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RESEARCH ARTICLE

Ohio Beyond the Mean: Socioeconomic Inequality in Body Mass Index Among Adults 2008-2021

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ABSTRACT

Background: Obesity is a serious public health problem in Ohio. This study evaluated the heterogeneous relationship between socioeconomic status (SES) and body mass index (BMI) across the BMI distribution and examined the evolution of the gradient across time.

Methods: The analyses were conducted using data from the 2008 Ohio Family Health Survey (OFHS) and the 2021 Ohio Medicaid Assessment Survey (OMAS). These surveys are repeated cross-sectional random probability samples of noninstitutionalized adults used to monitor the health and well-being of residential Ohioans. The sample consists of nonpregnant adults aged 19 years and older.

Results: The change in BMI between 2008 and 2021 was most dramatic for women, with the entire distribution shifting to the higher range of values with the largest percentage change occurring at the 75th and 90th percentiles. The results showed a persistent educational and income gradient in BMI especially among women. While the income gradient is steepest at higher levels of BMI, the main impact of educational attainment occurs around the median BMI. The difference across the BMI distribution between those with and without a 4-year degree is most striking among women.

Conclusion: Overall, women experienced the most significant shift in BMI compared to men. However, rates of BMI vary across socioeconomic indicators, with educational attainment having the greatest impact on BMI.

Keywords: Body mass index; Obesity; Health disparities; Socioeconomic inequality; Unconditional quantile regression

INTRODUCTION

In the last 15 years, Ohio experienced one of the steepest increases in the United States in the prevalence of adults with obesity, increasing from 28.1% in 2007 to 38.1% in 2022, making it the seventh most obese state in the union.[1] This is concerning given that obesity has been linked not only to other serious chronic diseases such as hypertension, heart disease, and diabetes, but also to lowered life expectancy.[2-5] Obesity is associated with increased health care expenditures and a decline in economic productivity, with recent estimates suggesting a loss of $20 million annually due to the high rates of obesity among Ohio's labor force.[6,7] At the same time, many studies have found that the burden of obesity falls along a socioeconomic gradient, with excess weight occurring among adults with lower educational attainment or less access to economic resources.[8] However, these studies may mask differences in the relationship between education and obesity at the upper and lower ends of the body mass index (BMI) distribution.

While understanding the prevalence of obesity is essential to monitor population health, this measure may mask differences at the upper and lower end of the BMI distribution. Most studies on the socioeconomic gradient of obesity examine how risk factors are associated with average differences in the prevalence of obesity (ie, using linear regression) or with the odds of obesity (ie, using logistic regression), while relatively few US studies examine whether the socioeconomic gradient varies differentially across the distribution of BMI.[8-10] One exception is a study utilizing multiple years of the National Health and Nutrition Examination Survey (1971-2006). This study found that the strongest relationship between income and BMI occurs at the tails of the BMI distribution such that the gradient was negative at the obesity threshold (BMI in kg/m2 at 30 or higher) and positive at the underweight threshold (BMI < 18.5).[11] However, this study did not consider whether a similar gradient might occur across levels of educational attainment, nor was it able to examine patterns at a subnational level. This is an important omission for 2 reasons. The first reason is that recent research has demonstrated that health inequality is increasing in Ohio, particularly along educational lines.[5] The second reason is that the population of Ohio has experienced a more rapid increase in obesity in recent years compared to most other states, the degree to which may not be reflected in national data that does not allow for state-level investigation. Given these reasons, a study on the evolving socioeconomic gradient of BMI in Ohio is warranted.

Traditional methods of measuring socioeconomic inequalities in the prevalence of obesity typically take a single measure representing the average or mean of the population. For example, in annual reports issued by the Ohio Department of Health, obesity prevalence is captured as the percentage of adults with BMI that places them at or above the obesity threshold (ie, BMI greater than or equal to 30). This mean level is then presented across levels of household income and education.[12] Using this method implies that the relationship between socioeconomic status (SES) and BMI is the same for all adults regardless of body mass. However, focusing on the mean level may mask substantial heterogeneity in the association between BMI and socioeconomic indicators across the population. This paper examines the relationship between 2 critical socioeconomic indicators (educational attainment and income) and BMI across the full range of BMI using unconditional quantile regression (UQR) on a population-based sample of residential Ohioans. A second goal is to examine the evolution of this relationship over time.

