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ABSTRACT

We examine the effects of fast-food restaurant advertising on television on the body composition of adolescents as measured by percentage body fat (PBF) and to assess the sensitivity of these effects to using conventional measures of youth obesity based on body-mass index (BMI). We merge measures of body composition from bioelectrical-impedance analysis (BIA) and dual-energy x-ray absorptiometry (DXA) from the National Health and Nutrition Examination Survey with individual level data from the National Longitudinal Survey of Youth 1997 and data on local fast-food restaurant advertising on television from Competitive Media Reporting. Exposure to fast-food restaurant advertising on television causes statistically significant increases in PBF in adolescents. These results are consistent with those obtained by using BMI-based measures of obesity. The responsiveness to fast-food advertising is greater for PBF than for BMI. Males are more responsive to advertising than females regardless of the measure. A complete advertising ban on fast-food restaurants on television would reduce BMI by 2 percent and PBF by 3 percent. The elimination of the tax deductibility of food advertising costs would still leave a considerable number of youth exposed to fast-food advertising on television but would still result in non-trivial reductions in obesity.

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Introduction

The proportion of youths between ages 12-19 who are obese has increased substantially in the U.S. from 5.0 % in the mid-1970s to 18.1 percent in late 2000s [1]. Suspected social causes of youth obesity include television advertising of unhealthy, nutrient-dense food on aimed at youths [2-4]. However, there has been little empirical evidence confirming such an effect until recently [5]. Accordingly, there has been a call from the White House Task Force on Childhood Obesity for additional research to demonstrate the link between advertising and food preferences and consumption by children and adolescents [6]. It is critical to provide further insights into the determinants of childhood obesity to help efforts of policy-makers in the design of more effective prevention policies. In a recent comprehensive study, Chou, Rashad, and Grossman [3] (CRG hereafter) use individual-level data from the National Longitudinal Survey of Youth 1997 (NLSY97), and find a positive and statistically significant association between fast-food restaurant advertising on television and youths' body mass index (BMI) and the probability of being obese (age-gender adjusted BMI ranking ≥ 95th percentile). In another study, Andreyeva, Kelly, and Harris [5] use a sample of 5th graders to document that soft drink and fast food television advertising is positively associated with the probability of being overweight (age-gender adjusted BMI ranking ≥ 85th percentile) but not with bodyweight. They hypothesize that the weak association may be due to mismeasurement by BMI-based proxies for youth obesity.

While BMI is a widely accepted proxy for obesity, its limitation in distinguishing body fat and lean body mass is well-documented [7-11]. For example, BMI provides limited information on the degree of obesity in youths older than 10 years of age [12] while the association of BMI with body fatness in children differ substantially by gender, race, and age [13]. Thus, an increasing number of studies highlight the importance of using alternative measures of obesity for estimation purposes [8]. Several studies recommend using body composition or percentage body fat (PBF) for identification of youth overweight status [14].

Body composition, however, is considerably more difficult to measure and therefore has not been used by social scientists until recently. With the advancements in measurement technologies such as bioelectrical impedance analysis (BIA) and dual energy x-ray absorptiometry (DXA), the cost of measuring body composition has been reduced substantially and these measures are now available in several in large-scale surveys [15]. Using such data, social scientists have begun to compare the sensitivity of BMI-based findings to those based on body composition among adults [16, 17]. To this date, no such sensitivity analysis has been conducted for youths. This is the first study to analyze the impact of fast-food advertising on body composition among youths. We also examine the sensitivity of the results obtained in CRG to our results using body composition measures of youth obesity.

Methods

To maintain comparability between the results in our paper and those in CRG, we draw on the same data sources as CRG.

