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How Many Calories in that Big Apple?

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
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Abstract

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This paper examines the impact of New York City Department of Health Code Â§81.50, (or "the Legislation") on the BMI of 1) all New York City residents based on individual-level analyses of New York City Community Health Survey data ("CHS") and 2) three New York City counties compared to ten control counties based on county-level analyses of Selected Metropolitan/Micropolitan Area Risk Trends data ("SMART"). There is no statistically significant effect of the Legislation on BMI in the results based on CHS. This lack of statistical significance holds true regardless of an individual's age, sex, race, or poverty level. In difference-in-difference analyses based on SMART, however, counties in New York City showed a statistically significant decrease in BMI relative to ten control counties. The Legislation had a bigger impact on some New York City counties rather than others.

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Jamie E. Landman[1]

This paper examines the impact of New York City Department of Health Code §81.50, (or "the Legislation") on the BMI of 1) all New York City residents based on individual-level analyses of New York City Community Health Survey data ("CHS") and 2) three New York City counties compared to ten control counties based on county-level analyses of Selected Metropolitan/Micropolitan Area Risk Trends data ("SMART"). There is no statistically significant effect of the Legislation on BMI in the results based on CHS. This lack of statistical significance holds true regardless of an individual's age, sex, race, or poverty level. In difference-in-difference analyses based on SMART, however, counties in New York City showed a statistically significant decrease in BMI relative to ten control counties. The Legislation had a bigger impact on some New York City counties rather than others.

1. Introduction

The Legislation was implemented in April 2008 on the premise of positively impacting residents' consumption behavior and, consequently, their health. The Legislation requires all food-service establishments with 15 or more locations nationally to list the calories for standard menu items either on menu boards, on the menu, or on a display tag. The New York State Restaurant Association ("The Association") initially fought menu labeling in

[1] Department of Economics, Emory University. I thank my advisor Hugo Mialon, and committee members David Frisvold and Allison Burdette.

New York City. The Association argued that labeling would increase menu-related costs, especially when caloric make-up was hard to quantify for meals with many variations.

New York City was the first city to implement mandatory calorie postings on menus. Other U.S. jurisdictions are following suit.[2] On March 23, 2010, President Barack Obama signed Section 4205 of the Patient Protection and Affordable Care Act of 2010 ("the Healthcare Act") into law; the Healthcare Act requires establishments with 20 or more locations nationwide to post calorie content on menus and menu boards.[3] Fearing the impact on the restaurant industry, The American Pizza Community and the Food Marketing Institute are currently fighting implementation of Section 4205 of the Healthcare Act.[4] Ironically however, most chain restaurants have recently changed their position and now support a national menu labeling law; these chains want uniform standards in order to avoid the costly process of creating different menus based on each restaurant location. Section 4205 mandates the FDA to promulgate regulations establishing the menu labeling requirements.[5] The FDA has taken public comments but has yet to publish a final rule. To date, the FDA has not published any data on the impacts of menu labeling.[6] So, my analysis is the first such effort to look directly at the link between menu labeling and individual BMIs and obesity/overweight rates.[7]

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[2] King County (Seattle), Washington, Philadelphia, Pennsylvania, and San Francisco, California implemented similar city ordinances. In 2008, California became the first state to pass a statewide menu labeling law.
[3] Of course, governments have many different anti-obesity laws to choose from including soda bans, taxes on high-fat foods, etc.
[4]Barkoukis, Lesh. "Menu Labeling: Another Job-Killing Regulation in ObamaCare." *Townhall.com*. N.p., 25 Nov. 2012.
[5] "Food Labeling: Nutrition Labeling of Standard Menu Items in Restaurants and Similar Retail Food Establishments." *Federal Register*. N.p., Fall 2011.
[6] "Implement Section 4205|." FDA U.S. Food and Drug Administration. Web.
[7] Other studies cited in the Literature Review section of this paper look at the impact on NYC menu labeling on consumer choices rather than BMI.

Prior to the Legislation, NYC banned trans-fats in all area restaurants in 2007. I interpret the outcomes of statistical models in this paper as outcomes due to the Legislation rather than the trans-fat ban. I discount the NYC trans-fat ban because at the time of the trans-fat ban, around 2007, many chain restaurants switched to trans-free oils nationwide instead of exclusively in New York City.[8] Therefore, any outcome of my analysis on NYC residents before and after 2008 should be attributed to the Legislation and not the trans-fat ban.[9]

This paper's purpose is to 1) provide evidence to help inform the ongoing debates about this and similar health codes; and, more importantly, 2) to aid health officials in deciding whether to implement a similar calorie labeling regulation on a national level.

In this research project, I collect and analyze data to determine if the Legislation had any statistically significant impact on residents' BMI in the treated area. In the first part of the paper, I answer this question by running a regression on NYC residents BMIs before and after the Legislation. Then, hypothesizing that the Legislation may affect some individuals more than others based on demographics, I run the same regression but only include data for specific subsets of the populations. The second part of the paper analyzes the potential effect of calorie labeling on a more macro-level. This analysis compares the prevalence of overweight and obese individuals in three treated counties of New York City to ten control counties across the nation.

[8] For example, McDonald's and Burger King in 2008 and KFC and Taco Bell in 2007.
[9] "Regulating Fats." *Cargill*. N.p., 2013. Web.

