI is computed, specifically the use of individual level predictors in a mixed-model (MM) analysis vs. the use of school level predictors in a simple linear regression. Because many students in their sample did not attend schools in their neighbourhood of residence, Procter *et al*. used a MM with both school and individual level indicators of socioeconomic status (SES). However, in the United States such 'open enrollment' is far less common. The two most common types of open enrolment in U.S. public schools are charter schools and magnet schools. Data from the National Center for Educational Statistics indicate that 6.4% of elementary students were enrolled in such schools in 2008–2009, the last year for which data were reported (37). Because at least some of these students would also be from the 'neighborhood', this estimate is probably slightly inflated.

Table 1 Characteristics of schools

School number	% Minority	Aver. enrol.(K-5)	FRL	Walkability score	Walkable description
A.1	33.3	231.5	82.9	74	Very walkable
A.9	14.2	168.5	54.8	9	Car dependent
A.10	19.6	407.5	38.2	31	Car dependent
B.1	17.6	352.0	53.8	54	Somewhat walkable
A.7	15.2	426.5	36.8	35	Car dependent
B.2	34.2	346.0	63.9	46	Car dependent
B.3	37.9	363.0	80.0	48	Car dependent
B.4	13.5	433.0	32.7	23	Car dependent
B.7	21.8	482.7	51.9	31	Car dependent
B.6	13.5	461.3	31.2	23	Car dependent
A.6	23.0	537.5	55.7	42	Car dependent
A.5	42.7	303.0	79.7	82	Very walkable
B.5	20.7	320.5	67.6	48	Car dependent
A.3	34.3	374.0	74.4	69	Somewhat walkable
A.2	31.7	415.5	62.4	66	Somewhat walkable
A.8	29.6	399.5	77.3	63	Somewhat walkable
A.4	35.5	320.0	76.0	68	Somewhat walkable
Summary statistics					
Minimum	13.5	168.5	31.2	9	Car dependent
Maximum	42.7	482.7	82.9	82	Very walkable
Average	25.8	373.1	60.0	47.8	Car dependent

As a result, school and individual level SES indicators are highly intercorrelated, often collinear, making their simultaneous use in a MM problematic. In addition, the computations involved in MMs are complex and require statistical packages and advanced skills. In contrast, linear regressions with only one predictor can be easily calculated on spreadsheets. If the process described by Procter *et al*. is to be widely used, a simpler approach would no doubt be preferable. However, it is important that this simpler approach produce the same results as a more complex approach. Thus, we examine the differences between these two computational approaches and, specifically, the extent to which results from these two approaches produce rankings of schools that are similar.

The second issue involves the extent to which the VAIs are stable from 1 year to another, an issue noted by Procter *et al*. If resources are to be allocated in response to the indices, it is important that they produce stable results. In other words, it is important that the VAI for a given school and, more importantly, the rank ordering of schools in an administrative area, are similar from 1 year to another. We examine this question by looking at data from a range of years and comparing the rank order of schools based on the indices from 1 year to another.

Methods

Sample

The sample for the analysis included students from 17 schools in two school districts in western Oregon. The districts are part of the same metropolitan area and separated by only a few miles. Several schools in the districts were omitted from the analysis because of lack of data. All of the omitted schools were in District A. Two schools were omitted because there were very little data available, two other schools were omitted because they had data for only 1 year or did not have individual level data on race–ethnicity, and data for 1 year for one school were omitted because data for that year were only available for one of the two grades examined.

Summary information on the schools' socio-demographic characteristics was obtained from the Oregon Department of Education and is given in Table 1. It indicates substantial variation in the sample. For instance, the schools ranged in size from less than 200 to almost 500 students in grades K–5, with an average of about 370 students. There was also substantial variation in the race-ethnic composition of the schools and the percentage of students receiving free or reduced lunch. The schools ranged from 13 to over 40% of students belonging to a racial-ethnic minority (mean = 26%). The percentage receiving free or reduced lunch varied from 31 to 83%, with an average of 60%. The sample was about evenly divided between boys and girls. A Web-based 'walkability' measure (http://walkability.com) was used to measure the extent to which the area surrounding the schools was 'car dependent' or 'walker friendly'. The scores are based on standard dimensions such as block size and connectivity and vary on a scale of 1–100, with a high value indicating greater walkability. On average, the schools were classified as 'car dependent', but again displayed substantial variability, with two schools considered to be highly walkable. Given school district attendance policies, very few students attended schools outside their attendance area. That is, they were all 'neighborhood' schools.