Primary Individual Data

Individual-level data on youths aged 12 to 18 are obtained from the NLSY97, which contains a nationally representative sample of the U.S. youths. The initial sample in 1997 consists of 8,984 respondents aged 12 to 16 years old and contains extensive information about youth labor market behavior and educational attainment. A parent questionnaire with information on family background and a youth questionnaire on weekly hours of time spent in watching television for youths aged 12 to 14 were also administered in Round 1. Following the CRG, we use 1997 values for 1998 and 1999. The pooled sample size is 14,852 after observations with missing values are deleted and before advertising and state-level data are merged.

Fast-food restaurant television advertising data

We also obtain fast-food restaurant television advertising data from Competitive Media Reporting (CMR), the largest provider of advertising tracking services in the U.S. The advertising exposure, which is the number of seconds restaurant advertising aired per week per area, is collected for fast-food restaurant chains in the U.S. from 1996 to 1999. The exposure data are then converted to the number of hours per week.

The unit of area for advertising exposure is Designated Market Area (DMA), which is similar to a Metropolitan Statistical Area (MSA). Each DMA is a television market composed of counties (and occasionally part of counties). The top 75 out of about 210 DMAs are contained in the CMR database. Merging the advertising exposure data by DMA results in an analysis sample of 7,069 person-years. Using the information on weekly hours of television viewed in NLSY97, we calculate the weekly hours of fast-food advertising seen as follows:

$$S_{ijt} = (T_{ijt}/168)A_{jt}K, \quad (1)$$

where T_{ijt} is the weekly number of hours that the youth watches television, 168 is the number of hours in a week, A_{jt} is the weekly number of hours of fast-food ads aired, and K is a positive constant. We take natural log to address positive skewness in S_{ijt} and T_{ijt}:

$$\ln S_{ijt} = \ln T_{ijt} - \ln 168 + \ln A_{jt} + \ln K, \qquad (2)$$

The natural log transformation mitigates the influence of outliers, while also allowing each control variable to have a diminishing marginal effect on BMI or obesity. Therefore we have three key variables: ln(TV-time), ln(Ads-aired), and ln(Ads-seen).

Alternative measures of youth obesity

Body composition is described by the following identity:

$$W \equiv BF + FFM \qquad (3)$$

where W is weight in kilograms, BF is body fat, and FFM is fat-free mass. PBF or percentage body fat is therefore,

$$PBF = 100 * \frac{BF}{BF + FFM}. \qquad (4)$$

We make use of both BIA and DXA measures of body composition that are available in the following waves of the National Health and Nutrition Examination Survey: NHANES III (1988 through 1994), NHANES 1999-2000, NHANES 2001-2002, and NHANES 2003-2004 [18].

In the BIA method, body composition is estimated by measuring the electrical resistance of a body to a weak electrical current [19]. The observed electrical resistance, which is negatively associated with FFM, is converted into FFM by entering it into a predetermined equation obtained from a multiple regression analysis along with a set of external measurements such as weight, height, age, and gender [20, 21]. After FFM is obtained from the prediction equation, BF is computed from the identity in equation (3), which is then combined with equation (4) to yield the following form:

$$PBF \equiv 100 * \frac{BF}{W} \equiv 100 * \frac{W - FFM}{W}. \qquad (5)$$

Following previous studies [16, 17], we employ a prediction equation developed by Chumlea [20] for particular use with NHANES III. We also used a prediction equation developed by Boileau [22] for children aged 8 through 16. These equations yield two sets of values for FFM and BF in NHANES.

A third set of body composition is obtained from the DXA measurement, also available in the NHANES. In this procedure, a complete body scan is administered in which two low dose x-rays are absorbed at different rates by bone and soft tissue mass [19, 23]. The computed amount of BF and FFM are directly reported in NHANES without the need for prediction equations.

Estimating alternative youth obesity measures

Because there is only one year of overlap between the NHANES waves and the CMR fast-food restaurant advertising data (1997-1999), we employ the procedures developed by Wada and Tekin [17] to obtain PBF measures in NLSY97, using information derived from NHANES. A similar strategy was also used by a recent study for examining the effect of body composition on European employment outcome [24].

