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Partially Adaptive Econometric Methods and the Modern Obesity Epidemic

Abstract

Assumptions about explanatory variables and errors are central in regression analysis. For example, the well-known method of ordinary least squares yields consistent and efficient estimators if the underlying error terms are independently, identically, and normally distributed. Additionally, the conditional distribution of the dependent variable is symmetric. The modern obesity epidemic is a well-known health dilemma where the BMI distribution was initially positively skewed but has become more symmetric, which may affect inferences about health and public resource allocation. This study applies partially adaptive estimation methods with flexible error distributions to account for possible skewness and leptokurtosis in the distribution of BMI.

JEL-Codes: C100, D130, J130.

Keywords: obesity epidemic, partially adaptive estimation, skewed generalized T distribution.

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I. Introduction

Few areas in health, statistics, and applied social sciences have attracted as much attention as the modern obesity epidemic. Obesity is generally measured according to the body mass index (BMI), which is weight in kilograms divided by height in meters squared, and the obesity epidemic is illustrated by the BMI distribution becoming less positively skewed. This flattening out of the BMI distribution is a public health concern because excess body weight—obesity—has negative health outcomes, which strains public resources and increases the cost of providing health. Regression analysis is one technique used to measure factors associated with increasing BMIs, and least squares (OLS) is the standard upon which numerous inferences are based. While not minimizing the conclusions derived from traditional least squares, use of the method is conditional on the properties of the error distribution. Least squares estimates are unbiased and have minimum variance among all linear estimates when the errors are independently and identically distributed and when the errors are orthogonal to the regressors, however is inefficient when errors are not distributed normally. When regression model errors are assumed to be from the normal distribution, the mean and variance summarize the distribution but this assumption is not valid for data which are skewed or have thick tails. In such cases, adaptive methods that assume greater flexibility may be appropriate.

Body mass index values reflect current net nutrition, and increasing BMIs causes concerns among health practitioners and public policy makers because high BMIs and obesity are related to a host of negative health outcomes (Atlas, 2011, pp. 103-107). While not naturally overweight and obese, over the past 25 years, populations in developed economies have experienced increased BMIs and obesity (Must and Evans, 2011, p. 13; Calle et al. 1999; Carson, 2016). In modern populations, Waaler (1984) finds an inverted U-shaped relationship between BMIs and mortality. Relative mortality risk is high for populations with BMIs less than 18.5, is low and stable for values between 18.5 and 27, but is high for individuals with BMIs over 27 (Allebeck and Berg, 1992; Andres, Elahis, Tobin, Mueller, and Bryant, 1985; Fogel, 1993; Fogel, 1994; Fogel and Costa, 1997; Koch, 2011; Stevens et al. 1998; McLannahan and Clifton, 2008, p. 17). For BMIs less than 18.5, infectious diseases are common (Calle et al. 1999, p. 1001; Jee et al 2006, p. 783), and for BMIs over 27, higher rates of diabetes, heart disease, high blood pressure, stroke, and certain cancers are common (Atlas, 2011, p. 104; Eckel et al. 2005, pp. 1417-1421; Popkin, 2009, p. 113). Costa (1993, p. 442) and Henderson (2005, p. 346) show this relationship is stable overtime, and Jee et al (2006) show the relationship is stable across ethnic groups. The explicit costs of obesity are also prohibitive with considerable social implications. In the early 2000s, the annual cost of obesity on the US health care system was around $150 billion per annum (Cawley, 2011, p. 1) and was responsible for 9.1 percent of annual medical spending (Finkelstein and Yang, 2011, p. 497). The cost to government provided health services is similarly affected. In 2004, the average tax payer was responsible for around $175 per person to cover obesity related medical expenditures (Finkelstein et al. 2003; Finkelstein et al. 2004), and Medicaid and Medicare spending would have been between 8.5 and 11.8 percent lower in the absence of obesity (Finkelstein and Yang, 2011, p. 498).

It is against this backdrop that this study considers two questions regarding the shape of the BMI distribution and appropriate regression models used in obesity research. First, during the mid-1980s and early 2000s when BMIs increased markedly, what is the appropriate assumption regarding regression model error terms? Using a linked data set from the National Longitudinal Survey, the Skewed Generalized t error performs better than other partially adaptive models when assessed with loglikelihood functions, and more flexible models with additional parameters outperform more restrictive models. Second, assuming a Skewed Generalized t error distribution, how do BMIs vary with respect to height, demographics, family size, marital status, and early life conditions? There is an inverse relationship between BMI and height, and after accounting for height, women have lower BMIs than men. Nonetheless, women have higher obesity rates, indicating that women have lower body mass, yet because of shorter statures, they are more likely to be classified as obese. During the modern obesity epidemic, high BMIs were associated with larger families during their youth; nevertheless, this family size effect was not significant by middle age.

II. Partially Adaptive Regression Estimation

Partially adaptive estimation allows the errors in a standard regression model to be distributed more flexibly than in a classical normal linear regression model where errors are assumed to be independently, identically, and normally distributed. The standard form of a regression model is

$$Y_i = X_i \beta + \varepsilon_i \qquad (1)$$

where Y_i is the i^{th} observed value of the of dependent variable, X_i is a 1xk vector of the explanatory variables, β is a kx1 vector of unknown coefficients, and ε_i is the error term. Various robust estimation methods are proposed as alternatives to least squares that are less sensitive to the assumptions regarding the error terms.

M-estimation is one robust estimation technique that minimizes an assumed function of errors, $\rho(\varepsilon)$, in the parameter β.

$$\hat{\beta}_M = \arg\min_{\beta} \sum_{i=1}^{N} \rho(Y_i - X_i\beta) \qquad (2)$$

where ρ is a differentiable function of ε. The corresponding influence function is

$$\psi(\varepsilon) = \frac{\partial \rho}{\partial \varepsilon} \qquad (3)$$

which measures the influence of errors with different magnitudes have on the estimator. M-estimators include many estimation methods as special cases. For example, L_p estimators are a special case of the M-estimator, defined by

$$\hat{\beta}_{L_p} = \arg\min_{\beta} \sum_{i=1}^{N} \left|Y_i - X_i\beta\right|^p \qquad (4)$$

with OLS and least absolute deviations (LAD) estimators corresponding to p=2 and 1, respectively. The influence functions corresponding to OLS and LAD are depicted in Figure 1.