2. Contributions

This work presents two main contributions relative to prior literature. First, while previous literature study small subsets of individuals in restaurant settings, there has yet to be an aggregate analysis of calorie postings in a naturalistic setting. My analysis is the first such quasi-experimental study used to determine the effects of calorie postings. I use the implementation of the Legislation in New York City as a vehicle to perform this aggregate analysis, and I perform the analysis on comprehensive data sets. Second, the economic literature focuses on calorie postings affect on consumer decision-making; in contrast, my research focuses on the direct health effects that menu labeling has on individuals. My contribution will link: 1) the previous works' conclusions about behavior and purchasing changes after exposure to calorie postings to 2) New York City residents BMI levels after the Legislation was enacted.

In the section analyzing CHS (4.), I perform a simple before and after comparison of residents' BMI. In analyzing BMI levels, I control for demographic attributes that could otherwise explain post-Legislation changes in BMI. These demographic categories include age, gender, race, and poverty level. I hypothesize that the Legislation may be correlated with a statistically significant change in BMI for individuals that are part of a certain demographic category compared to those not in that category. Past literature from Downs et al., the BMJ Group, Elbel et al., and Vadiveloo et al. leads me to this conclusion because individuals are more likely to change (or not change) purchasing behavior if they are of a certain gender, age, poverty, or racial background. Next, based on my hypothesis, I examine BMI changes for subsets of individuals that are part of a certain age, race, or gender category. For example, I look at the potential post-Legislation impact on BMIs of women in my sample. In the SMART analyses section (5.), I compare three New York City counties to ten untreated counties. While the CHS analysis is a helpful baseline study for readers to begin to uncover how the Legislation affected individual BMI levels, the results from SMART are important to help readers determine if the Legislation impacted BMI in New York City counties even after controlling for obesity trends within each county.

The CHS data shows no statistically significant change in individuals' BMI in New York City after the Legislation. This lack of change is consistent across population subsets including sex, age, race, and poverty level. So if one looks only at the CHS results, the Legislation appears to not have had a significant impact for the sample as a whole. In contrast, my analysis using SMART do show a significant association between weight and the Legislation because while BMI did not go down after 2008 in New York City, BMI also did not go up. This lack of change stands in stark contrast to the ten (untreated) control counties, where obesity went up after 2008. In the SMART section, I also separate the analysis into the three respective counties of New York City (instead of all counties combined) to determine if the Legislation had a larger impact on some areas of New York City rather than others. I found that relative to the control counties, obesity rates for Kings County (Brooklyn)[10] significantly fall in 2009 and 2010, while those of New York County's significantly fall in 2009.

The CHS section below describes the statistical model and results for regressions testing the Legislation's impact on BMI after 2008 for individuals living in New York

[10] Queens County refers to Queens, Bronx County to Bronx, Richmond County to Staten Island, and New York County to Manhattan.

City. The SMART section describes the statistical model and results of difference-in-difference regressions across time and across counties.

3. Literature Review

This section will summarize literature from previous researchers who analyze the effect of calorie postings on individuals' purchasing and consumption behavior. I will first discuss studies that use transaction data (i.e. receipts) to determine calorie posting effects. I will then discuss studies that use survey data to determine the calorie posting effects and, lastly, I will discuss studies that use a hybrid of both transaction and survey data.

In the studies in which receipts are collected from consumers, calorie labeling was found to have mixed outcomes on behavior. Some studies show significant behavioral changes after menu labeling while other studies do not. Among those that find significant changes are Cinciripini et al. (1984) who evaluates the effect of calorie labeling on food selection in a university cafeteria, and Yamamoto et al. (2005) who evaluates the effect of calorie labeling on food selection of middle and high school students in a restaurant.[11,12] Both of these studies show that subjects modified their meal choices after exposure to calorie labeling.

In contrast, the Mayer et al. report (1987) and the Downs et al. (2009) report show no effect on customer selection choices when calorie content is made available. Using an ABA experimental design, Mayer et al. evaluates the influence of calorie labeling on

[11] Cinciripini P: Changing food selection in a public cafeteria: An Applied Behavior Analysis. Behav Modif 1984, 8:520-539

[12] Yamamoto J, Yamamoto J, Yamamoto B, Yamamoto L: Adolescentfast food and restaurant ordering behavior with and withoutcalorie and fat content menu information.J Adol Health2005,37:397-402

food choices in a Fortune 500 company office building cafeteria.[13] Downs et al. (2009) finds that labeling has mixed effects on food choices. Downs uses a natural experiment where receipts are collected outside a coffee shop in Manhattan and outside of two of the same hamburger chains: one of the chains was in Manhattan and the other in Brooklyn. At the coffee shop and the hamburger restaurant in Manhattan, menu labeling did not have significant effects on calorie consumption with one exception. African Americans consumed a significantly greater amount of calories after the postings. At the restaurant in Brooklyn, older individuals consumed fewer calories after the postings.[14]

Bollinger et al. (2010) collects transaction data on all Starbucks locations in New York City before and after the Legislation using data from a sample of anonymous Starbucks cardholders. Bollinger finds mandatory calorie postings at Starbucks were correlated with a 6% decrease in calories purchased. The decrease in calories purchased was entirely related to food purchases, rather than beverage purchases. Bollinger finds that reduced caloric intake came primarily from two areas. First, three quarters of the reduced caloric intake per transaction was from consumers purchasing fewer items. Second, the consumers actually substituted lower calorie items.[15]

Finkelstein et. al (2010) examines the effect of the King County regulation using a difference-in-difference approach comparing transactions at one fast food Mexican restaurant chain in seven King County locations to seven control locations outside King County. In this sample, the researchers found no evidence that mandatory labeling

[13] Mayer J, Brown T, Heins J, Bishop D: A multi-component inter-vention for modifying food selections in a worksite cafeteria.J Nutr Educ1987, 19:277-280

[14] Downs, J.S., G. Loewenstein and J. Wisdom (2009): "The Psychology of Food Consumption:Strategies for Promoting Healthier Food Choices,"American Economic Review: Papers &Proceedings, 99(2), 159–64.