METHODS

Data for the study come from the 2008 Ohio Family Health Survey (OFHS) and the 2021 Ohio Medicaid Assessment Survey (OMAS). These data are cross-sectional population-based samples of residential Ohioans that provide valuable information on their health status (including self-reported height and weight), socioeconomic characteristics such as household income and educational attainment, and their use and access to health insurance and health services. More detailed information on the survey procedures and the publicly available data used in this project can be found at https://grc.osu.edu/OMAS. The study population consisted of nonpregnant adults aged 19 years and older, including 48 267 respondents in 2008 and 31 861 respondents in 2021, with valid measures of BMI and SES indicators. A critical advantage of using these data compared with the only other state-based data that includes measures of BMI, the Behavioral Risk Factor Surveillance Survey (BRFSS), concerns sample size. To examine the relationship between our socioeconomic indicators and BMI across the full range of values stratified by sex, a large sample size is needed. The OFHS/OMAS sample is substantially larger than the BRFSS which gives us the statistical power to examine this relationship in Ohio, a state that is particularly burdened by high rates of obesity. Other data that may include measures of BMI, such as the National Health Interview Survey or the National Health and Nutrition Survey do not release state-level identifiers. This analysis was considered exempt by the authors' university institutional review board (IRB). The IRB approved a waiver of the consent process, as this study comprised deidentified, publicly available secondary data.

Empirical Strategy

Unconditional quantile regression was used with BMI as the dependent variable. All models control for age, age-squared, and race/ethnicity. We use an approach developed by Firpo and colleagues based on a linear approximation of the unconditional quantiles through a recentered influence function (RIF).[13] More specifically, the RIF is defined as follows:

$$RIF(y;q_\tau) = q_\tau + \frac{\tau - \mathbf{1}\{y \le q_\tau\}}{f_Y(q_\tau)} \quad (1)$$

where y is BMI, τ indicates a specific quantile (eg, 0.10 or 0.90), q_τ is the value of y at that specific quantile, $1\{y \le q_\tau\}$is a function that equals 1 when a respondent's value of y is less than or equal to the value of y at quantile τ, and 0 otherwise; and $f_Y(q_\tau)$ is the density of y at quantile τ. Once the RIF estimates were obtained, the following regression was then estimated using ordinary least squares (OLS):

$$RIF(y;q_\tau) = X\beta^{UQR} + \varepsilon \quad (2)$$

Importantly, the explanatory variables do not contribute to the transformation of equation (1), even though the Xs in the model change, the interpretation of the estimated effects does not vary across models, so alternative models can be compared.[14] Using UQR allows an examination of how each measure of SES varies in strength and association across the full BMI distribution. Unconditional quantile regression differs from conditional quantile regression in which the interpretation of the coefficients is related to the quantiles of the distributions defined by the covariates (the conditional distribution), instead of the unconditional distribution of BMI.[15] Another advantage of UQR is that the estimates are robust to BMI outliers.[16] Recentered influence function estimates were obtained from both years of the data, and UQR was used to reveal the heterogeneity in the predictors (ie, educational attainment, household income) at various levels of the BMI distribution for 2008 and 2021. Complex sample design weights were applied to all analyses, and missing values were assumed to be missing at random.

Variables

The dependent variable is BMI, defined as an individual's weight divided by their height squared, typically expressed in kg/m^2. We use the natural logarithm transformation of BMI to adjust for skewness and to estimate relative or proportion changes across the full range of values. Supplementary analyses were conducted using BMI without a transformation and the findings were substantively similar. Two measures of SES used to measure the socioeconomic gradient in BMI were educational attainment and equivalized household income. Educational attainment was measured in 4 categories: less than a high school degree, a high school degree or some college, a 2-year associate degree, and a 4-year college degree or higher. The public versions of the OFHS/OMAS do not include a continuous measure of household-income-to-poverty ratio. However, they do include continuous measures of household income, the number of adults, and the number of children. Using this information, we created an equivalence-adjusted household income estimate based on a 3-parameter scale weighted on household size and composition, often used by the United States Census Bureau to measure household income inequality.[17] The 3-parameter adjustment is calculated as follows: One or two adults: scale = (number of adults) 0.5; Single parents: scale = (number of adults + 0.8*first child + 0.5 other children)0.7; All other families: scale = (number of adults + 0.5*number of children)0.7. To standardize across years of the surveys, we defined 5 intervals of equivalence-adjusted household income (ie, lowest 20% to highest 20%). Given that prior research has found a stronger association between socioeconomic indicators and obesity prevalence among women, as compared to men, we stratify the analysis by sex.[8,18] Race/ethnicity was captured as non-Hispanic White, non-Hispanic Black, non-Hispanic of other races, and Hispanic of any race.