Procedures and measures

Students' height and weight were measured at the start of each school year. The 2005 data were obtained through a request for baseline county data made by the county Health Department, a child obesity coalition with the assistance of a paediatrician and a nutritional anthropologist. A letter from these organizations and individuals was sent to all school districts in the county. Administrators or staffs (primarily school nurses) who were interested in participating sent data from their health screening to Moreno-Black for analysis. Some schools were interested in continuing to receive analysis from their screenings and voluntarily supplied the information to Moreno-Black during the 2006–2007 to 2008–2009 periods. Each school was responsible for their own data collection and no attempt was made to standardize collection procedures or demographic categories (e.g. ethnicity) throughout the district. The 2008–2009 data from District B were collected by Moreno-Black as part of a separate NIH project focusing on child obesity in one of the school districts. Student IDs were not included in the material sent from the schools for analysis and project ID numbers were assigned to each child, ensuring student confidentiality. Data included gender, date of screening, birth date, grade level (not specific class), height and weight. All of the data were entered into the EPI Info NutStat program for analysis (38). This study was determined to be exempt by the University of Oregon Committee on the Protection of Human Subjects.

Analyzed data were returned to the school nurses and aggregate data were presented at an annual meeting to the principals and elementary staff of each district. Names of specific schools were not made available during these presentations although specific requests were accommodated. All public dissemination of the information was presented only on an aggregate level and no specific schools or school districts were identified.

Data on each student's height, weight, gender and age were used to calculate their BMI. For this analysis, the BMI scores were translated into standard scores (z-scores), which provide a measure of children's weight relative to the national means for their age and sex. In the description below, these are referred to as BMI-Z. The use of z-scores was important in allowing comparisons across grade levels and over time (39) and replicated the procedures used by Procter and associates. The use of z-scores also enhanced the ability to interpret the VAIs, for they are also in standard deviation (SD) units. Given data availability, we focused on grades 1 and 5. Procter *et al*.'s analysis was based on reception class (age 5) and year 4 (age 9) students. Full-day kindergarten is very rare in the districts in our sample, so our age range and the degree of school exposure for the younger cohort are comparable to their sample.

Analysis

Our analysis paralleled that of Procter and associates and was focused on comparing expected and observed BMI values to calculate a VAI. However, our analysis expanded upon their work to address the methodological issues regarding stability of results across methods and time. In other words, our analyses examined the extent to which the rank orderings of schools by VAIs were similar (i) when computed with the MM analysis used by Procter and associates or with a simple linear regression (the comparison across methods); and (ii) from 1 year to another (the comparison across time).

Identifying 'hot' and 'cold' spots via observed obesity measures

We first calculated the 'observed' scores: the average BMI-Z for each grade and year for each school as well as for all years combined. By rank ordering of schools on these average values, 'hot' and 'cold' spots, those with relatively higher and lower BMI-Z-values, could be identified. 'Hot' spots are schools with higher observed BMI-Z-values, while 'cold' spots are those with lower values.

Calculating expected obesity values based on 'at-risk' status

Second, we calculated the average 'expected' BMI-Z values for the schools, based on the students' race–ethnicity, the risk factor most readily available from school records. Two different techniques were used, addressing our first aim of comparing results with different methods. Both approaches used individual students' BMI-Z scores as the dependent variable. The first replicated the work of Procter and associates, using a MM analysis with students' individual race–ethnicity (measured as a simple dummy variable with 1 = minority) as an independent variable and schools as a random effect. The second method was a simple linear regression (ordinary linear regression, or OLS), again using individual BMI-Z as the dependent measure, but the school's average percentage of racial-ethnic minorities as a predictor variable. Although individual measures of receipt of free or reduced lunch were not available, school level data were. The percentage of students receiving free or reduced lunch and the percentage of students of minority status were highly correlated (r = 0.90), suggesting that results would have been identical if free or reduced lunch status had been used as the predictor variable.)

The results of the OLS and MM analyses were then used to calculate the expected BMI-Z values for each student, using the standard equation

$$\text{Pred. BMI-Z} = \text{constant} + b_{re} * \text{RE}, \quad (1)$$

where b_{re} is the regression coefficient and RE refers to race–ethnicity, measured at either the school level or the level of individuals as described above.

Equations were calculated using results with both OLS and MM models and with data across all years combined and for each year separately. Thus, for schools with data in all 4 years, there were five prediction equations for each analysis model (one with data combined across all years and four for the separate years), resulting in nine expected values for each analysis method (five expected values based on the equation using data across all years and four expected values using only data for a given year). For schools with data in only 2 of the 4 years, there were three prediction equations for each model, resulting in five expected values for each analysis model (three based on the equation using data across all years and two using data for a given year).

The resulting predicted values were then used to calculate average expected values (E_i) for each school, i, and grade, j.

$$E_i = \left(\sum \text{Pred. BMI-Z}_{ij}\right)/N_{ij}, \quad (2)$$

where N_{ij} = the enrolment for school i and grade j.