[15] Bollinger B, Leslie P, Sorensen A. Calorie posting in chain restaurants. National Bureau of Economic Research (NBER). 2010: Working Paper 15648.

promoted healthier food-purchasing behavior.[16]

Unlike the studies where researchers collect receipts from consumers, the BMJ group surveys consumers. The BMJ group (2011) published a research study titled, “Changes in energy content of lunchtime purchases from fast food restaurants after introduction of calorie labeling: cross sectional customer surveys.”[17] The researchers compiled data in the pre-and post-Legislation period by surveying and collecting receipts from individuals outside of restaurant chains in New York City. The researchers collected data in each period from similar restaurants, consisting primarily of big name chains such as McDonald’s and Subway. Their results found that only 15% of customers report using calorie information when making their purchase decision for that day, and this 15% purchased on average 106 fewer calories than those who did not report using the calorie information. Women were the most likely to use the information, and the younger population (ages 18-24) were the least likely. At three of the chains, McDonald’s, Au Bon Pain, and KFC, there were statistically significant reductions in mean calories per purchase after the Legislations, while at Subway there was a significant increase in calories purchased. The BMJ researchers speculate that this result is perhaps due to Subway’s advertising campaigns at the time, or, the fact that, prior to the Legislation Subway had already voluntarily placed limited calorie information on deli cases. For the sample at large, the results of the BMJ study do not show a significant relationship between the Legislation and food purchases.

Elbel et al. (2011) collects both survey and receipt data from before and after the

[16] Finkelstein EA, Strombotne KL, Chan NL, Krieger J. Mandatory menu labeling in one fast-food chain in King County, Washington. Am J Prev Med. 2011;40:122–127. doi: 10.1016/j.amepre.2010.10.019.
[17] Dumanovsky T, Huang CY, Nonas CA, Matte TD, Bassett MT, Silver LD. BMJ. 2011 Jul 26; 343:d4464. Epub 2011 Jul 26.

Legislation in low income areas in New York City and Newark, NJ (as a control city). Elbel collects data from McDonald's, Burger King, Wendy's and KFC— the four largest fast-food chains, based on yearly revenue in 2010. He also surveys youths aged 1-17 and finds no statistically significant difference in calories purchased after mandatory labeling, even in cases where youths reported that their parents had influence over their order.[18,19]

Vadiveloo et al. (2011) further examines the data that Elbel et. al collected. Vadiveloo isolated a subset of 1,170 low-income adults aged 18 years and older from the data. Vadiveloo studied two variables in the food choices of these low-income adults: 1) the frequency of fast food consumption and 2) the content of purchases. Vadiveloo's results show that after the Legislation, more adults purchased high-caloric beverages and chose regular vs. low-fat salad dressings, but those adults that reported noticing the calorie postings ate out at fast food restaurants less often. Vadiveloo et al. finds that overall the Legislation did not favorably impact food selection choices of poor individuals. He explains that his results reflect the limited availability of healthy food choices in fast food restaurants, and perhaps the consumers are under-whelmed by the minimal caloric differences in regular vs. low-fat salad dressings. Vadiveloo et al. further speculates, based on his results and other similar studies, that menu labeling legislation combined with other strategies, such as an increased presence of healthful food offerings in low-

[18] Elbel, B., Gyamfi, J., and Kersh, R. (2011). Child and adolescent fast-food choice and the influence of calorie labeling: a natural experiment. International journal of obesity 2005 *35*, 493-500.

[19] "Menu labeling is prominent among the 'recommendations for empowering parents and caregivers' in the May 2010 report of the White House Task Force on Child Obesity. Because 57% of parents/caregivers indicated that they chose their child's meal, it is surprising that there are statistically insignificant findings post-Legislation."

income areas might be key to promoting behavioral change.[20]

4. Results Based on CHS

4.1. Dataset and Equation Structure

The CHS analysis is based on the New York City Community Health Survey (CHS) for years 2006 until 2010. This health survey is administered by the New York City Department of Health and Mental Hygiene. The CHS is conducted based upon the National Behavioral Risk Factor Surveillance System (BRFSS), overseen by the Centers for Disease Control and Prevention. The CHS is a cross-sectional survey that samples approximately 10,000 adults each year, aged 18 and older, from all five boroughs of New York City: Manhattan, Brooklyn, Queens, Bronx, and Staten Island. A computer-assisted telephone interviewing (CATI) system is used to collect survey data from the participants and, therefore, all data is self-reported. Data collection for each year begins in March and ends in November.[21] Table 1 displays summary statistics from the CHS in years 2006-2010.