In this procedure, we predict FFM and BF values in NLSY97 using regression coefficients obtained from the NHANES analysis. First, we separately regress FFM and body fat on weight, weight^2, height, height^2, age, age^2, and weight*height in NHANES. This estimation is implemented for each of the six gender-race/ethnicity combinations (white non-Hispanic males, white non-Hispanic females, black non-Hispanic males, black non-Hispanic females, Hispanic males, and Hispanic females). We use persons of all ages in NHANES to increase the power in these regressions. The explanatory power in these regressions is high, with R^2 values ranging between 0.80 and 0.90. The coefficients from these regressions and the values of the independent variables in NLSY97 are then used to impute values for FFM and BF in NLSY97.

After computing FFM and BF in NLSY97, we use the three sets of BF and FFM estimates to calculate the corresponding PBFs using equations (4) and (5). Therefore, we obtain one measure of PBF based on DXA (PBF-D), another based on BIA with Chumlea's equation (PBF-C), and a third one based on BIA with Boileau's equation (PBF-B).

Conventional measures of youth obesity

Traditional obesity measures are BMI and an obesity indicator that equals one if the adolescent is obese (age-gender adjusted BMI ranking ≥ 95th percentile). BMI is calculated as W/H^2, where W is weight in kilograms and H is height in meters.

State-level data

Following CRG, we include in our models state-level variables that are merged with the NLSY97 by state and year. These include the number of fast-food restaurants, the number of full-service restaurants, the price of a meal in each type of restaurant, an index of price of food at home, the price of cigarettes, and clean indoor air laws. Detailed descriptions of their sources, definitions, and relevance have been previously discussed [25].

Estimation strategy

We use a multiple regression method. Given the large sample size, we fit linear probability models for binary obesity outcome. The coefficients from linear probability models are consistent estimates of average probability derivatives, but the standard errors are biased as a result of heteroskedasticity [26]. Thus, we report standard errors that are robust to any form of heteroskedasticity. We also employ sampling weights and cluster standard errors on DMA, given that the advertising variables are repeated within DMA.

Our most comprehensive regression model is:

$$Y_{ijt} = \gamma_0 + \gamma_1 \ln S_{ijt} + \gamma_2 \ln T_{ijt} + \beta_1 X_{ijt} + \beta_2 M_{ijt} + \beta_3 Z_{ijt} + \mu_j + \nu_t + \varepsilon_{ijt}. \qquad (6)$$

In this equation, the dependent variable (Y_{ijt}) is the various obesity measures for youth i in DMA j surveyed in year t. The regressors are the ln of the weekly hours of television fast-food restaurant advertising seen ($\ln S_{ijt}$); the ln of the weekly hours spent watching television ($\ln T_{ijt}$); a vector of demographic variables for youths, including age, race, and gender (X_{ijt}); a vector of variables containing mother's employment status, household income, a dummy for missing income, and dummy variables indicating whether the mother is overweight ($BMI \geq 25$) or obese ($BMI \geq 30$) (M_{ijt}); a vector of state-specific variables including the per capita number of fast-food restaurants, the per capita number of full-service restaurants, the real cigarette price, dichotomous indicators for clean indoor air laws, the real full-service restaurant price, the real food at home price, and the real fast-food restaurant price (Z_{ijt}); and vectors indicating DMA (μ_j) and year (ν_t). The disturbance term is ε_{ijt}. An advantage of the specification given by equation (6) is that it allows the amount of time spent watching television to have an effect on weight outcomes that is independent of the number of hours of fast-food restaurant advertising ads seen.