This is simply the average of the predicted scores for each grade and year in each school, the average BMI-Z value that would be expected given students' race–ethnicity (with the MM equations as the basis of prediction) or the percentage of minority students in the school (with the OLS equations as the basis of prediction).

Calculating the Value Added Index

Third, the observed and expected values were used to calculate the VAI developed by Procter and associates. This index is the difference between the observed and expected mean BMI-Z at grade 1 compared with that for grade 5. Following footnote b to Table 1 in Procter *et al*., the VAI was calculated as

$$\text{VAI} = [O_i - E_i]_{Y5} - [O_i - E_i]_{Y1}, \quad (3)$$

where O_i is the observed average (mean) value for school i, E_i is the expected average value for school i, and Y_5 and Y_1 refer to data for grades 5 and 1, respectively. In other words, the VAI simply compares the extent to which the observed and expected values differed in grade 5 to the extent to which they differed in grade 1. A higher value indicates that obesity increased relative to the expected value from first grade to the higher grade; or, alternatively, that the gap between observed and expected values was greater in grade 5 than in grade 1. Following the logic of Procter *et al*., this could indicate that something about the school environment may be involved in increasing obesity.

Comparing across methods and time

We then expanded upon the work of Procter *et al*. by comparing results with our two analysis methods and across different years. Four estimates of a school's VAI were available for each year for which there were data: (i) using the OLS method and all years of data as the basis for the equation; (ii) using OLS but only the data for a given year as the basis for the equation; (iii) using MM and all years of data as the basis for the equation; and (iv) using MM but only data for a given year as the basis for the equation. To examine consistency of results across methods, we used rank–order correlations to compare the relative ranking of the schools when the different regression methods (OLS and MM) were used. To examine stability from 1 year to another, we compared the relative ranking of the schools from 1 year to another. Our use of rank–order correlations in these analyses replicates the work of Procter *et al*. Rank–order correlations are appropriate given the purported aim of highlighting 'hot' and 'cold' spots, the schools on which policy attention and resources should be focused.

Results

We first describe variations among the schools in our sample in observed BMI-Z values, then describe the results obtained with the two different regression techniques (MM and OLS), the variations among schools in expected values and VAIs, and, finally, the stability in results across the two methods and across time.

Observed data

Table 2 summarizes information on the BMI-Z values (the observed data) for each school in the analysis, reporting the minimum and maximum values, mean, SD and sample size for both grade levels. The years for which data were available are summarized in the footnote to the table. One school had data for each of the 4 years, four schools had data for 3 years and the remaining 12 had data for 2 years out of the 4. Almost all of the average BMI-Z scores were positive, indicating scores that were higher than the national average. However, there was substantial variability among the schools. For first graders, average scores ranged from a minimum of –1.3 to a maximum value of +1.6, and average scores for fifth graders ranged from .23 to 1.21. In other words, the schools varied in their average BMI-Z scores by one SD or more, slightly more than reported by Procter *et al*. At the same time, however, the SDs indicate a fair amount of variability within each school, with SDs usually close to 1.0 (the value that would be expected for z-scores). In other words, at each grade level there was substantial variability between the schools, but also within the schools over time.

The ordering of the schools in Table 2 (as well as in Table 1) reflects the average observed rankings for first grade for all years combined. The schools with the lowest observed values are in the top rows and those with the highest values are in the bottom rows. Using the terminology of Procter *et al*., based on the observed data, School A.1 might be seen as a 'cold spot', with a relatively low BMI-Z (average total value of –0.67) while Schools A.8 and A.4 were 'hot spots' with high values (0.94 and 0.95, respectively). The rankings for fifth grade using the data combined over