RESULTS

Table 1 presents descriptive statistics of changes in percentiles of BMI between 2008 and 2021 for both males and females. Among men, there was almost no change in the left-tail distribution, a minimal shift at the median, and the largest change at the 90th percentile. For women, the change in BMI is more dramatic, with the entire distribution shifting to the right, with the largest percentage change occurring at the 75th and 90th percentiles.

Tables 2 and 3 present the OLS coefficients and the UQR estimates showing the association of the SES variables with logged BMI at the 10th, 25th, 50th, 75th, and 90th percentiles for 2008 and 2021 for males and females, respectively, controlling for age, age-squared, and racial/ethnic group. We set the reference categories as a 4-year college degree and the highest equivalized household income.

Among men (Table 2, Panel A), the OLS estimates do not suggest a 'traditional' SES gradient in BMI, with BMI dropping as educational attainment increases, but a bifurcation between those with and without a 4-year degree. For example, in 2008 the OLS coefficients for less than high school, high school, and associate degree are larger and statistically different from those with a 4-year degree, all else equal, meaning that those with a 4-year degree have lower BMI on average than those with each of the educational categories shown. However, the significance tests between educational categories (ie, high school degree compared with associate degree) show no meaningful differences. On the other hand, the UQR estimates suggest that the gradient was primarily driven at the median BMI or above, where the gradient was steeper at the upper BMI values. To illustrate, in 2008, the OLS estimates show that men lacking a high school degree had a BMI that was, on average, 3% higher than men with at least a 4-year college degree. The OLS estimates are independent of the quantile of BMI considered, so no matter if the respondent has a low or high BMI, the difference between those with the lowest and highest education is roughly 3%. However, the UQR estimates show that the difference between the men with the lowest and the highest educational attainment is much larger as we move to the right tail of the BMI distribution. At the 75th percentile, men lacking a high school degree had a BMI that was 12% higher than men who held at least a 4-year college degree.

The results for 2021 (Table 2, Panel B) show a similar association between education and BMI as found in 2008, with the key differences occurring between men with and without a 4-year college degree. However, the UQR estimates provide some evidence of a positive gradient for men who were close to underweight; those in the 10th percentile with a 4-year degree had a 12% higher BMI than those without a high school degree, illustrating a protective effect of education at the extreme left-tail of the distribution.

Examining the quintiles of equivalence-adjusted household income shows that for both years, most of the differences across income levels are driven by men at the higher levels of BMI, namely the 50th percentile and above. However, among men, there is some evidence of a positive gradient for those below the median BMI (eg, the 10th and 25th quantiles). In 2008 and 2021, men at the highest level of income had relatively higher BMI than men with the lowest income. At the same time, the gradient for men in right-tail of the BMI distribution (the 90th percentile) follows the expected pattern with those at the highest incomes having slightly lower BMI than those at lower incomes. In contrast, the OLS estimates showed minimal differences across income levels,

Table 1. Body Mass Index at Selected Percentiles, 2008 and 2021

	Males				Females			
Percentile	2008	2021	Difference	% Change	2008	2021	Difference	% Change
15^{th}	23.0	23.1	0.09	0.4%	21.5	22.2	0.76	3.5%
30^{th}	25.1	25.1	0.02	0.1%	23.5	24.9	1.35	5.7%
50^{th}	27.3	27.9	0.57	2.1%	26.5	28.3	1.86	7.0%
75^{th}	31.0	32.3	1.27	4.1%	31.0	34.3	3.28	10.6%
90^{th}	35.3	37.4	2.18	6.2%	37.1	41.0	3.89	10.5%

highlighting the importance of examining the gradient across the full BMI distribution.

Among women (Table 3), the protective effect of a 4-year college degree has remained relatively stable across the BMI distribution between 2008 and 2021. The OLS estimates for both years show that women with less than a high school degree had BMI 7% higher than women with a 4-year college degree, on average. However, the UQR estimates reflect a somewhat inverted U-shaped relationship at different parts of the BMI distribution, with the most substantial impact found near the median and less at the extreme ends of the distribution. For example, in 2021, the difference in BMI at the 50th percentile between a woman with a 4-year degree and a woman with less than a high school degree was 26% but was 7% at the 90th percentile.