Using the definition of S_{ijt} in equations (1) and (2), equation (6) can be rewritten as

$$Y_{ijt} = \gamma_0 + \gamma_1 \ln K - \gamma_1 \ln 168 + \gamma_1 \ln A_{jt} + (\gamma_1 + \gamma_2) \ln T_{ijt} + \beta_1 X_{ijt} + \beta_2 M_{ijt} + \beta_3 Z_{ijt} + \mu_j + \nu_t + \varepsilon_{ijt}. \qquad (7)$$

Results

Table 1 displays descriptive statistics for the five obesity outcomes of interest for all youths and by gender. These five outcomes are BMI, an indicator that equals 1 if a youth is obese (Obese) according to age-gender adjusted BMI ranking, and the three measures of PBF described earlier (PBF-D, PBF-C, and PBF-B). The sample sizes for PBF measures are slightly lower due to restricting the sample to non-Hispanics whites, non-Hispanics black, and Hispanics. As shown in Table 1, the means for the three PBF measures are very similar. For males, the mean PBF is between 19 and 20 percent, while for females, it is between 29 and 31 percent. The PBF estimates based on DXA are slightly higher than the estimates based on BIA. In turn, PBF-B is slightly higher than PBF-C.

To compare our estimates of PBF in NLSY97 with actual measures in NHANES, we present means and standard deviations of the three PBF variables in Table 2. We have computed these figures from NHANES 1999-2000, 2001-2002, and 2003-2004. Except in the case of male PBF-B, the means in Table 2 are larger than those in Table 1, which is likely due to under-reporting of weight in the NLSY. For males, the range is between 20 and 24 percent, while for females, it is between 29 and 34 percent. For comparison purposes, we also show the statistics for BMI and Obese in NHANES 1999-2000. The under-reporting of weight by females is clearly reflected in the difference between the percentage of obese females of 14 percent in NHANES and 7 percent in NLSY97.

There is a high correlation among our five body composition measures. As expected, the correlation coefficients among the three measures of PBF are very high within gender ranging from 0.91 to 0.99 for males and from 0.97 to 0.99 for females. BMI also is highly correlated with the measures of PBF. The correlations fall between 0.89 and 0.96 for males and between 0.91 and 0.92 for females. Given the dichotomous nature of the Obese indicator, the raw correlations between Obese and each of the other four variables are smaller. Specifically, they are between 0.67 and 0.76 for males and between 0.54 and 0.72 for females.

Table 3 reproduces the regression results obtained by CRG. Regressions in which BMI or Obese is used as the dependent variable are estimated with a slightly smaller sample, but yield results that are almost identical to those in CRG.

Table 4 presents the estimation results from two alternative specifications with the three measures of PBF. In each of the nine specification (6) regressions in Table 5, we find a positive and significant relationship between television viewing time and the PBF. All nine coefficients of advertising ads are positive and five are statistically significant. The exceptions pertain to the three coefficients for females and the male coefficient for PBF-DXA, which is consistent with the non-significant advertising coefficients in the female regressions in Table 3 from CRG.

In each of the nine specifications in Table 4, we test the hypothesis that coefficient of the ln(TV-time) is equal to the coefficient of the ln(Ads-aired). Similar to Table 3, we fail to reject the hypothesis that the two coefficients are the same in every case. Therefore, we estimate a second model [specification (2)] in which the ln(Ads-aired) and the ln(TV-time) are replaced with the ln(Ads-seen). This is equivalent to constraining the coefficient of the ln(TV-time) to equal the coefficient of the ln(Ads-aired). In this specification all nine coefficients are significant.

Focusing on the gender-specific results for specification (2) in Table 4, one sees that the coefficients of the ln(Ads-seen) do not vary much, ranging from 0.58 (female PBF-D) to 0.76 (male PBF-B). The male coefficient is larger than the corresponding female coefficient except for PBF-C. The last finding aside, these results mirror those in Table 3.

One way to gauge the magnitudes of the effects is to compute their elasticities with respect to the number of ads seen (ln S in the version of equation (6) that omits ln T). Given the semi-logarithmic form of the equation, the elasticity is $\gamma_1/\overline{Y}$, where $\overline{Y}$ is the mean of the dependent variable in the regression and γ_1 is the regression coefficient of lnS. The elasticities are presented in the left panel of Table 5 using the population mean from NHANES. All the male elasticities exceed the corresponding female elasticities, and the PBF elasticities exceed the corresponding BMI elasticities. A 10 percent increase in the number of ads seen increases each outcome by between 0.2 percent and 0.4 percent. Yet as shown below, a small absolute or percentage increase in BMI can have a substantial impact on the percentage increase in the number of obese youths. It is notable that an average of the three male PBF elasticities is almost 40 percent larger than the BMI elasticity. For females, the average PBF elasticity is 25 percent larger than the BMI elasticity.