Table 2 Range of observed BMI-Z by school and grade

School	Mean		SD		Sample size	
	Min	Max	Min	Max	Min	Max
First grade						
A.1	–1.32	–0.04	1.08	1.54	32	32
A.9	–0.05	0.80	0.69	0.91	11	26
A.10	0.36	0.81	0.86	1.34	60	68
B.1	0.44	0.55	0.79	0.86	25	54
A.7	0.50	0.71	0.76	0.95	44	76
B.2	0.09	0.55	0.98	1.05	41	49
B.3	0.45	0.80	1.01	1.93	51	67
B.4	0.66	0.68	0.98	1.16	59	66
B.7	0.47	0.73	1.21	1.43	62	72
B.6	0.57	0.87	0.88	0.95	67	68
A.6	0.36	1.10	0.83	1.00	68	93
A.5	0.35	1.00	0.75	1.36	41	53
B.5	0.53	0.94	0.86	1.02	41	51
A.3	0.63	0.86	0.91	1.03	63	68
A.2	0.61	1.07	1.10	1.11	52	64
A.8	0.80	1.16	0.94	1.12	40	64
A.4	0.54	1.61	0.90	1.04	48	53
Total	–1.32	1.61	0.69	1.93	11	93
Fifth grade						
A.1	0.23	0.65	1.08	1.38	27	43
A.9	0.54	0.61	0.87	1.08	19	38
A.10	0.44	0.68	0.95	1.16	50	73
B.1	0.53	0.77	1.12	1.13	51	52
A.7	0.54	0.78	0.95	1.25	50	85
B.2	0.85	1.06	0.93	1.10	53	53
B.3	0.62	0.88	1.15	1.21	44	61
B.4	0.52	0.78	0.96	1.07	38	69
B.7	0.75	0.80	0.90	0.92	55	74
B.6	0.66	0.71	1.08	1.13	69	76
A.6	0.28	1.15	0.81	1.18	71	84
A.5	0.59	0.86	0.98	1.30	34	50
B.5	0.65	1.01	0.99	1.20	51	53
A.3	0.54	0.95	0.85	1.23	38	70
A.2	0.83	0.95	1.04	1.12	58	63
A.8	0.80	1.11	1.04	1.18	59	63
A.4	0.90	1.21	1.00	1.11	37	41
Total	0.23	1.21	0.81	1.38	19	85

Note: One school (A.10) had data for all 4 years (2005, 2006, 2007 and 2008). Four schools had data for 2006, 2007 and 2008 (A.3, A.4, A.5 and A.7). The remaining schools had data for 2 of the 4 years. All of the schools in District B had data for 2005 and 2008; School A.6 had data for 2006 and 2007; School A.2 had data for 2007 and 2008; and Schools A.1, A.8 and A.9 had data for 2006 and 2008. Values in the 'total' row represent the minimum and maximum values of the descriptive statistics given in each panel of the table.

Table 3 Regressions of BMI-Z on school level and individual level measures of race–ethnicity

	Total	2005	2006	2007	2008
Regressing individual BMI-Z on school level minority					
Coefficients					
Minority % Sch.	0.01	-0.01	0.004	0.02	0.004
Constant	0.57	0.75	0.71	0.20	0.59
R^2	0.002	0.002	0.001	0.02	0.001
Prob. R^2	0.01	0.16	0.34	<.001	0.18
Mixed models with individual race–ethnicity as predictor					
Fixed effects					
Minority	0.25	0.06	0.28	0.21	0.34
Constant	0.61	0.60	0.71	0.65	0.56
Random effects					
Intercept	0.04	0.01	0.05	0.03	0.13
Residual	1.17	1.40	1.01	0.99	1.14
–2LL model	13139	2932	2730	2257	5104
Intercept-only model					
Intercept	0.04	0.01	0.05	0.03	0.13
Residual	1.18	1.40	1.03	1.00	1.16
Fit statistics					
–2LL	13179	2932	2743	2264	5136
Change in LL	40.89	0.32	12.28	7.01	31.40
Corr ratio	0.03	0.01	0.04	0.03	0.10
PRE	0.07	-0.01	0.02	-0.03	0.03
Sample size					
N individuals	4372	922	952	794	1704
N schools	17	8	9	7	16
Minimum N/school	94	94	49	86	45
Max N/school	514	137	152	164	161
Average N/school	257.2	115.3	105.8	113.4	106.5

Note: For the regressions with the school level measure, race–ethnicity was measured as the percentage of students in the school who were non-Hispanic whites. For the mixed-model regressions, race–ethnicity was a dummy variable with 1 indicating the student belonged to a racial-ethnic minority and 0 indicating that the student was non-Hispanic white.

all the years generally paralleled that for first grade, with School A.1 having the smallest average observed value (0.48) and Schools A.8 and A.4 having the largest (0.94 and 1.03).

Regressions

Table 3 summarizes the results of the regression analyses using the two different predictors and the analyses for each year. Results with the OLS analysis are in the top panel, and results with the MM analysis are in the second panel. Results are given for all years combined (the column labelled 'total') and separately for data available for each year. The number of students, the number of schools, and the range and average of the number of students per school for each analysis are given in the bottom panel.

For the OLS analysis, the R-squared values were all quite small, and the regressions were statistically significant for only the total combined analysis and for the 2007 data. The coefficients associated with the percentage minority were positive for four of the five analyses (all but that for 2005). While the results with the MMs cannot be directly compared with those with the school level data, they indicate better fit of the data than the simple linear regressions. When the individual level measure of race–ethnicity was added to the intercept-only models, the fit was significantly better in all cases but the analysis for 2005. (See the change in –2 log likelihood [–2LL] values, which have a chi-square distribution. With d.f. = 1, $P < 0.001$ in all cases but 2005.) In all cases, the fixed coefficients associated with minority status were positive, indicating that minority students had higher BMI-Z scores.