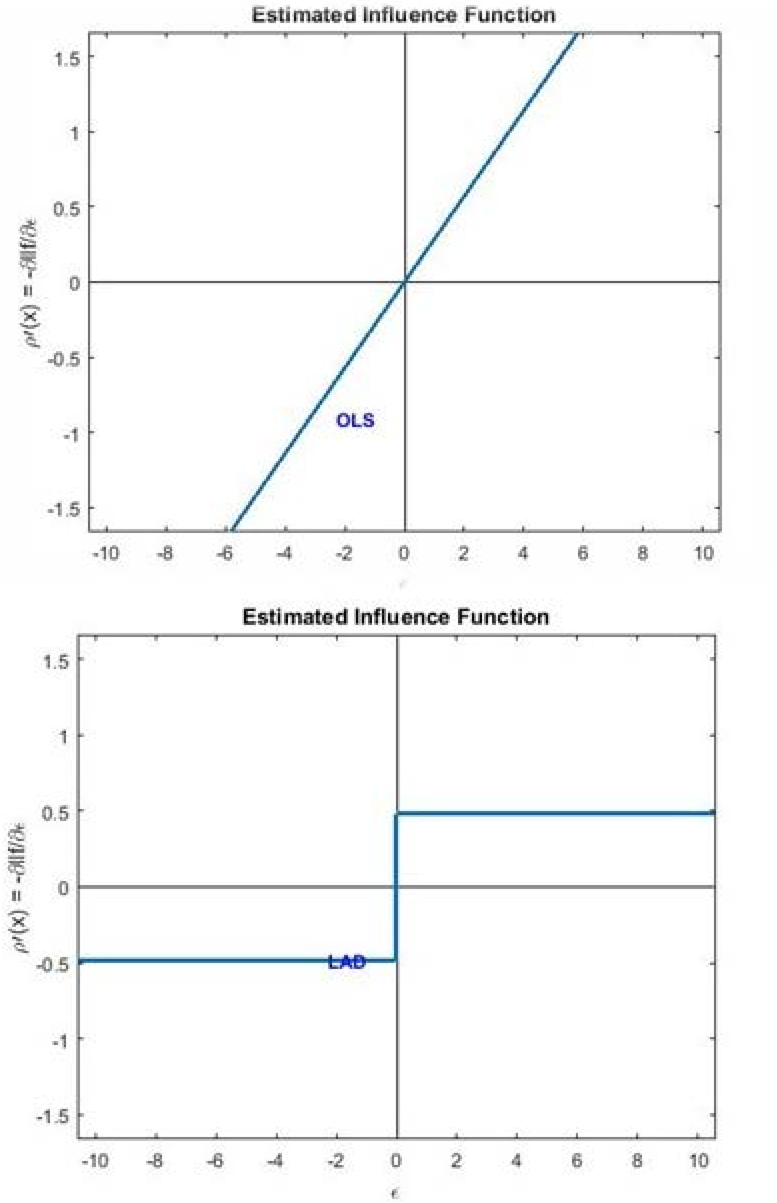

Figure 1 1985 OLS and Laplace Influence Functions

Figure 1 shows that OLS estimators are sensitive to outliers; whereas, LAD is not. Tails of the error distribution are thicker than the normal distribution when p is less than 2, and L_p estimators are applications of the more robust M-estimation technique (Butler et al. 1990, p. 321).

In this study, we use partially adaptive estimation where a more flexible distribution for equation 1's error terms is assumed, which is particularly suitable in BMI studies where the distribution can be skewed.

$$\hat{\beta}_{PAE} = \arg\min_{\beta,\theta} \sum_{i=1}^{N} -\left(\ln f\left(Y_i - X_i\beta;\theta\right)\right) \qquad (5)$$

where $f()$ denotes the probability density function (pdf) of the error term, and θ is vector of distributional parameters. Partially adaptive estimators are maximum likelihood estimators if $f()$ is the correct pdf (Davidson and Mackinnon, 2004, p. 399). This approach allows the influence to adjust to accommodate diverse data characteristics. If $f()$ is a flexible pdf, the corresponding estimators of β can have more desirable properties compared to least squares.

In this paper, we consider the possible advantages of selecting $f()$ to be a flexible 5-parameter distribution, the Skewed Generalized t (SGT) distribution, defined by Theodossiou (1998). The SGT includes many other distributions, including the Generalized t (GT, McDonald and Newey, 1988), the Skewed Generalized Error Distribution (SGED, Theodossiou, 2015), the Generalized Error Distribution (GED), the Laplace Distribution, Normal, and Student-t distribution. How these distributions are related is visualized in Figure 2.

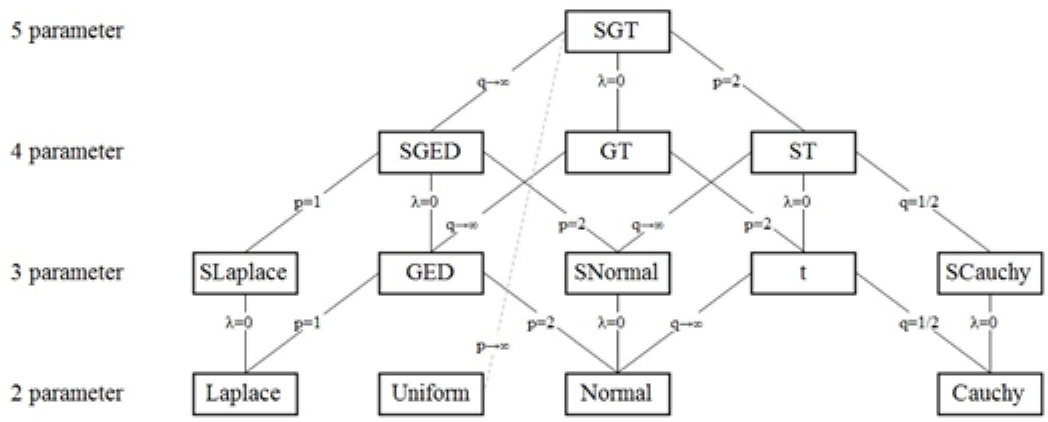

Figure 2 Skewed Generalized T distribution tree

The distributions considered in this study are nested in the SGT. As a generalized distribution, the SGT and subsequent restricted distributions are used in regression models applied in the same format as outlined above. Partially adaptive procedures based on the SGT distribution simultaneously estimate the vector of regression coefficients, β, and the parameters λ, ϕ, p, and q by maximizing the log-likelihood function corresponding to the pdf defined by