CRG put their results into context by simulating an increase in the number of ads seen that is equal to its coefficient of variation. On average, youths view approximately half an hour per week of fast-food advertising ads. Since the coefficient of variation of this variable is approximately equal to one in each regression, these computations reveal the impacts of an increase in exposure to this type of advertising of half an hour per week. They only make these computations for the obesity indicator, but we compute them for all five dependent variables. Following the approach by CRG, we conduct similar simulations. As shown in the right panel of Table 5, increasing exposure to fast-food advertising by half an hour per week will increase the probability of being obese by 2.5 percentage points among males. This translates into a 17 percent increase in the number of obese male youths in a fixed population. The corresponding figures for females are a 0.6 percentage point increase and a 4 percent increase in the number of obese adolescent girls in a fixed population. The simulations for the other four continuous outcomes suggest much smaller effects, especially among males. Focusing on percentage changes, the corresponding figures range from about 1 percent (female BMI) to approximately 3 percent (male PBF-B). It should be realized, however, that only the obesity indicator is discrete. To highlight this difference, suppose that the BMI of each male and each female in our sample increased by the amount predicted in Table 5, i.e., 0.38 and 0.25, respectively. Then the probability of being obese would rise by 1.1 percentage points for males and by 0.5 percentage points for females. These effects translate into a 7 percent increase in the number of obese male youths in a fixed population and to a 3 percent increase in the number of obese female youths. While these are smaller than those obtained directly from the regression for the probability of being obese, they are non-trivial.

Discussion

Our results indicate that exposure to fast-food restaurant advertising on television causes statistically significant increases in PBF in youths. We obtain a larger effect by using PBF rather BMI as youth obesity outcome. Our results indicate that a complete advertising ban would reduce BMI by about 2 percent and would reduce PBF by around 3 percent. Note that very modest changes in body composition can be associated with substantial reductions in the number of obese youths. The BMI effects translate into a 6 percent reduction in the number of obese youths by the advertising ban. Similar to CRG, we conclude that exposure to fast-food restaurant advertising on television causes statistically significant increases in the body mass index of youths and on the probability that they are obese. The obesity effect is larger in absolute value. A complete ban on these advertisements would reduce the number of obese youths by 14 percent. Another policy option alternative to banning such advertising on television could be the elimination of the tax deductibility of food advertising costs. While such a policy would still leave a considerable number of youth exposed to fast-food advertising on television, it may still result in non-trivial reductions in obesity

Since the PBF effects in Table 5 are larger than the corresponding BMI effects, it would be useful to employ an obesity indicator defined by PBF as an additional outcome. We have placed this issue on an agenda for future research because obesity cutoffs based on PBF are not yet well developed. For example, Boreham, Twisk, and Savage [27] classify male youths with PBF greater than 20 percent as obese and adolescent girls with PBF greater than 24 percent as obese. If these cutoffs are applied to our NLSY data, approximately 50 percent of males and 90 percent of females are classified as obese. Even if the cutoffs for adults recommended by the National Institute of Diabetes and Digestive and Kidney Diseases [28] for adults of greater than 25 percent for males and greater than 30 percent for females are used, approximately 22 percent of males and 60 percent of females are identified as obese. It is valuable to examine the characteristics of individuals classified as obese by one measure but not the other and vice versa. It also is valuable to obtain PBF cutoffs that result in the same percentage of obese youths as BMI cutoffs.