Table 4 Expected values and Value Added Indexes by school

School	Expected value average		Value Added Index				
	Grade 1	Grade 5	Average	Minimum	Maximum	Range	Count
A.1	0.73	0.72	1.14	0.69	1.55	0.87	10
A.9	0.65	0.65	0.23	–0.25	0.65	0.91	10
A.10	0.66	0.66	–0.06	–0.32	0.11	0.43	18
B.1	0.66	0.64	0.17	0.10	0.28	0.18	10
A.7	0.64	0.65	0.06	–0.20	0.28	0.48	14
B.2	0.68	0.69	0.64	0.51	0.76	0.26	10
B.3	0.69	0.69	0.13	0.08	0.18	0.10	10
B.4	0.63	0.64	–0.02	–0.18	0.12	0.30	10
B.7	0.66	0.65	0.19	0.02	0.35	0.33	10
B.6	0.64	0.64	–0.04	–0.16	0.09	0.24	10
A.6	0.68	0.69	0.00	–0.10	0.08	0.19	10
A.5	0.76	0.77	–0.06	–0.25	0.25	0.50	14
B.5	0.66	0.65	0.10	–0.30	0.54	0.84	10
A.3	0.75	0.73	0.04	–0.10	0.12	0.22	14
A.2	0.71	0.70	0.06	–0.12	0.24	0.36	10
A.8	0.72	0.72	–0.01	–0.05	0.03	0.08	10
A.4	0.75	0.73	0.09	–0.71	0.66	1.37	14
Total	0.69	0.68	0.16	–0.71	1.55	0.45	11.4

Note: The minimum and maximum values in the total row are the minimum or maximum in the respective columns; the values for average, range and count for the total rows are the mean values for the columns.

Expected values and Value Added Indexes

The coefficients in Table 3 were used to compute expected values for each student using equation (2). The average expected value for each grade and year was then computed for each school and the VAI was calculated using equation (3). As described above, depending upon the years for which data were available, this resulted in a range of 10–18 estimates of the VAI for each school. The first two columns of Table 4 give the average of the expected values for each grade. Recall that the expected BMI-Zs were calculated from a formula based on data for all students in the analysis. Thus, variations in the expected values from one grade to another within a school reflect differences in the race-ethnic composition of the two grades. As would be expected, the average expected values are very similar across the grades within each school and also relatively similar from one school to another. In general, they range from about one-half to one SD above the mean of zero. Replicating Procter *et al*.'s results, the expected values were positively correlated with the observed values. Using data combined for all years for the observed values and the average of the expected values, rho = 0.41 for first grade and 0.34 for fifth grade.

The VAIs show much more variability, again replicating the results of Procter and associates. Recall that the VAI is based on comparisons of the average expected and observed values – the difference in fifth grade minus the difference in first grade. A positive score indicates that the difference of the observed and expected BMI-Z is larger for fifth graders than for first graders, while a negative score indicates that the difference is greater for first graders or, alternatively, that the observed value is less than the expected value. In short, a positive value indicates that obesity is more problematic for fifth graders than for first graders in a school, even with minority status controlled. Using the value added logic of Procter and associates, this could indicate that something in the school environment is adding to the obesogenic tendencies. Additionally, this result is not totally surprising since recent literature indicates that the prevalence of overweight and obesity increases with age in in these grades (40). Because the observed and expected values used to calculate the VAI are BMI-Z scores, the index can be interpreted in SD terms. Across all of the schools, the VAIs range from –.71 to 1.55, a span that is more than two SDs. Some schools had substantial variation in their VAIs. Four schools had a range of over .80 SD (A.1, A.9, B.5 and A.4). Notably, three of these schools were at the extreme range of observed BMI-Z values in grade

Table 5 Rank–order correlations of Value Added Index across years

Years in comparison	Number of schools	Spearman's rho
2005 and 2008	8	–0.02
2006 and 2008	9	–0.19
2006 and 2007	6	0.42
2007 and 2008	7	–0.81

Note: The Spearman's rho values represent the average of the rank–order correlations obtained over all possible pairs of comparisons.

1, with either the lowest (A.1 and A.9) or highest values (A.4). Some schools had relatively low variation, with a range of VAI scores of .20 or less (B.1, B.3, A.6 and A.8). Again, replicating the results of Procter *et al*., the VAIs had very low associations with the expected values. Rank–order correlations of the VAIs with expected values for first graders ranged from –0.20 to +0.13. Procter *et al*. reported a value of –0.39.