The gradient of obesity, according to equivalence-adjusted household income, was steeper for women than for men in both years. The OLS estimates show that in 2008 and 2021, women in the lowest income group had a BMI that was, on average, 6% higher

Table 2. Association Between Socioeconomic Status Indicators and Body Mass Index (logged) Among Ohio Males Aged 19 Years and Older, 2008 Ohio Family Health Survey and 2021 Ohio Medicaid Assessment Survey

	OLS estimates (mean difference in BMI)		Unconditional quantile regression estimates (difference in BMI at specific quantiles)									
Panel A: 2008			q10		q25		q50		q75		q90	
Educational attainment												
Less than high school	0.03	***	0.00		0.05		0.12	***	0.12	***	0.07	***
High school or some college	0.03	***	0.03	*	0.06	**	0.11	***	0.09	***	0.06	***
Associate degree	0.04	***	0.05	**	0.09	**	0.13	***	0.13	***	0.07	***
(ref cat: 4-year college degree)												
Equalized household income												
Income 20–lowest income quintile	-0.01	+	-0.10	***	-0.15	***	-0.06	*	0.01		0.05	**
Income 40	0.01		-0.04	*	-0.03		0.02		0.07	**	0.05	**
Income 60	0.01	*	0.00		0.00		0.02		0.04	*	0.04	**
Income 80	0.01		-0.01		0.00		0.02		0.03		0.03	*
(ref cat: highest income quintile)												
Panel B: 2021												
Educational attainment												
Less than high school	-0.01		-0.12	**	-0.08		-0.01		0.06		0.03	
High school or some college	0.03	***	-0.02		0.03		0.12	***	0.14	***	0.08	***
Associate degree	0.03	***	0.03		0.06	*	0.08	*	0.11	***	0.06	**
(ref cat: 4-year college degree)												
Equalized household income												
Income 20–lowest income quintile	0.00		-0.07	**	-0.09	**	0.01		0.03		0.03	
Income 40	0.03	**	-0.01		0.03		0.05		0.09	**	0.09	***
Income 60	0.02	*	0.01		0.02		0.08	*	0.05	+	0.04	*
Income 80	0.02	+	-0.01		0.00		0.04		0.04		0.05	**
(ref cat: highest income quintile)												

+ p < .10, * p < 0.05, ** p < 0.01, *** p < 0.001. Models are weighted and control for age, age-squared and racial/ethnic group.

Table 3. Association Between Socioeconomic Status Indicators and Body Mass Index (logged) Among Ohio Females Aged 19 Years and Older, 2008 Ohio Family Health Survey and 2021 Ohio Medicaid Assessment Survey

	OLS estimates (mean difference in BMI)		Unconditional quantile regression estimates (difference in BMI at specific quantiles)									
Panel A: 2008			q10		q25		q50		q75		q90	
Educational attainment												
Less than high school	0.07	***	0.09	***	0.16	***	0.23	***	0.17	***	0.11	***
High school or some college	0.05	***	0.06	***	0.14	***	0.16	***	0.11	***	0.06	***
Associate degree	0.05	***	0.07	***	0.13	***	0.17	***	0.08	***	0.06	***
(ref cat: 4-year college degree												
Equalized household income												
Income 20–lowest income quintile	0.06	***	0.01		0.09	***	0.16	***	0.17	***	0.11	***
Income 40	0.04	***	0.01		0.07	**	0.13	***	0.12	***	0.03	*
Income 60	0.03	***	0.02		0.09	***	0.09	***	0.09	***	0.04	**
Income 80	0.01		0.01		0.03		0.03		0.04	*	0.00	*
(ref cat: highest income quintile)												
Panel B: 2021												
Educational attainment												
Less than high school	0.07	***	0.03		0.11	**	0.26	***	0.14	***	0.07	**
High school or some college	0.06	***	0.05	**	0.13	***	0.22	***	0.12	***	0.06	***
Associate degree	0.06	***	0.06	***	0.17	***	0.20	***	0.11	***	0.03	*
(ref cat: 4-year college degree												
Equalized household income												
Income 20–lowest income quintile	0.06	***	0.02		0.08	**	0.12	***	0.19	***	0.10	***
Income 40	0.08	***	0.02		0.12	***	0.19	***	0.22	***	0.11	***
Income 60	0.05	***	0.04	*	0.09	***	0.12	***	0.15	***	0.08	***
Income 80	0.03	***	0.01		0.06	**	0.08	**	0.09	***	0.05	***
(ref cat: highest income quintile)												

+ p < .10, * p < 0.05, ** p < 0.01, *** p < 0.001. Models are weighted and control for age, age-squared and racial/ethnic group.

than women in the highest income group. The UQR estimates show substantial heterogeneity for women across the BMI distribution. The gap between the lowest and highest income group was the largest among overweight or obese women (ie, at the 75th percentile), with estimates showing a 17% difference in 2008 and a 19% difference in 2021.