We conclude by re-emphasizing that it would be useful to develop an obesity indicator defined by the PBF, to use this outcome as an additional dependent variable, and to examine non-linear effects. These might take the form of greater sensitivity to advertising by youths just below the BMI obesity cutoff or to the corresponding PBF cutoff than by other youths. The ideal data for such an investigation would contain both actual measures of the PBF and detailed information on exposure to fast-food restaurant advertising.

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Table 1: Means and Standard Deviations

Variable	Definition	All	Male	Female
BMI	Body mass index	22.10 (4.438)	22.54 (4.581)	21.65 (4.237)
Obese	Equals 1 if BMI is ≥ the 95th percentile	0.103 (0.304)	0.135 (0.342)	0.070 (0.255)
PBF-D	Percentage body fat based on DXA	25.68 (8.218)	20.17 (5.877)	31.48 (6.052)
PBF-C	Percentage body fat based on Chumlea	23.89 (8.035)	19.16 (5.447)	28.87 (7.275)
PBF-B	Percentage body fat based on Boileau	24.37 (8.078)	19.92 (6.390)	29.05 (6.938)
ln(TV-time)	Time spent watching television (hours/week; in logs)	2.65 (0.805)	2.718 (0.795)	2.579 (0.809)
ln(Ads-aired)	Hours of fast-food restaurant advertising Ads-aired per week in respondents DMA (in logs)	1.269 (0.383)	1.265 (0.389)	1.274 (0.378)
ln(Ads-seen)	Hours of fast-food restaurant advertising ads seen (in logs)	-1.205 (0.911)	-1.141 (0.900)	-1.271 (0.917)
Sample size	Person-years	7,069	3,665	3,404

Note: Standard deviations are in parentheses. Means and standard deviations employ the NLSY sampling weights. For the three PBF measures, the sample size is 6,979 for all, 3,625 for males, and 3,354 for females.

Table 2: Means and Standard Deviations, Body Composition Measures, NHANES, Ages 12-18

Variable	All	Male	Female
BMI	22.82	22.52	23.13
	(7.367)	(7.279)	(7.463)
Obese	0.148	0.153	0.144
	(0.450)	(0.461)	(0.441)
PBF-D	28.07	24.12	33.74
	(12.15)	(10.94)	(9.504)
PBF-C	25.43	20.35	30.99
	(13.42)	(10.89)	(11.78)
PBF-B	24.43	19.89	29.38
	(14.14)	(13.06)	(12.08)

Note: Standard deviations are in parentheses. BMI and Obese are from NHANES 1999-2000. PBF-D, PBF-C, and PBF-B are from NHANES 1999-2000, 2001-2002, and 2003-2004.

Table 3: Regression Results, Body Mass Index and Obese

	Specification 1			Specification 2		
	All	Male	Female	All	Male	Female
	A. Body Mass Index					
ln(Ads-aired)	0.266*	0.381*	0.117			
	[1.630]	[1.365]	[0.557]			
ln(TV-time)	0.474***	0.556***	0.380***			
	[4.479]	[4.049]	[3.274]			
ln(Ads-seen)				0.463***	0.547***	0.367***
				[4.721]	[4.280]	[3.367]
T-test on equality of coefficients	0.346	0.606	0.298			
R-squared	0.193	0.191	0.236	0.193	0.191	0.236
Sample size	7,069	3,665	3,404	7,069	3,665	3,404
	B. Obese					
ln(Ads-aired)	0.021**	0.028**	0.014			
	[1.967]	[1.846]	[0.822]			
ln(TV-time)	0.021***	0.036***	0.009			
	[3.071]	[3.414]	[1.224]			
ln(Ads-seen)				0.021***	0.036***	0.009*
				[3.316]	[3.555]	[1.383]
T-test on equality of coefficients	0.961	0.65	0.805			
R-squared	0.100	0.108	0.127	0.100	0.108	0.127