$$SGT(y;m,\phi,p,q)=\frac{p}{\left[2\phi q^{1/p}B\left(1/p,q\right)\times\left(1+[y-m]^{p}/\left(1+\lambda sign(y-m)^{p}q\phi^{p}\right)\right)^{q+1/p}\right]} \qquad (6)$$

$$-\infty < y < \infty$$

where B(.,.) is the beta function. m is the mode of y. The parameter λ $(|\lambda|<1)$ measures the degree of skewness. The distribution is symmetric when λ=0 and is positively or negatively skewed depending on whether λ is positive or negative. The parameter ϕ is a positive scale parameter. Parameters p and q control the height and tails of the distribution (Hansen et al. 2010, p. 157).

As the parameter $p \to \infty$, the SGT approaches the Skewed Generalized Error Distribution (SGED, Theodossiou, 2015).

$$SGED(y; m, \lambda, \phi, p) = \frac{pe^{-\left(|y-m|^p / \left((1+\lambda sign(y-m))^p \phi^p\right)\right)}}{\left[2\phi\Gamma\left(1/p\right)\right]} \quad (7)$$

$$-\infty < y < \infty$$

where $\Gamma\left(1/p\right)$ is a gamma function, p controls the height and tails of the distribution, while λ continues to determine the degree of skewness.

For $\lambda = 0$, the SGT simplifies to the Generalized T distribution (McDonald and Newey, 1988).

$$GT(y; \phi, p, q) = \frac{p}{\left[2\phi q^{1/p} B\left(1/p, q\right)\left(1 + |y|^p / q\phi^p\right)^{q+1/p}\right]} \quad (8)$$

$$-\infty < y < \infty$$

where ϕ is a positive scale parameter, and p and q continue to control the shape of the distribution. As p and q increase, the distribution has thinner tails, and as they decrease the distribution has thicker tails.

The Skewed Generalized T distribution nests other important distributions. When $p = 2$, the SGT is the Skewed T distribution (ST, Hansen, 1994).

$$ST\left(y;\,\phi,p,q\right)=\frac{p}{\left[2\varphi q^{1/2}B\left(\tfrac{1}{2},q\right)\left(1+\left[y\right]^{2}/\left(1+\lambda q\phi^{2}\right)\right)^{q+\frac{1}{2}}\right]} \tag{9}$$

$$-\infty<y<\infty$$

Further limiting cases of the SGT exist. For example, when $p=1$, the SGED is the Skewed Laplace distribution (SLaplace); when λ=0, the SGED is the Generalized Error Distribution (GED); when $q\rightarrow\infty$, the SGED is a Skewed Normal distribution (SNormal). When $q\rightarrow\infty$, the Generalized T approaches the Generalized Error distribution, GED. The GT includes the Student's T distribution when p = 2. The Skewed T is a Skewed Normal distribution when $q\rightarrow\infty$. The ST is the Student T when $\lambda\rightarrow 0$ and a Skewed Cauchy distribution when $q=\frac{1}{2}$.

Each distribution has a corresponding influence function, which measures an error's influence in estimation and is more adaptive the greater the number of parameters. This allows adjusting the assumed error distribution to reflect tail behavior and how errors influence the estimation process. The Skewed Generalized T, Generalized T, Generalized Error and normal distribution's influence functions are

$$\psi_{SGT}\left(\varepsilon,\lambda,\phi,p,d\right)=\left(pq+1\right)sign\left(\varepsilon\right)\left|\varepsilon\right|^{p-1}/\left[q\phi^{p}\left(\left(1+\lambda sign\left(\varepsilon\right)\right)^{p}+\left|\varepsilon\right|^{p}\right)\right] \tag{10}$$

$$\psi_{GT}\left(\varepsilon,\phi,p,q\right)=\left(pq+1\right)sign\left(\varepsilon\right)\left|\varepsilon\right|^{p-1}/\left(q\phi^{p}+\left|\varepsilon\right|^{p}\right) \tag{11}$$

$$\psi_{GED}\left(\varepsilon,p,\phi\right)=p\left|\varepsilon\right|^{p-1}sign\left(\varepsilon\right)/\phi^{p} \tag{12}$$

$$\psi_{Normal}\left(\varepsilon,\,\phi\right)=\frac{2\varepsilon}{\phi^{2}} \tag{13}$$

The shapes of the GT and SGT influence functions corresponding to respective distributions in this analysis are presented in Figure 3.