Tests of stability by method and year

Spearman rank–order correlations were first used to examine the stability of the rank ordering of the schools from one analysis approach to another (OLS and MM) and using either data across all years or data from a specific year (see description above). The results were very similar. Fifteen of the 24 correlations were perfect (rho = 1.00) and the others ranged from 0.96 to 0.99. In short, the rank ordering of the schools was virtually identical for the computational methods when using OLS or MM or when using data for all years combined or data for a specific year.

There was much less stability in results over time. Given the availability of data for different years, it was possible to compare the rank ordering in four different pairs of years: 2005 and 2008 (eight schools), 2006 and 2008 (nine schools), 2006 and 2007 (six schools), and 2007 and 2008 (seven schools). Table 5 summarizes the correlations. In contrast to the comparisons across methods, the rank orders varied substantially from 1 year to another. Only one of the four comparisons was positive, that with 2006 and 2007 (average rho = 0.43). Two were near zero and one was strongly negative (2007 and 2008, where the average rho = –0.81). In other words, whether or not a school would be identified as a potential hot or cold spot could vary depending upon when the data were examined. For instance, School A.4 would be identified as a cold spot in 2008, with a VAI of –0.71, but as a hot spot in 2007, with a VAI of 0.66. Similarly, in 2008, School A.9 had a relatively high VAI (0.65), but 2 years earlier it had a negative value of –0.25, one of the lowest in the sample for that year.

Discussion

Given the sharp increase in childhood obesity, schools are receiving increasing attention as an appropriate site for policy interventions. Given budgetary restrictions, it is important that these interventions be targeted at the areas with the greatest need. The VAI developed by Procter and associates is designed to help school administrators and policy makers determine which schools have greater 'value added', i.e. to identify the schools in which the rate of obesity is increasing relatively more over time and thus may be in more need of intervention.

Our analysis, involving data from 17 schools across 4 years, replicated several findings reported by Procter and associates. For instance, our analysis demonstrated that data collected by schools in regular health screenings could be used to calculate the VAI. Results of our calculations were similar to those of Procter and associates. We found strong correlations between observed and expected BMI-Z values and low correlations between the VAI scores and the observed and expected BMI-Z values. Thus, like Procter and associates, our analysis provided data that could allow policy makers to identify hot and cold spots, the schools that appeared to have the greatest change over time from what would be expected.

However, our analysis suggests that these results could be obtained with procedures that were much simpler than those that they used. Analyses using simple linear regressions and school level predictors produced rank orderings of schools that were virtually identical to those obtained with individual level predictors and complex MMs. In other words, analyses that could be obtained with simple spreadsheet software were virtually identical to those that require expensive software and advanced statistical training. Such similarity is noteworthy given the very poor fit of the OLS models to the data and suggests that when the interest is simply rank ordering of schools, rather than individual level predictions, the easily computed OLS-based analyses are more than sufficient.

A more cautionary result involves the stability of rankings of schools from 1 year to another. While our results were stable from one type of analysis technique to another, they were not stable across the years used in the analysis. In other words, the rank

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ordering of schools based on the VAI varied across the 4 years that were included in our analysis. A school identified as a hot spot in 1 year was not necessarily identified as a hot spot in a subsequent year. This could suggest that investing resources based on the index might not be a wise decision, for the indicated target of those funds could vary quite dramatically from 1 year to another.

It should be emphasized that our analysis involved 'neighborhood schools', those in which the student body composition matched that of the neighbourhood. This situation is common in the United States, but unlike the situation in the UK, the site of the Procter *et al*. analysis. In addition, all of the schools in our sample had BMI-Z values that were well above the national norm for all years for the fifth-grade students. Given national trends in childhood obesity, we suspect that such schools are not at all uncommon.

From a school health perspective, understanding the social environmental factors affecting obesity is vital for prevention and promotion of healthy lifestyles. Consequently, it is important for school health professionals, administrators and staff to understand how the school environment may contribute to overweight and obesity. The use of a relatively simple method to identify hot spots within a district would be valuable for examining differences among district schools that may be related to differences in the prevalence of overweight/obesity. Consistent instability over time may be an indicator that obesogenic factors are more related to features outside the school environment, while less instability or consistent rankings may point the way to the need to examine the specific school environment itself.