My studies objective is to estimate the association between BMI and calorie postings on menus. I do this by looking at BMIs before and after the Legislation. I run a linear regression for the dependent continuous variable, BMI, based on self-report height and weight data. I regress BMI on 2009 and 2010 dummy variables, as well as, the linear combination of the two, labeled “Post-CP” to denote both years after the calorie posting was implemented. Since the Legislation was enacted on April 30 and the yearly survey

[20] Vadiveloo MK, Dixon LB, Elbel B. Consumer purchasing patterns in response to calorie labeling legislation in New York City. International Journal of Behavioral Nutrition and Physical Activity. 2011;8(51).
[21] "Data and Statistics." *NYC.gov Health and Mental Hygiene*. N.p., 2010. Web.

runs from March until November, I do not test the significance of a 2008 year dummy. In 2008, therefore, the Community Health Survey ran for a full two months before the Legislation was enacted. Any significance on a 2008 dummy variable would be dismissed because it could be attributable to changes of individuals before the Legislation).

I seek to estimate the following equation for individual *i* in neighborhood *n* during year *t*:

$$BMI_{int} = \beta_1 PostCP + \beta_2 X_{int} + \alpha_n + \mu_{nt} + \varepsilon_{ct} \quad (1)$$

BMI_{int} is a continuous variable indicating the body mass index of individual *i* at time *t*. *PostCP* is a dummy variable equal to 1 if an individual is surveyed in years 2009 or 2010, and thus is an indicator for the time period post-Legislation. X_{int} is a collection of demographic controls, including gender, race, age, education, and poverty. α_n and μ_{nt} are neighborhood and year fixed effects, and $\boldsymbol{\varepsilon_{ct}}$ is the error term. Robust standard errors are adjusted for clustering on neighborhoods.

In subsequent regressions using CHS, I restrict the sample to subsets of the population of females, college graduates, various race categories, individuals older than 25 years, and those above the 600% poverty line.

4.2. Results

Looking purely at the effect of the Legislation on New York City, overall, individual BMIs seem to show no statistically significant change (Table 2). This lack of change remains true for all demographics, according to results listed in Table 3**.** Still, it is notable that the time coefficients are positive for each demographic tested except white individuals in the combined years of 2009 and 2010, and older individuals (not including 18-24) in year 2009. If the regression was without endogeneity problems, the white and older populations may have shown significantly lower BMIs after the Legislation. Although not significant in this model, the direction of the coefficient on the subsets is consistent with decision-making outcomes cited by the BMJ Group and Downs et. al., that is, postings show no effect on purchasing for younger individuals and African Americans.

4.3. Discussion and Limitations

Statistically insignificant findings on weight outcomes for individuals are not surprising given that on average, prior works find no significant relationship between calories purchased and menu labeling. However, prior works employ a much smaller sample size and different methodology than I use in my study. Unfortunately, the Community Health Survey does not contain data on behavioral/ordering changes due to the postings. Future research should attempt to address the link between individuals' behavioral response to those same individuals' health outcomes.

My research findings are limited somewhat by their reliance on CHS data. First, the cross-sectional data limits the ability to draw conclusions about causality. Second, because the BMI are self-reported, individuals may be less inclined to divulge increases in weight, which potentially biases results toward the null. In addition, the endogeneity within the OLS model due to trends in New York City may also bias the results to the null. In other words, to the extent that obesity is increasing on a national level, it is hard to determine whether the trend is comparatively less evident for the New York City residents.

5. Results Based on SMART

5.1. Dataset

In order to alleviate the endogeneity problem inherent in the analysis of CHS, I examine the health outcomes of treated versus untreated counties after the legislation. I use Selected Metropolitan/Micropolitan Area Risk Trends data (SMART) for years 2006 to 2010 (from the Centers for Disease Control and Prevention website). The dataset consists of aggregated data of the Behavioral Risk Factor Surveillance System (BRFSS), a state-based system of telephone health surveys conducted annually with information on health risk behaviors, preventive health practices, and health care access.[22] I merge the BRFSS data with the 2006 through 2010 waves of the American Community Survey (ACS) data. ACS uses a series of monthly samples of household surveys to generate estimates in five-year time spans. I obtain the merged data for Kings County, New York County, and Queens County. The two remaining counties, Bronx and Richmond Counties, are excluded because of missing values.[23]

5.2. Equation Structure

I employ a difference-in-difference model over time and counties to determine if the Legislation enacted counties of New York City will cause health changes over and above those of untreated counties after 2008. The ten control counties consist of those counties

[22] "2010 SMART: BRFSS City and County Data." Centers for Disease Control and Prevention. N.p., 2010. Web.
[23] "American Community Survey." *About the – About the Survey – – U.S. Census Bureau*. N.p., 2010. Web.

that are similar to the New York City counties. The summary statistics in Table 4 show the similarities in demographics of treated and untreated categories.

Dependent variables include the grouping of the dichotomous overweight and obese variables, as well as each respective term on its own. Overweight is classified as a BMI range of 25.0 – 29.9. Obesity is classified as a BMI range of 30.0 – 99.8. Variables that control for demographic composition include age, gender, race/ethnicity (black, white, Hispanic, Asian, and other race), education, income, poverty, health coverage, and physical activity. All control variables are in the form of ratios to the total sample population, except for household income and average income of the poor, which are kept as dollar units. Regressions include county fixed effects and year effects. Robust standard errors are adjusted for clustering on counties. I first employ a difference-in-difference model to determine changes in NYC (for those observations in any one of the three counties) versus the ten control counties following the postings. Then, a second difference-in-difference model compares each respective county to the ten control counties.