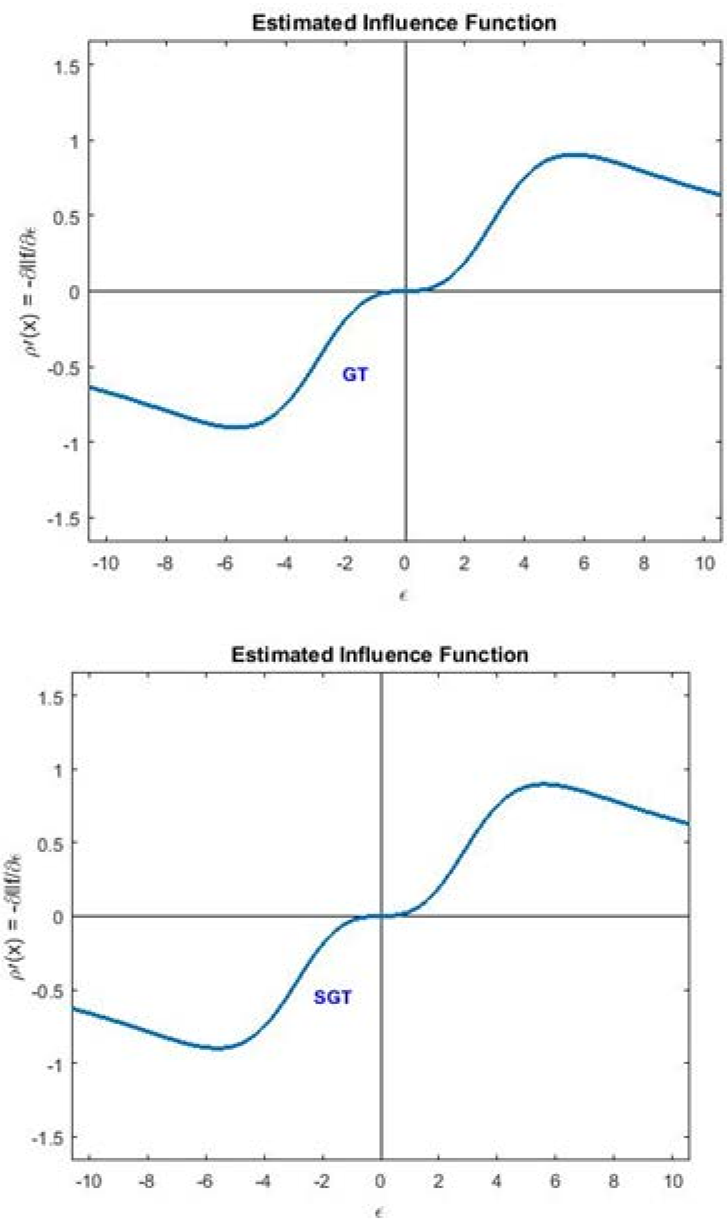

Figure 3 1985 Generalized t and Skewed Generalized t Influence Functions

Whereas OLS gives greater weight to outliers, and LAD gives the same weight to errors. The GT and SGT influence functions initially give greater weight to errors as they vary to accommodate the shape of the error terms. The influence functions of the GT and SGT increase over a range and then descend, consequently discounting large outliers with data determining where the discounting begins.

III. National Labor Survey

Data to analyze the dynamic relationships between body mass, early life conditions, marital status, and family size requires a comprehensive modern BMI data set. The 1979 National Longitudinal Survey of Youth (NLSY79) is one such data set collected for the purpose of analyzing the changing American labor market and is an on-going nationally representative sample of African-Americans, Hispanics, and Non-black/non-Hispanics—primarily whites of European descent. Along with several variables related to labor market outcomes, the NLSY79 survey designers linked weight and height from which BMIs are constructed. Individuals in the NLSY79 were interviewed every two years between 1979 and 2012, and their various characteristics were updated every other year. In 1979, the Bureau of Labor Statistics randomly identified 12,686 young males and females ages 14 to 22 that were born between 1957 and 1964. In 2012, these respondents were between ages 45 and 54. Of the 12,686 individuals in the initial survey, 6,403 are males and 6,283 are females. There are 3,174 African-Americans, 2,002 Hispanic/Latino, and 7,510 mostly white, non-black/non-Hispanics. With few exceptions, all members within each cross-section are available to be interviewed across multiple follow up surveys; however, in no year after 1979 are all individuals available, and successful linkages decrease over time.

Although the purpose of the NLSY79 is to monitor the behavior and event history of the dynamic US labor market in the late 20th and early 21st centuries, the content of the sample is broader. For example, annual update questions include demographic variables, educational attainment, training updates, job and residential status, and various health conditions. For the purpose of this study, height was recorded in 1985 and 2012. Because stature growth still occurred after 1979, we focus our analysis on observations in 1985 and 2012, when individuals reached their adult terminal stature. Additional variables related to BMI values included in this study are age, gender, marital status, family size, urbanization, and ethnic status.

Table 1, 1985 and 2012 BMIs, Family Size, and Urbanization

	1985		*2012*	
BMI				
Mean	23.77		29.23	
S.D.	4.15		6.04	
Skewness	1.51		1.05	
Kurtosis	7.31		4.77	
Centimeters				
Mean	170.40		170.47	
S.D.	10.44		10.42	
Skewness	.040		.091	
Kurtosis	2.61		2.55	
Family Size				
Mean	3.24		2.61	
S.D.	1.95		1.42	
Skewness	1.26		1.18	
Kurtosis	5.52		6.10	
Age				
Mean	23.60		51.32	
S.D.	2.26		2.24	
Skewness	5.12		.145	
Kurtosis	.082		1.93	
	Percent		Percent	
Underweight	4.22		.578	
Normal	62.48		21.19	
Overweight	24.42		36.50	
Obese	8.00		40.73	
	N	**Percent**	**N**	**Percent**
Gender				
Female	5,464	50.53	3,551	51.32
Ethnic Status				
Black	2,822	26.10	2,156	31.16
Hispanic	1,794	16.59	1,328	19.19
Non-Black, Non-Hispanic	6,198	57.31	3,436	49.65
Marital Status				
Married	3,888	35.95	3,765	54.41
Residence				
Urban	7,664	70.87	5,354	77.37
Total	10,814	100.00	6,920	100.00

Source: National Survey of Youth, 1979.

This longitudinal sample allows for detailed comparison across time and space (Table 1). Blacks and Hispanics were smaller portions of the population; however, their composition of the sample increased overtime. For this randomly collected sample, average BMI's increased by 23 percent. Consistent with national BMI studies over the same period, the percent in the overweight and obese categories increased significantly over time that is unexplained by changes in age, demographics, and economic factors (Calle et al. 1999). The percent in the underweight category decreased by 86%; whereas, the percent in the overweight and obese categories increased by 49.0 and 409 percent, respectively. In both 1985 and 2012, there were slightly more females than males, and while non-black, non-Hispanic—primarily whites—are a larger share of the samples, the share of African-Americans and Hispanics increased over time. The percent of the sample that was married increased over time, and like the general population, the share of urban residents increased by around 10 percent. Average height and skewness are similar between 1985 and 2012, while average age increased by 117.5 percent, and average family size decreased by 19.5 percent (Haines, 2000, pp. 307 and 358; Easterlin, 2000). Average age in the 1985 sample was 23.60, while average age in the 2012 sample is 51.32.