Finally, in regard to developing policies targeting obesity within a school district, the simplest avenue, at least within school districts with data such as those in our sample, might be using a more universalistic, rather than targeted, approach to interventions. Even though there was variation across schools in BMI-Z as well as in the VAI, all of the schools had higher BMI-Z scores than would be expected given the norms. Thus, they all would presumably benefit from intervention. A universalistic approach could also avoid what some might see as a troubling decision related to the use of socio-demographic risk factors in the analysis. The VAI approach uses socio-demographic characteristics, such as race–ethnicity or poverty status, to determine the expected risk of obesity and then suggests that resources should be targeted at those schools where BMI-Z departs from this expected level. However, we suggest the most beneficial approach for school districts would be to examine the prevalence rates over time using the OLS method rather than the more complex MM approach to calculating the VAI used by Procter and associates. Districts could then use a more qualitative or in-depth analysis, in which they would look at the consistency of rankings over time as well as schools' placement in the rankings relative to others. As indicated above, the use of ranking stability as well as absolute rank could provide invaluable insight into trends within the district and guidance for deciding on intervention strategies. Furthermore, since current information points to the trend of higher grades having higher prevalence of obesity, as also shown in this analysis, we suggest focusing on intermediary elementary grades such as grade 3 may also be an important component of school planning strategy. Such an approach may especially be of greater value to target schools that have higher obesity rates at both grade levels.

Given the current climate concerning the effects of the school food system, obesogenic aspects of the built environments and school physical activity programs, as well as the general interest in the role schools have in preventing obesity-related health problems, we suggest school policy must go to a deeper place through creating a supportive healthful environment that reaches children and the wider community. Such efforts must include methods that help clarify the way school environments contribute to health problems as well as implementing practices and policies supporting healthy lifestyles.

Conflict of interest statement

No conflict of interest was declared.

Acknowledgements

The authors appreciate the work of Alisha Perry, Aiden Holpuch and Caitlin Turnbull for their assistance with data entry and management. Additionally, the authors appreciate the assistance of the county health department and the staff and administrators of the school districts. We thank the reviewers of the paper for their very helpful comments.

References

1. CDC. Data and statistics. 2012. [WWW document]. URL http://www.cdc.gov/obesity/childhood/data.html (accessed March 25, 2013).