The following equations show the outcome on weight in counties *c* during year *t*:

$$Weight_{ct} = \gamma_1(NewYorkCity \times 2009_t) + \gamma_2(NewYorkCity \times 2010_t) + \beta X_{ct} + \alpha_c + \mu_{ct} + \varepsilon_{ct} \qquad (2)$$

$$Weight_{ct} = \gamma_1(Kings \times 2009_t) + \gamma_2(Kings \times 2010_t) + \gamma_3(NYCounty \times 2009_t) + \gamma_4(NYCounty \times 2010_t) + \gamma_5(Queens \times 2009_t) + \gamma_6(Queens \times 2010_t) + \beta X_{ct} + \alpha_c + \mu_{ct} + \varepsilon_{ct} \qquad (3)$$

$Weight_{ct}$ is the percent of obese or overweight individuals across each county *c* in time period year *t*. $NewYorkCity$ is a dummy variable equal to 1 if the county observed is

Kings County, *New York County*, or *Queens County*, and equal to 0 if the county observed is a control county. *Kings* is a dummy variable equal to 1 if the county observed is Kings County and equal to 0 for any other county in the sample. *New York County* and *Queens County* follow. 2009_t is a dummy variable equal to 1 if the year is 2009, and thus is an indicator for the first year post-Legislation. 2010_t is a dummy variable equal to 1 if the year is 2010, and thus is an indicator for the second year post-Legislation. The average marginal effect (γ) on the interaction terms then measure the difference-in-differences effect the Legislation on the respective county or counties. Lastly, α_c and μ_{ct} are county and year fixed effects, and ε_{ct} is the error term. Robust standard errors are adjusted for clustering on counties.

The previous equations are useful for a first look at whether the Legislation had an effect on overweight or obesity rates in New York City counties compared to the control counties. However, further controls are necessary to make accurate conclusions. The treated counties in this model on average are similar in the make-up of individuals to the untreated counties but the two groups do not necessarily follow the same trends; Figures 2 and 3 show that the percentage of overweight and obese indivdiuals varies over time within each county. I introduce two additional difference-in-difference models that include county-specific time trends to dismiss the likelihood that the difference in trends between counties would bias results. The third and fourth specifications include these county-specific linear trend variables:

$$Weight_{ct} = \gamma_1(NewYorkCity \times 2009_t) + \gamma_2(NewYorkCity \times 2010_t) + \beta X_{ct} + \Psi_c + \alpha_c + \mu_{ct} + \varepsilon_{ct} \tag{4}$$

$$Weight_{ct} = \gamma_1(Kings \times 2009_t) + \gamma_2(Kings \times 2010_t) + \gamma_3(NYCounty \times 2009_t) + \gamma_4(NYCounty \times 2010_t) + \gamma_5(Queens \times 2009_t) + \gamma_6(Queens \times 2010_t) + \beta X_{ct} + \Psi_c + \alpha_c + \mu_{ct} + \varepsilon_{ct} \tag{5}$$

Where Ψ denotes the time trend for county c. Robust standard errors are adjusted for clustering on counties.

5.3. Results

In all three New York City counties, individuals who report being overweight or obese decrease in 2009, with that decrease mainly driven by the 'overweight' category (Table 6). Although the combination of the counties shows a change after the Legislation, each separate county within New York City shows outcomes independent of the outcome of the set (Table 7). In Kings County, the Legislation is associated with a decreased prevalence of overweight and obese individuals for the combined 2009 and 2010 years. Residents of Queens County show a significant decrease in the combination of overweight and obese individuals in 2009 at the 10% level. The presence of postings leads to a significant increase of overweight individuals in Queens County in 2010, and when combining obese and overweight variables, the statistical significance drops.

After further controlling for county-specific time trends, the significance for the aggregate counties in NYC extends to the year 2010, and both 2009 and 2010 show a significant drop in residents weight (Table 8). The effect however is a decrease in obesity, and the 'overweight' category here is now insignificant. During the two years after the Legislation, obesity rates in the three NYC counties fell by 14 percent. This is significant compared to the 21% average obesity rate in the three counties.

County-specific time trend adjustment further shows that obesity rates fall in Kings County in the combined 2009 and 2010 years as well as in New York County in 2009 (Table 9). The finding for Kings County remains significant (as it was before adjusting for county-specific time trends), except that the outcome in the regression with county-specific time trends shows lower amount of obese individuals (compared to the before, overweight individuals). During the two years after the Legislation in Kings County, number of obese and overweight individuals dropped by 9 percent (from an average of 35 percent) relative to control counties. During the first year post-Legislation, number of obese individuals in New York County dropped by 5 percent (from an average of 15 percent), relative to control counties. Individuals in Queens show no significant change in BMI post-Legislation, and the significant increase of overweight individuals found before the county-specific time trends model was implemented may well have been due to increasing overweight trends within that county (Figure 3). Based on the significance of two counties separately, it makes sense, then, that the estimated impact on the three combined counties is significant.

Tables 10 and 11 show falsification tests and consist of the same specifications above. The difference is the dependent variable in these specifications: "percentage of individuals who have been diagnosed with pregnancy-related diabetes." It is indeed promising that the coefficients are insignificant in Table 10 (all three NYC counties post-Legislation period) and in Table 11 (each respective county post-Legislation period). These results remain true when controlling for county-specific time trends, as shown in Tables 12 and 13.