The body mass index is the primary means of assessing whether a person is obese, and the World Health Organization has established thresholds to classify obesity status.[1] Ideally obesity would be classified with percent body fat; however, evaluating obesity with advanced techniques is expensive and difficult to acquire, subsequently, this information is non-existent for

[1] Underweight is classified as a BMI under 18.5. Normal weight is a BMI greater or equal to 18.5 but less than 24.9. Overweight is a BMI of 24.9 and less than 29.9. Obesity is a BMI over 29.9. A BMI is classified as morbidly obese if it is over 40.

most populations. As a result, BMI is the standard means to classify obesity because it only requires weight and height. Nonetheless, as a measure, BMI is not without criticism. For example, BMI overestimates weight and obesity for individuals with greater muscular builds, and African-Americans tend to have greater protein and percent muscle mass than white and Asian populations (Schutte et al. 1984; Barondess et al. 1997; Wagner and Heyward, 2000; Aloi et al. 1997). Black BMIs, are subsequently, over-stated using modern WHO standards (Burkhauser and Cawley, 2008, pp. 519-520). Nonetheless, when other means of classifying obesity are unavailable, BMIs provide a reasonable approximation for obese and overweight status.

The shape of the BMI distribution indicates much about a population's current net nutrition. BMIs increase with age; however, the percent of individuals that are obese have increased more rapidly than is accounted for by increases in age. In sum, the BMI distribution has shifted right, become more symmetric, and the increase in obesity exceeds that which is explained by only the increase in age and demographic characteristics.

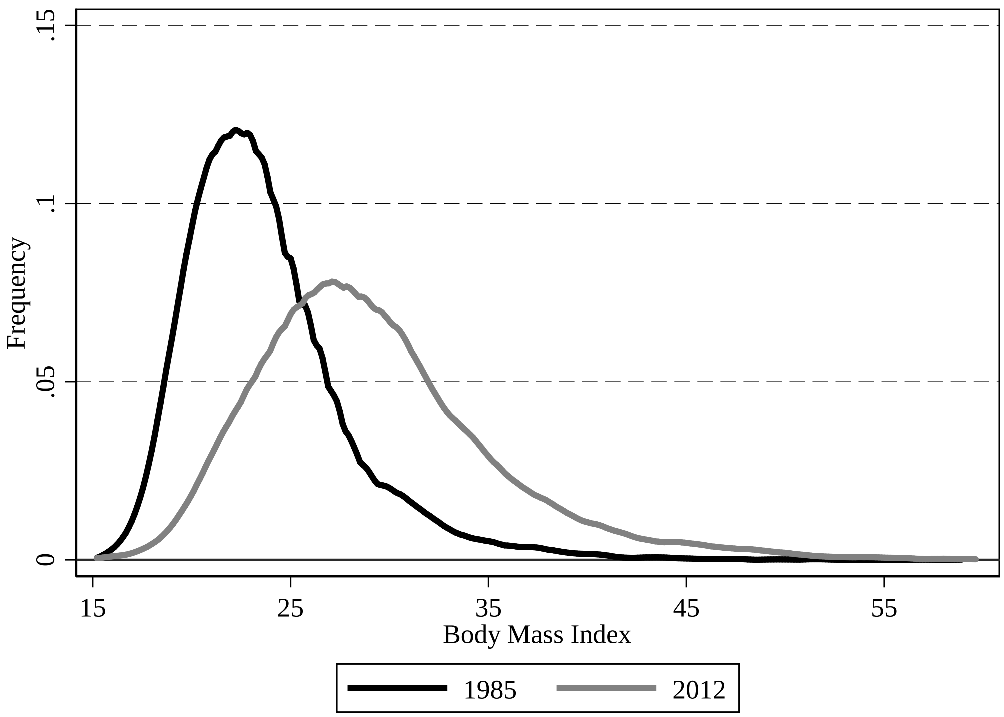

Figure 4, 1985 and 2012 US BMI Distributions

Source: See Table 1

Notes: BMIs are an aggregation of Black, Hispanic, and non-Black, non-Hispanic males and females.

Obesity as a health dilemma is a recent phenomenon, and historical US populations were in the normal BMI category (Carson, 2009; Carson, 2012; Carson, 2016). Figure 4 illustrates that average BMIs increased for individuals in their teens and early 20s in 1985 from 23.77 to 29.23 for the same cohort in 2012 (Flegal et al. 2010; Hales et al. 2018). The World Health Organization had classified BMI categories into four model groups for underweight, normal weight, overweight, and obese. At an average age of 23.6 in 1985, 4.22 percent were underweight, 64.52 percent were in normal weight category, 23.87 percent were overweight, and 8.00 percent were obese. Among the same cohort in 2012 at an average age of 51.32 only .578

percent were underweight, 21.19 percent were in the normal category, 36.50 percent were overweight, and 40.73 percent were obese. Subsequently, among a randomly select-set of individuals in their teens and early 20s in the 1980s, there was an increase of 23 percent for age BMI, and increases of 49.5 (36.5/24.42-1=49.5) and 409 (40.73/8.00-1=4.09) percent increases in the overweight and obese categories.

IV. Partially Adaptive BMI Regression Application

Partially adaptive estimation is now used to evaluate BMIs and the appropriate model for the modern obesity epidemic. Two periods are considered: the mid-1980s when individuals were in their late teens and early 20s, and 2012 when the linked subset is evaluated in their mid-50s.

$$\begin{aligned} BMI_{85} = \theta_0^{85} + \theta_c^{85} Centimeters_i + \theta_F^{85} Female_i + \theta_A^{85} Age_i + \theta_B^{85} Black_i + \theta_H^{85} Hispanic_i + \theta_{FS}^{85} Family\,Size_i \\ + \theta_{FS^2}^{85} Family\,Size_i^2 + \theta_M^{85} Married_i + \theta_{Urban}^{85} Urban_i + \theta_U^{85} Underweight85_i + \theta_O^{85} Obese85_i \\ + \theta_{BF}^{85} Black_i \times Female_i + \theta_{HF}^{85} Hispanic_i \times Female_i + \varepsilon_i^{85} \qquad (14) \end{aligned}$$

and

$$\begin{aligned} BMI_{12} = \theta_0^{12} + \theta_c^{12} Centimeters_i + \theta_F^{12} Female_i + \theta_A^{12} Age_i + \theta_B^{12} Black_i + \theta_H^{12} Hispanic_i + \theta_{FS}^{12} Family\,Size_i \\ + \theta_{FS^2}^{12} Family\,Size_i^2 + \theta_M^{12} Married_i + \theta_{Urban}^{12} Urban_i + \theta_U^{12} Underweight85_i + \theta_O^{12} Obese85_i \\ + \theta_{BF}^{12} Black_i \times Female_i + \theta_{HF}^{12} Hispanic_i \times Female_i + \varepsilon_i^{12} \qquad (15) \end{aligned}$$