2. O'Malley P, Johnston L, Delva J, Bachman J, Schulenberg J. Variation among American secondary school students by school and school characteristics. *Am J Prev Med* 2007; 33(S1): S187–S194.
3. Ogden C, Carroll M, Curtin L, Lamb M, Flegal K. Prevalence of high body mass index in US children and adolescents, 2007–2008. *JAMA* 2010; 303/3: 242–249.
4. Dietz W. Health consequences of obesity in youth: childhood predictors of adult disease. *Pediatrics Suppl* 1998; 101: S518–S525.
5. Freedman D, Khan L, Dietz W, Srinivasan S, Berenson G. Relationship of childhood overweight to coronary heart disease risk factors in adulthood: the Bogalusa Heart Study. *Pediatrics* 2001; 108: 712–718.
6. Friedlander S, Larkin E, Rosen C, Palermo T, Redline S. Decreased quality of life associated with obesity in school-aged children. *Arch Pediatr Adolesc Med* 2003; 157: 1206–1211.
7. Wang C, McPherson K, Marsh T, Gortmaker S, Brown M. Health and economic burden of the projected obesity trends in the USA and the UK. *Lancet* 2011; 378: 815–825.
8. Farhat T, Iannotti R, Simons-Morton B. Overweight, obesity, youth, and health-risk behaviors. *Am J Prev Med* 2010; 38: 258–267.
9. Mustillo S, Worthman C, Erkanli A, Keeler G, Angold A, Costello E. Obesity and psychiatric disorder: developmental trajectories. *Pediatrics* 2003; 111/4: 851–859.
10. Vila G, Zipper E, Dabbas M, *et al*. Mental disorders in obese children and adolescents. *Psychosom Med* 2004; 66: 387–394.
11. Zametkin A, Zoon C, Klein H, Munson S. Psychiatric aspects of child and adolescent obesity: a review of the past 10 years. *J Am Acad Child Adolesc Psychiatry* 2004; 43/2: 134–150.
12. Krebs N, Jacobson M. Prevention of pediatric overweight and obesity. *Pediatrics* 2003; 112/2: 424–430.
13. Koplan J, Liverman C, Kraak V. *Preventing Childhood Obesity: Health in the Balance*. National Academies Press: Washington, DC, 2005.
14. Story M, Nanney M, Schwartz M. Schools and obesity prevention: creating school environments and policies to promote healthy eating and physical activity. *Milbank Q* 2009; 87/1: 71–100.
15. Thompson J, Card-Higginson P. Arkansas' experience: statewide surveillance and parental information on the child obesity epidemic. *Pediatrics* 2009; 124(S1): S73–S82.
16. Jackson L. Body Mass Index legislation prepared for the Children, Families, Health, and Human Services Interim Committee June 2010. [WWW document]. URL http://leg.mt.gov/content/Committees/Interim/2009_2010/Children_Family/Assigned_Studies/SJR_35/sjr35-bmi-legislation-national.pdf (accessed March 25, 2013).
17. Linchey J, Madsen K. State requirements and recommendations for school-based screenings for body mass index or body composition. *Prev Chronic Dis* 2011; 8: A101. [WWW document]. URL http://www.cdc.gov/pcd/issues/2011/sep/11_0035.htm (accessed March 25, 2013).
18. Nihiser A, Lee S, Wechsler H, *et al*. BMI measurement in schools. *Pediatrics* 2009; 124(S1): S89–S97.
19. National Conference of State Legislatures. 2010. Childhood obesity–2009 update of legislative policy options. Updated January 2010. National Conference of State Legislatures Website. [WWW document]. URL http://www.ncsl.org/?tabid=19776 (accessed July 7, 2011).
20. Silveira J, Taddei J, Guerra P, Nobre M. Effectiveness of school-based nutrition education interventions to prevent and reduce excessive weight gain in children and adolescents: a systematic review. *J Pediatrics* 2011; 87/5: 382–392.
21. Burrows L, Wright J. Prescribing practices: shaping healthy children in schools. *Int J Children's Rights* 2007; 15: 83–98.
22. Madsen K. School-based Body Mass Index screening and parent notification. *Arch Pediatr Adolesc Med* 2011; 165/11: 987–992.
23. McMurty M, Jelian E. Reporting body mass index in the schools: are we missing the mark? *Child and Adolescent Newsletter* 2010; 26/1: 5–7.
24. Soto C, White J. School health initiatives and childhood obesity: BMI screening and reporting. *Policy Polit Nurs Pract* 2010; 11: 108–114.
25. Raczynski J, Thompson J, Phillips M, Ryan K, Cleveland H. Arkansas Act 1220 of 2003 to reduce childhood obesity: its implementation and impact on child and adolescent body mass index. *J Public Health Policy* 2009; 30: S124–S140.
26. Stalter A, Chaudry R, Polivka B. Facilitating factors and barriers to BMI screening in schools. *J Sch Nursing* 2010; 26/4: 320–330.
27. Murkowski L. Preventing obesity in children: the time is right for policy action. *Am J Prev Med* 2007; 33(4S): S167–S168.
28. Harkin T. Preventing childhood obesity: the power of policy and political will. *Am J Prev Med* 2007; 33(4S): S165–S166.
29. IOM. 2012. IOM partners in 'the weight of the nation,' a new national initiative to confront obesity crisis. [WWW document]. URL http://www.iom.edu/Global/News%20Announcements/The-Weight-of-the-Nation.aspx (accessed March 25, 2013).
30. Bethell C, Simpson L, Stumbo S, Carle A, Gombojav N. National, state, and local disparities in childhood obesity. *Health Aff* 2010; 29/3: 347–356.
31. Connelly J, Duaso M, Butler G. A systematic review of controlled trials of interventions to prevent childhood obesity and overweight: a realistic synthesis of the evidence. *Public Health* 2007; 121: 510–517.
32. Kersh R. The politics of obesity: a current assessment and look ahead. *Milbank Q* 2009; 87/1: 295–316.
33. Summerbell C, Waters E, Edmunds L, Kelly S, Brown T, Campbell KJ. Interventions for preventing obesity in children. *Cochrane Database Syst Rev* 2005; (3): CD001871. doi: 10.1002/14651858.CD001871.pub2.

34. Taber D, Chriqui J, Chaloupka F. Geographic disparities in state and district policies targeting youth obesity. *Am J Prev Med* 2011; 41/4: 407–414.
35. Waters E, de Silva-Sanigorski A, Hall B, *et al*. Interventions for preventing obesity in children. *Cochrane Database Syst Rev* 2011; (12): CD001871. doi: 10.1002/14651858.CD001871.pub3.
36. Procter K, Rudolf M, Feltbower R, *et al*. Measuring the school impact on child obesity. *Soc Sc Med* 2008; 67: 341–349.
37. U.S. Department of Education. 2010 National Center for Education Statistics, Core of Data (CCD), 'public elementary/secondary school universe survey,' 1990–91 through 2008–09. [WWW document]. URL http://nces.ed.gov/programs/digest/d10/tables/dt10_100.asp (accessed April 28, 2012), downloaded 4/28/2012.
38. NutStat. 2000. Centers for Disease Control and Prevention, Atlanta, Georgia EpiInfo. [WWW document]. URL http://wwwn.cdc.gov/epiinfo/ (accessed/downloaded April 22, 2005).
39. Must A, Anderson S. Body mass index in children and adolescents: considerations for population-based applications. *Int J Obes* 2006; 30: 590–594.
40. Hughes A, Sherriff A, Lawlor DA, *et al.* Incidence of obesity during childhood and adolescence in a large contemporary cohort. *Prev Med* 2011; 52: 300–304.