5.4. Discussion

This Discussion section will explore causal mechanisms that may explain statistical significance and then analyze the results. My statistically significant findings might be due to the response of restaurants to the Legislation rather than due to changes in individual decision-making. The McDonald’s menu has changed quite a bit after the 2008 menu-labeling legislation. As pictured on the two drive-thru menus in Figure 1, real fruit smoothies and additional snack wrap variations became available after the Legislation. Because previously mandated calorie postings online and in pamphlets were not as visible as the calorie labels on menus, the restaurants developed stronger incentives to lower calorie count. Indeed, snack wraps run about 350-370 calories and there are 330 calories in a large real fruit smoothie. Restaurants’ incentives to lower calorie count may result in a missed opportunity to focus on better overall nutritional value. For example, a large McDonald’s real fruit smoothie contains 70g of sugar. Still, a decline in caloric consumption is associated with a lower BMI, which could lead to other positive health outcomes. Further, the snack wrap menu choice seems to be a healthier alternative to other menu-items. Similar to McDonald’s, I speculate that chain restaurants in New York City that are required to post calorie count may have also added lower calorie items to the menu. In addition, restaurants could have made other changes to food content behind the scenes, without a change in the actual menu, such as lower calorie salad dressings and lower calorie French fries (with no trans-fat).[24]

Interestingly, my findings show a divergence of outcomes for each treated county. The Legislation is correlated with lower obesity rates in Kings County, and unchanged

[24] McDonald's USA. *Nutrition Journey*. *Newsroom*. N.p., Sept. 2012. Web.

obesity rates in New York County, even though the Legislation applies to both counties. Table 5 shows the concentrations of Big 5 restaurants per hundred thousand people in each county. A plausible reason for county divergence is that there is a much larger concentration of Big 5 restaurants per hundred thousand people in Kings county than in Queens and New York Counties. Assuming that Big 5 restaurants are an appropriate proxy for all treated restaurants, i.e. chains of more than 15 locations in which calorie posting was mandatory after 2008, then it makes sense that BMI significantly decreased in Kings county more than the other New York City counties. To further quantify this divergence, I run a separate linear regression model in the Appendix (7.) using the individual-level data (from the CHS section), which tests only the subset of neighborhoods with a larger percentage of top chain restaurants.

5.5. Limitations

In this section I will outline my study's limitations; 1) the lack of complete data and 2) the limitations of the regression models. The SMART excludes Bronx and Richmond counties of New York City. My results derived from using this somewhat truncated data set shows the Legislation is correlated with significant changes in obese or overweight individuals in some New York City counties while there are no significant correlations in others. Therefore, the two remaining treated counties could play a key role in determining the real impact of the Legislation on New York City as a whole.

A second limitation of my study is that it is solely focused on BMI and obesity/overweight levels and not on other health outcomes. Although the Legislation led to a significant change in BMIs, a more complete evaluation of the Legislation's effectiveness would be to regress an array of different health outcomes on the Legislations presence. Because low BMI is sometimes directly correlated with improved health, posting calories on menus may lead to improvement in other related health outcomes, such as heart disease and diabetes.

6. Conclusion

In this paper, I present the first study looking at the link between postings of calories on menus and improved weight outcomes. I use individual data at the city level collected between 2006 and 2010 that included BMI and demographic classifications of NYC residents. I then use county-level data for multiple counties collected between 2006 and 2010 that included weight and demographic classifications of each respective county. My results suggest that the Legislation implemented in 2008 leads to a decline in obesity in Kings County and New York County relative to control counties. The Legislation does not affect BMI for all individuals, per se, but the county-wide results prove that BMI increased more in untreated counties than it did in New York City counties post-Legislation. Findings suggest that there are pathways other than consumer changes in purchasing where it is possible for statistically significant changes in BMI to occur.

Table 1: CHS Summary Statistics

BMI			
Mean	Std. Dev	Min	Max
26.970	5.981	3.108	98.732

Weight (based on BMI)	Frequency	Percent	Cum.
Under weight	1,126	2.57%	2.57%
Normal weight	16,615	37.95%	40.52%
Over weight	15,470	35.34%	75.86%
Obese	10,569	24.14%	100.00%
Total	43,780	100.00%	

Race	Frequency	Percent	Cum.
White	19,089	42.09%	42.09%
Black	10,942	24.12%	66.21%
Hispanic	11,006	24.27%	90.48%
Asian/Pacific Islander	3,294	7.26%	97.74%
Other	1,025	2.26%	100.00%
Total	45,356	100.00%	

Gender	Frequency	Percent	Cum.
Male	17,581	38.76%	38.76%
Female	27,775	61.24%	100.00%
Total	45,356	100.00%	

Education	Frequency	Percent	Cum.
Less than high school	7,212	16.06%	16.06%
High school graduate	10,710	23.86%	39.92%
College/technical school	9,186	20.46%	60.38%
College graduate	17,787	39.62%	100.00%
Total	44,895	100.00%	

Poverty Based on Income	Frequency	Percent	Cum.
<100%	8,414	20.31%	20.31%
100%-200%	6,921	16.70%	37.01%
200%-400%	6,694	16.16%	53.17%
400%-600%	6,601	15.93%	69.10%
>600%	8,869	21.41%	90.51%
Don't know	3,934	9.49%	100.00%
Total	41,433	100.00%	