Stature in centimeters is included to assess the relationship between BMI and height. A gender dummy variable is included to assess the relationship between BMI and gender. BMIs vary by ethnic status, and dummy variables are included to assess how individuals of African and Mexican decent compare to non-black, non-Hispanics, mostly whites. Although the causal relationship between BMI and marriage is not clear, married individuals have greater BMIs than their non-married counterparts, and a married dummy variable is included to assess the relationship between BMI and marital status (Komlos and Carson, 2017). Family size and family size squared variables are included to account for the relationship between BMI and the number of persons in a household (Carson, 2014). An urban dummy variable is added to account for the relationship between BMI and urban residence. To account for the relationship between early life conditions and BMI and genetics, 1985 underweight and obese dummy variables are included in equations (14) and (15) (McLannahan and Clifton, 2008, pp. 120-121). We now compare and contrast the estimated relationships obtained using the different methods outlined earlier.

The main results of estimating equations (14) and (15), using the partially adaptive procedures corresponding to the alternative error distributions discussed earlier, are reported in Tables 2 and 3. In particular, the coefficient estimators and their standard errors corresponding to a normal (OLS), Laplace (LAD), GED, Student's t, GT, SGED, ST, and SGT error distribution along with their loglikelihood values (l) are reported for the 1985 and 2012 specifications. The first five columns are based on an assumed symmetric error distribution; whereas, the last three columns allow for but don't impose skewness. The estimated distributional parameters for the different years and distributions are reported in Table 4. Comparisons of coefficient estimators across distributional specifications is insightful. The coefficient estimates based on the assumption of a symmetric error distribution are often similar, but frequently differ from estimates obtained using an asymmetric partially adaptive estimation procedure which are in rather close agreement with each other. For example, the estimated coefficients for "female" obtained using a symmetric distribution for 2012 are around 1.0; whereas, the corresponding estimated coefficients are approximately 1.7 when asymmetry is taken account of in the estimation procedure. From Table 4, the estimated skewness coefficient (λ) is seen to be approximately .6 and .4 in 1985 and 2012, respectively. Thus, skewness is significant in both time periods and decreasing over time. This raises the question as which estimates or specification are most appropriate. If the errors are independently and identically normal, OLS will be most efficient, having smaller variances than an over specified model such as the SGT. However, if the error distribution is SGT and differs from the normal, then the standard errors of the SGT-based estimators will be smaller than those obtained using OLS. The relative size of the standard errors observed in Tables 2 and 3 are consistent with this observation. For example, the reported standard errors for the "female" coefficient in (15) is about .229 for OLS and .194 for the SGT specification. A Monte Carlo simulation would provide better evidence of the magnitude of this difference by comparing the distributions of the alternative estimators (McDonald and White, 1993).

Table 2, 1985 Body Mass Index Values by Demographics, Family Size, and Urbanization

1985 DATA	*OLS*	*LAD*	*GED*	*T*	*GT*	*SGED*	*ST*	*SGT*
Intercept	25.364***	25.030***	25.310***	25.221***	25.155***	25.698***	23.792***	25.692***
	(0.701)	(0.706)	(0.698)	(0.690)	(0.675)	(0.535)	(0.544)	(0.525)
Height								
Centimeters	-0.021***	-0.200***	-0.021***	-0.020***	-0.019***	-0.018***	-0.018***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Gender (Male-Reference)								
Female	-1.656***	-1.920***	-1.733***	-1.735***	-1.607***	-1.415***	-1.454***	-1.373***
	(0.087)	(0.088)	(0.087)	(0.086)	(0.086)	(0.069)	(0.068)	(0.069)
Age	0.072***	0.075***	0.073***	0.074***	0.070***	0.048***	0.050***	0.045***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Ethnicity (Non-Black, Non-Hispanic Reference)								
Black	0.050	0.045	0.072	0.068	0.033	0.083	0.092	0.078
	(0.087)	(0.087)	(0.086)	(0.084)	(0.083)	(0.067)	(0.068)	(0.068)
Hispanic	0.397***	0.400***	0.435***	0.434***	0.372***	0.150*	0.158**	0.184**
	(0.104)	(0.104)	(0.104)	(0.102)	(0.098)	(0.078)	(0.079)	(0.077)
Family Size								
Family Size	0.123***	0.136***	0.120***	0.115***	0.105***	0.009	0.011	0.010
	(0.039)	(0.039)	(0.039)	(0.038)	(0.036)	(0.028)	(0.028)	(0.028)
Family Size Squared	-0.012***	-0.014***	-0.012***	-0.011***	-0.011***	-0.003	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Marital Status (Non-married Reference)								
Married	0.191***	0.215***	0.217***	0.219***	0.174***	0.083**	0.087**	0.085**
	(0.058)	(0.059)	(0.058)	(0.057)	(0.056)	(0.043)	(0.043)	(0.042)
Urbanization (Rural Reference)								
Urban	-0.151***	-0.195***	-0.153***	-0.144**	-0.127**	-0.089**	-0.094**	-0.085**
	(0.057)	(0.058)	(0.057)	(0.056)	(0.055)	(0.043)	(0.043)	(0.042)
Obesity Status (Overweight Reference)								
Under	-4.893***	-4.320***	-4.734***	-4.774***	-5.150***	-3.497***	-3.516***	-3.634***
	(0.129)	(0.130)	(0.114)	(0.117)	(0.202)	(0.111)	(0.109)	(0.135)
Obese	10.443***	9.620***	10.176***	10.006***	10.084***	10.247***	10.180***	10.257***
	(0.095)	(0.095)	(0.102)	(0.099)	(0.091)	(0.069)	(0.069)	(0.069)
Interactions								
Black and Female	0.946***	0.874***	0.931***	0.926***	0.894***	0.531***	0.535***	0.523***
	(0.121)	(0.122)	(0.121)	(0.119)	(0.116)	(0.092)	(0.092)	(0.091)
Hispanic and Female	0.142	0.142	0.114	0.116	0.151	0.125	0.128	0.095
	(0.142)	(0.143)	(0.143)	(0.141)	(0.134)	(0.104)	(0.106)	(0.103)
Log-Likelihood	-25875.4	-26166.1	-25839.6	-25762.1	-25696.9	-25160.6	-25151.1	-25127.5
AIC	51778.7	52334.3	51709.2	51554.2	51425.8	50353.2	50334.3	50289.0
BIC	51880.8	52341.6	51818.5	51663.5	51542.4	50469.8	50450.9	50412.9

Note: *** significant at .01; ** significant at .05; significant at .10.