Note: All regressions are weighted by NLSY sampling weights. T-ratios, reported in brackets, are based on standard errors that are clustered at the DMA level. Sample sizes in the regressions in panel B are the same as in the corresponding regressions in panel A. All coefficients are adjusted for individual characteristics, state variables, DMA fixed effects, and year fixed effects. Individual variables include age, black non-Hispanic, Hispanic, other race, male (in regressions that are not gender-specific), family income, missing income dummy, mother overweight, mother obese, and mother employed. State variables include the per capita number of fast-food restaurants, per capita number of full-service restaurants, real cigarette price, dummies for clean indoor air laws, real full-service restaurant price, real food at home price, and real fast-food restaurant price. *: p < 0.10 (one-tailed test); ** : p < 0.05 (one-tailed test); ***: p< 0.01 (one-tailed test).

Table 4: Regression Results, Percentage Body Fat

	Specification 1			Specification 2		
	All	Male	Female	All	Male	Female
	A. Percentage Body Fat - DXA					
ln(Ads-aired)	0.395**	0.427	0.323			
	[1.969]	[1.170]	[0.825]			
ln(TV-time)	0.722***	0.735***	0.595***			
	[4.974]	[4.362]	[3.319]			
ln(Ads-seen)				0.706***	0.719***	0.581***
				[5.236]	[4.581]	[3.469]
T-test on equality of coefficients	0.246	0.478	0.553			
R-squared	0.574	0.211	0.243	0.574	0.211	0.243
Sample size	6,979	3,625	3,354	6,979	3,625	3,354
	B. Percentage Body Fat - Chumlea					
ln(Ads-aired)	0.470**	0.606**	0.416			
	[2.122]	[1.746]	[0.966]			
ln(TV-time)	0.681***	0.651***	0.697***			
	[4.316]	[3.962]	[3.253]			
ln(Ads-seen)				0.670***	0.649***	0.682***
				[4.563]	[4.243]	[3.406]
T-test on equality of coefficients	0.491	0.915	0.583			
R-squared	0.492	0.215	0.246	0.492	0.215	0.246
	C. Percentage Body Fat - Boileau					
ln(Ads-aired)	0.470**	0.601*	0.334			
	[2.004]	[1.542]	[0.779]			
ln(TV-time)	0.733***	0.765***	0.653***			
	[4.616]	[4.105]	[3.342]			
ln(Ads-seen)				0.720***	0.756***	0.637***
				[4.869]	[4.389]	[3.478]
T-test on equality of coefficients	0.408	0.732	0.521			
R-squared	0.482	0.24	0.299	0.482	0.24	0.299

Note: All regressions are weighted by NLSY sampling weights. T-ratios, reported in brackets, are based on standard errors that are clustered at the DMA level. Sample sizes in the regressions in panels B and C are the same as in the corresponding regressions in panel A. See note to Table 4 for additional variables included in the regressions. The dichotomous indicator of other race is deleted since these observations are not included in the regressions. *: p < 0.10 (one-tailed test); ** :p < 0.05 (one-tailed test); ***: p< 0.01 (one-tailed test).

Table 5: Effects of Fast-Food Restaurant Advertising Ads

	Elasticities with Respect to Fast-Food Restaurant Advertising Ads and Simulations			Effect of Half an Hour per Week Increase in Advertising Exposure on Body Composition Measures			
	All	Male	Female	Male		Female	
Variable				Absolute	Percentage	Absolute	Percentage
Obese	-	-	-	2.50	16.63	0.62	4.30
BMI	0.020	0.024	0.016	0.38	1.69	0.25	1.10
PBF-D	0.025	0.029	0.017	0.50	2.07	0.40	1.19
PBF-C	0.026	0.032	0.022	0.45	2.21	0.47	1.52
PBF-B	0.029	0.038	0.022	0.52	2.61	0.44	1.50

Note: For all outcomes except BMI, the absolute increase is expressed in percentage points. For BMI, the absolute increase is expressed in BMI points: weight in kilograms divided by height in $meters^2$. Percentage changes employ the NHANES means in Table 2.