Age Group (in Years)	Frequency	Percent	Cum.
18-24	2,331	5.15%	5.15%
25-44	14,171	31.31%	36.46%
45-64	17,608	38.91%	75.37%
65+	11,145	24.63%	100.00%
Total	45,255	100.00%	

Table 2: Impact of Legislation on BMI

Dependent Variable: BMI	(1)	(2)
2006 Year Dummy	-0.043	-0.043
	(0.094)	(0.094)
2007 Year Dummy	-0.044	-0.044
	(0.065)	(0.065)
2009 Year Dummy	-0.001	-0.001
	(0.102)	(0.102)
2010 Year Dummy	0.137	0.137
	(0.116)	(0.116)
PostCP		0.135
		(0.181)
Observations	38,745	38,745
R-squared	0.091	0.091
Adj. R-Squared	0.089	0.089

*** p<0.01, ** p<0.05, * p<0.1

Robust Standard Errors in ( )

SE's clustered by neighborhood

These regressions control for neighborhood fixed effects, race, sex, education, poverty, age, and age^2

Table 3: Impact of Legislation on BMI by Demographic Category

Dependent Variable: BMI	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(5)	(5)	(6)	(6)
For subset:	females	females	college degree	college degree	white	white	black	old	old	no poverty	no poverty
2006 Year Dummy	0.159	0.159	0.074	0.074	-0.076	-0.076	0.002	-0.053	-0.053	0.048	0.048
	(0.120)	(0.120)	(0.123)	(0.123)	(0.166)	(0.166)	(0.193)	(0.100)	(0.100)	(0.136)	(0.136)
2007 Year Dummy	0.062	0.062	0.049	0.049	-0.133	-0.133	-0.012	-0.088	-0.088	-0.060	-0.060
	(0.116)	(0.116)	(0.111)	(0.111)	(0.091)	(0.091)	(0.137)	(0.062)	(0.062)	(0.122)	(0.122)
2009 Year Dummy	0.027	0.027	0.100	0.100	-0.120	-0.120	0.213	-0.029	-0.029	0.077	0.077
	(0.138)	(0.138)	(0.103)	(0.103)	(0.141)	(0.141)	(0.206)	(0.106)	(0.106)	(0.113)	(0.113)
2010 Year Dummy	0.133	0.133	0.204	0.204	-0.007	-0.007	0.233	0.123	0.123	0.073	0.073
	(0.163)	(0.163)	(0.149)	(0.149)	(0.143)	(0.143)	(0.205)	(0.115)	(0.115)		(0.142)
PostCP		0.160		0.304		-0.127			0.094		0.150
		(0.247)		(0.219)		(0.249)			(0.183)		(0.222)
Observations	23,259	23,259	15,219	15,219	16,022	16,022	9,357	36,669	36,669	14,679	14,679
R-squared	0.125	0.125	0.111	0.111	0.098	0.098	0.058	0.088	0.088	0.121	0.121
Adj. R-Squared	0.123	0.123	0.108	0.108	0.095	0.095	0.053	0.086	0.086	0.118	0.118

*** p<0.01, ** p<0.05, * p<0.1

Robust Standard Errors in ( )

SE's clustered by neighborhood

These regressions control for neighborhood fixed effects, race, sex, education, poverty, age, and age^2

Table 4: County-level Summary Statistics (Means)

County[a]	Overweight/Obese[4]	Overweight	Obese	18-24	25-44	45-64	65+	CollegeGrad[2]	Insured[3]	Diabetes[5]	HealthStatus[6]	Exercise[7]	Fruit/Veg[8]	White	Black	Hispanic	Male	HHincome[9]
Control Counties	59%	35%	24%	15%	38%	32%	16%	35%	88%	8%	85%	76%	26%	56%	25%	13%	47%	51,880
NYC Counties Total[1]	55%	34%	21%	13%	41%	30%	16%	38%	85%	8%	83%	74%	27%	40%	21%	23%	47%	53,656
Kings County	59%	35%	24%	14%	40%	31%	15%	28%	85%	9%	81%	70%	31%	37%	33%	19%	46%	42,097
New York County	47%	32%	15%	13%	43%	28%	15%	57%	88%	6%	85%	81%	25%	51%	13%	23%	46%	65,158
Queens County	58%	36%	22%	12%	40%	32%	16%	29%	84%	9%	82%	71%	24%	32%	18%	25%	48%	53,714

a. sample size respectively 50,15,5,5,5
1. excludes Bronx and Richmond County
2. includes college, masters, professional school, or doctorate
3. health care coverage
4. includes obese and overweight, based on BMI of >25
5. told by a doctor, does not include pre-borderline diabetes
6. reported health status of excellent, very good or good health
7. participation in physical activity in past month
8. fruits and vegetables five or more times per day
9. median HH income

Table 5: Restaurant Statistics

County	%Subway/Total Restaurants	%Big4/Total Restaurants	# Subway / 100,000 pp	# Big 4 / 100,000 pp
Kings County, NY	2.30%	3.62%	17.812	27.990
New York County, NY	2.09%	1.68%	9.116	7.347
Queens County, NY	2.36%	3.70%	8.733	13.674

Table 6: Impact of Legislation on Obese and Overweight (by aggregrated NYC counties)