Table 3, 2012 Body Mass Index Values by Demographics, Family Size, and Urbanization

2012 DATA	***OLS***	***LAD***	***GED***	***T***	***GT***	***SGED***	***ST***	***SGT***
Intercept	39.391***	37.070***	38.150***	38.161***	38.238***	37.306***	36.081***	37.532***
	(2.207)	(2.210)	(2.155)	(2.114)	(2.101)	(1.917)	(1.867)	(1.903)
Height								
Centimeters	-0.038***	-0.030***	-0.034***	-0.034***	-0.034***	-0.030***	-0.032***	-0.031***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Gender (Male-Reference)								
Female	-0.910***	-1.020***	-0.973***	-1.077***	-1.104***	-1.709***	-1.707***	-1.712***
	(0.229)	(0.229)	(0.220)	(0.217)	(0.216)	(0.196)	(0.194)	(0.195)
Age	-0.092***	-0.083	-0.086	-0.087	-0.087	-0.071	-0.076	-0.073
	(0.029)	(0.029)	(0.028)	(0.027)	(0.027)	(0.025)	(0.024)	(0.025)
Ethnicity (White-Reference)								
Black	0.847***	1.010***	0.946***	0.903***	0.880***	0.695***	0.690***	0.696***
	(0.213)	(0.213)	(0.203)	(0.197)	(0.197)	(0.176)	(0.181)	(0.179)
Hispanic	0.632***	0.777***	0.683***	0.731***	0.752***	0.822***	0.812***	0.822***
	(0.253)	(0.253)	(0.236)	(0.234)	(0.236)	(0.216)	(0.216)	(0.215)
Family Size								
Family Size	0.027	0.031	-0.021	0.013	0.023	0.097	0.127	0.108
	(0.138)	(0.138)	(0.145)	(0.137)	(0.133)	(0.133)	(0.129)	(0.133)
Family Size Squared	0.000	0.000	0.005	0.001	0.000	-0.015	-0.019	-0.016
	(0.017)	(5.2E-5)	(0.019)	(0.018)	(0.017)	(0.018)	(0.017)	0.0178
Marital Status (Non-married Reference)								
Married	0.334**	0.359**	0.371**	0.384**	0.388**	0.554***	0.515***	0.540***
	(0.158)	(0.158)	(0.157)	(0.152)	(0.150)	(0.136)	(0.137)	(0.137)
Urbanization (Rural Reference)								
Urban	-0.096	-0.231	-0.186	-0.169	-0.160	-0.120	-0.134	-0.124
	(0.156)	(0.157)	(0.150)	(0.148)	(0.148)	(0.134)	(0.133)	(0.134)
Obesity Status (Overweight Reference)								
Under	-5.356***	-4.900***	-5.151***	-5.042***	-5.000***	-4.007***	-4.035***	-4.016***
	(0.341)	(0.342)	(0.288)	(0.302)	(0.309)	(0.283)	(0.286)	(0.283)
Obese	8.671***	8.200***	8.445***	8.342***	8.323***	7.199***	7.211***	7.204***
	0.23111	(0.231)	(0.240)	(0.247)	(0.247)	(0.221)	(0.218)	(0.218)
Interactions								
Black and Female	2.009***	1.930***	1.931***	1.996***	2.019***	2.154***	2.128***	2.144***
	(0.293)	(0.293)	(0.286)	(0.280)	(0.280)	(0.250)	(0.251)	(0.251)
Hispanic and Female	0.400	0.340	0.461	0.449	0.423	0.480	0.452	0.470
	(0.343)	(0.343)	(0.333)	(0.324)	(0.324)	(0.295)	(0.294)	(0.294)
Log-Likelihood	-21347.1	-21383.6	-21264.9	-21241.2	-21239.2	-20974.8	-20977.0	-20973.9
AIC	42722.2	42774.9	42559.9	42512.5	42510.4	41981.6	41985.9	41981.9
BIC	42818.0	42768.0	42662.5	42615.1	42619.8	42091.1	42095.4	42098.2

Note: *** significant at .01; ** significant at .05; significant at .10.

Table 4. Estimated Distributional Parameters

1985 DATA	***OLS***	***LAD***	***GED***	***T***	***GT***	***SGED***	***ST***	***SGT***
Sigma	2.6481		2.64744	2.63299	2.62765	2.684803	2.6879	2.65969
	0.018		0.01967	0.02045	0.01992	0.020495	0.0214	0.02086
Lambda						0.619816	0.6052	0.62112
						0.014613	0.0143	0.01557
P			1.69327		3.7444	2.009123		2.66855
			0.03393		0.24112	0.043441		0.1187
Q				6.76838	1.57156		22.1867	4.86893
				0.66348	0.18626		5.89686	0.86806

2012 DATA	***OLS***	***LAD***	***GED***	***T***	***GT***	***SGED***	***ST***	***SGT***
Sigma	5.29045		5.29181	5.31836	5.34256	5.31077	5.32602	5.31557
	0.04497		0.05381	0.06279	0.06989	0.05625	0.06182	0.05818
Lambda						0.41658	0.42403	0.41867
						0.01608	0.01686	0.01655
P			1.4576		2.30289	1.56392		1.69562
			0.03586		0.16327	0.03893		0.11298
Q				3.51709	2.35046		5.12921	15.9563
				0.29489	0.44904		0.60721	13.04

We have observed differences in the estimators and now turn to ways that these alternative specifications can be compared. For nested models, such the SGED and SGT, a likelihood ratio test can be employed to test for statistically significant improvements of the more general model to the restricted model. The likelihood ratio test is defined by $LR = 2(\ell - \ell^*)$ where ℓ and ℓ^* denote the optimized loglikelihood values for the unrestricted and restricted models, respectively. Under fairly general conditions the *LR* test statistic has an asymptotic chi-square distribution with degrees of freedom equal to the difference in the number of parameters of the two models being compared. For example, to test the hypothesis that the Normal and GED specifications are equivalent in 2012 the corresponding LR test statistic is equal to