Overall, socioeconomic inequalities in BMI remain a reality in Ohio, but most predominately for women. The OLS estimates show (with the reference categories set as the highest educational attainment and highest income group) a general direction of higher levels of BMI for those with less than a 4-year degree and high BMI at successively lower levels of household income. However, the UQR estimates reflect heterogeneity in these relationships, with stronger associations between SES and BMI at the upper ends of the BMI distribution.

DISCUSSION

The findings from this study demonstrate that BMI has shifted to the right-tail of the distribution in Ohio, particularly for women, with the largest percentage change occurring at or above the 75th percentile. Indeed, the 2021 OMAS shows that 42% of women in Ohio experienced obesity, up from 30% in 2008. However, these rates varied widely across indicators of SES. We found that income had a more substantial impact among women with obesity (ie, at the upper tail of the unconditional BMI distribution). In contrast, education level had the greatest impact on the median level of BMI, particularly in 2021. This increasing importance of education for women's healthy BMI supports recent research on the widening health gap between those with low and high levels of educational attainment. Numerous national studies show that the gains in health and longevity are eroding among those with the least education, and Ohio is no exception.[19,20]

The strengths of this study include a large and sufficient sample size from a population-based sample of Ohioans, which allowed for the examination of socioeconomic gradients across the full range of BMI for males and females separately and across different time periods. Unconditional quantile regression showed changes along with socioeconomic inequalities across the full BMI spectrum. However, this study does have some limitations. The sample size, while sufficient to examine a full range of BMI, did not allow for stratified analyses by racial/ethnic group. Nonetheless, our statistical models controlled for race/ethnicity and age. Another limitation is that the OFHS/OMAS does not include detailed measures such as physical activity, nutrition quality, or local food environment that may affect the distribution of social inequality and BMI. To address this shortcoming, we performed supplemental analyses using a measure of local food environment made available at the county level by the United States Department of Agriculture (USDA) Food Environment Atlas. More specifically, we included a measure of 'food swamps' described as counties with a high-density of restaurants and stores selling high calorie fast/junk foods, relative to more healthy options. Prior research conducted at the county-level has shown that food swamps are associated with prevalence rates of obesity.[21] Because county identifiers are available on the public versions of the 2008 OFHS and the 2021 OMAS, we were able to attach the percentage of food retail outlets that were characterized as food swamps to the county in which the respondents of our samples resided. We included this measure of local food environment in our models and, importantly, the results showing the relationship between SES and BMI remain unchanged. Finally, our results may not be interpreted in terms of causality, given the cross-sectional nature of the data. Nonetheless, the findings suggest income-related and education-related inequalities of excess weight are a reality in Ohio, particularly among women, and this could aggravate the socioeconomic gradient in health even further into the future.

PUBLIC HEALTH IMPLICATIONS

The results presented here support recent calls in the public health literature to extend investigations into population health beyond the average and focus on the determinants of distributions.[22] Here, we demonstrated the importance of examining the socioeconomic gradient in BMI across the full range of the distribution, finding larger effect sizes in the right tail. By limiting research to often used overweight or obesity cut points and estimating just average effects through linear regression, we underestimate the effects of SES, particularly among those in the worst health (ie, those at upper levels of BMI). This clouds our understanding of how to target obesity prevention programs. Our findings also point to the widening gap in BMI among women by educational attainment, particularly the gap between those with a 4-year college degree and those without.

Education serves a dual role as both a driver of opportunity and a reproducer of health inequality.[23] State-level investment in education and the health and well-being of children early in the life course could disrupt the expanding health inequality found in Ohio. For example, the Ohio Healthy Programs (OHP) initiative supports training on healthy eating and physical activity for young children in childcare settings with the goal of reducing obesity and preventing later physical and mental health problems. More research is needed on the long-term impacts of programs such as these in Ohio, as they could inform future models and interventions across all ages.

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Author Contribution

Kelly Stamper Balistreri: literature review, designed the study, data analysis, manuscript drafting/editing. Rachael Ioele: literature review, manuscript drafting/editing.

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