$LR = 2(\ell_{GED} - \ell_{Normal}) = 2(21347.1 - 21264.9) = 164.4$, which is distributed as a chi-square with one degree of freedom and is statistically significant. Table 5 reports the LR values corresponding to various hypotheses for 1985 and 2012. For 1985, the SGT is seen to yield a statistically significant improvement relative to the other specifications considered. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), reported in Tables 2 and 3, are frequently used to compare different model specifications which need not be nested. Both of these criteria reward goodness of fit as measured by the optimized value of the loglikelihood function and impose a penalty for model complexity as measured by the number of parameters *(k)* in the estimated model and are defined by $AIC = 2(k - \ell)$ and $BIC = k\log(n) - 2\ell$. Based on either the AIC or BIC, the SGT is selected for the year 1985. For 2012, the SGED, ST, and SGT yield similar results which dominate the results for the symmetric specifications.

Table 5, Partially Adaptive Likelihood Ratio Tests

Hypotheses:	*1985*	*2012*
SGT=ST	47.3	6.1
SGT=SGED	530.5	66.2
SGT=GT	1138.8	530.6
SGT=t	1269.2	534.6
SGT=GED	1424.2	581.9
SGT=Laplace	819.3	2077.3
SGT=Normal	746.3	1495.7

Source: See Tables 2 and 3.

Because of the strong overall performance of the SGT, we focus attention on SGT partially adaptive BMI results and the corresponding parameter estimates. BMIs are inversely related to historical height; however, with the modern obesity epidemic, it is not clear what the relationship is between modern BMI and height (Carson, 2009; Carson, 2012). For both youths and adults, BMIs are inversely related to height in the modern obesity epidemic. Taller statures allow weight to be distributed over greater physical dimensions. Taller heights are also related to higher metabolisms, and more calories are required for taller individuals resulting in lower body mass (Schneider, 2017; Gluckman et al 2008). Regardless of the assumed error distribution, once height is accounted for, women have lower BMIs than men; however, this difference is less pronounced over time. Women are shorter than men, and after controlling for height, women are more likely to be obese even though they have lower BMIs, especially, African-American women (McLannahan and Clifton, 2008, p. 25-26; Komlos and Brabec, 2010; Komlos and Brabec, 2011; Matorell et al. 2000). Nevertheless, women are also physically less active than men, have less muscle tissue, and muscle is heavier than fat (Ferraro et al 1992; Arciero et al 1993). Nevertheless, women are shorter and after controlling for height, women are more likely to be obese even though they have lower BMIs, especially, black women (McLannahan and Clifton, 2008, p. 25-26; Komlos and Brabec, 2010; Komlos and Brabec, 2011). For both the GT and SGT models, BMIs increase with age during youth (Table 4), yet because physical activity and basal metabolic rates decrease with age, BMIs in the mid-50s decrease due to a loss in lean muscle tissue (Table 5; McLannahan and Clifton, 2008, p. 42; Piasecki et al. 2015).

In historical studies, individuals with darker complexions have greater BMIs than individuals with fairer complexions, and independent of gender, modern Hispanic populations have greater weights than non-Black, non-Hispanic populations (Schutte et al. 1984; Carson, 2016). Alternatively, Komlos and Brabec (2010, 2011) demonstrate that black and white male US populations have comparable BMIs; however, black females have significantly higher BMIs than men and non-black females (Tables 4 and 5). Multiple explanations account for this pattern. Individuals with darker complexions are on average shorter than individuals with fairer complexions, and BMI is inversely related to height. Individuals with darker complexions may also have greater BMIs because they have greater protein in muscle tissue per unit tissue mass, and muscle is heavier than fat (Schutte et al. 1984; Aloi et al. 1997; Barondess et al. 1997; Heyward and Wagner, 2000). In the mid-1980s, individuals in larger households had greater BMIs, and youth BMIs increased in family size at a decreasing rate (Table 4). However, by adulthood in 2012, there was no relationship between BMIs and household size (Table 5). Marital status is similar. Young married individuals have greater BMIs than married adults; however, the marital status difference is insignificant by middle age. The relationship between BMI and urban residence in a developed economy also illustrates an age specific result, and young individuals in urban areas consistently have lower BMIs than their rural counterparts. However, the difference is insignificant by middle age. In modern populations, there is little evidence to indicate a pronounced relationship between BMI and urban residence (Martonell et al. 2000). BMI status was also significantly related to early-life BMI classification, and individuals classified as underweight or obese in 1985 were likely to retain that status when observed in 2012 (Parsons et al. 1999; Baird et al. 2005, p. 930). Consequently, in both modern and historical populations, BMIs are directly related to darker complexions; however, across various error distributions, the effect of family size, marital status, and urban residence are no longer significant by middle age.

V. Conclusion

Over the last 10 years, few areas in medicine and the social sciences have attracted as much attention as the increase in modern BMI values. Traditional least squares estimation has minimum variance of all linearly unbiased estimates if regression model errors are independently and identically distributed. Least squares is also efficient when the errors are normally distributed but need not be efficient when they follow some other distribution. Using precision equations and likelihood ratio tests, this study shows that the errors associated with 1982 and 2012 US BMI regression models are better modeled with the more flexible Skewed Generalized t distribution, indicating partially adaptive estimation provides useful insight into the modern obesity epidemic. BMIs changed considerably between 1985 and 2012, yet some patterns are robust. There is an inverse relationship between BMI and height, and after accounting for height, women have lower BMIs than men. Nonetheless, women have higher rates of obesity, indicating that women have lower body mass, yet because of shorter statures, women are more likely to be classified as obese. During the modern obesity epidemic, BMIs were associated with larger families during their youth; nevertheless, this size effect was insignificant by middle age.

Various alternative estimation techniques to least squares are now available. Partially adaptive estimation presented here is based on very flexible assumptions regarding how regression model errors are distributed. The Skewed Generalized t is a very flexible distribution and performs better than least squares indicating that estimator precision can be improved by using a more flexible error distribution that adjusts to changing characteristics encountered during the modern obesity epidemic.

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