	(1)	(2)	(2)	(2)	(3)	(3)
Dependent Variable:	Overweight/Obese	Overweight/Obese	Overweight	Overweight	Obese	Obese
2006 Year Dummy	-5.212	-5.212	-3.018	-3.018	-2.193	-2.193
	(3.410)	(3.410)	(3.584)	(3.584)	(3.017)	(3.017)
2007 Year Dummy	-1.189	-1.189	-0.721	-0.721	-0.468	-0.468
	(2.134)	(2.134)	(2.315)	(2.315)	(1.595)	(1.595)
2009 Year Dummy	0.218	0.218	0.985	0.985	-0.766	-0.766
	(1.664)	(1.664)	(1.388)	(1.388)	(1.287)	(1.287)
2010 Year Dummy	0.763	0.763	1.256	1.256	-0.492	-0.492
	(2.834)	(2.834)	(2.278)	(2.278)	(1.750)	(1.750)
newyork_2009	**-7.781***	**-7.781***	**-5.479****	**-5.479****	-2.302	-2.302
	(3.808)	**(3.808)**	**(2.512)**	**(2.512)**	(2.223)	(2.223)
newyork_2010	-0.660	-0.660	1.863	1.863	-2.523	-2.523
	(3.536)	(3.536)	(3.504)	(3.504)	(2.026)	(2.026)
newyork_PostCP		-8.441		-3.616		-4.825
		(6.764)		(5.616)		(3.629)
Constant	666.626	666.626	869.170	869.170	-202.544	-202.544
	(687.941)	(687.941)	(522.774)	(522.774)	(329.785)	(329.785)
Observations	64	64	64	64	64	64
R-squared	0.841	0.841	0.609	0.609	0.874	0.874
Adj. R-Squared	0.687	0.687	0.230	0.230	0.752	0.752

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty

Table 7: Impact of Legislation on Obese and Overweight (by separated NYC counties)

	(1)	(1)	(2)	(2)	(3)	(3)
Dependent Variable:	Overweight/Obese	Overweight/Obese	Overweight	Overweight	Obese	Obese
2006 Year Dummy	-8.692**	-8.692**	-7.412**	-7.412**	-1.280	-1.280
	(3.733)	(3.733)	(3.352)	(3.352)	(3.712)	(3.712)
2007 Year Dummy	-2.814	-2.814	-2.620	-2.620	-0.194	-0.194
	(1.833)	(1.833)	(1.986)	(1.986)	(1.706)	(1.706)
2009 Year Dummy	1.069	1.069	2.328*	2.328*	-1.259	-1.259
	(1.765)	(1.765)	(1.277)	(1.277)	(1.306)	(1.306)
2010 Year Dummy	2.361	2.361	3.759	3.759	-1.398	-1.398
	(3.225)	(3.225)	(2.206)	(2.206)	(2.079)	(2.079)
kings_2009	**-12.165*** **	**-12.165*** **	**-7.132** **	**-7.132** **	**-5.033* **	**-5.033* **
	(2.970)	**(2.970)**	(2.555)	(2.555)	**(2.369)**	**(2.369)**
kings_2010	-1.625	-1.625	0.204	0.204	-1.830	-1.830
	(2.520)	(2.520)	(1.984)	(1.984)	(1.733)	(1.733)
kings_PostCP		**-13.791** **		-6.928		**-6.863* **
		(4.731)		(4.040)		**(3.247)**
newyorkcounty_2009	-3.797	-3.797	-3.270	-3.270	-0.527	-0.527
	(5.052)	(5.052)	(3.594)	(3.594)	(3.150)	(3.150)
newyorkcounty_2010	-2.202	-2.202	-1.156	-1.156	-1.047	-1.047
	(6.827)	(6.827)	(5.754)	(5.754)	(4.327)	(4.327)
newyorkcounty_PostCP		-6.000		-4.426		-1.573
		(11.662)		(9.178)		(7.011)
queens_2009	**-4.402* **	**-4.402* **	-1.824	-1.824	-2.578	-2.578
	(2.229)	**(2.229)**	(1.974)	(1.974)	(2.517)	(2.517)
queens_2010	4.697	4.697	**10.403*** **	**10.403*** **	-5.706	-5.706
	(4.342)	(4.342)	**(3.048)**	**(3.048)**	(3.326)	(3.326)
queens_PostCP		0.295		8.579		-8.284
		(6.436)		(4.843)		(5.720)
Constant	322.111	322.111	624.860	624.860	-302.748	-302.748
	(953.589)	(953.589)	(788.990)	(788.990)	(468.223)	(468.223)
Observations	64	64	64	64	64	64
R-squared	0.864	0.864	0.667	0.667	0.886	0.886
Adj. R-Squared	0.694	0.694	0.251	0.251	0.745	0.745

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty

Table 8: Impact of Legislation on Obese and Overweight (by aggregrated NYC counties)

	(1)	(1)	(2)	(2)	(3)	(3)
Dependent Variable:	Overweight/Obese	Overweight/Obese	Overweight	Overweight	Obese	Obese
2006 Year Dummy	-0.907	-0.907	-16.803	-16.803	15.896	15.896
	(37.200)	(37.200)	(43.278)	(43.278)	(19.087)	(19.087)
2007 Year Dummy	0.815	0.815	-7.536	-7.536	8.351	8.351
	(18.675)	(18.675)	(21.404)	(21.404)	(9.528)	(9.528)
2009 Year Dummy	-3.300	-3.300	6.918	6.918	-10.218	-10.218
	(18.759)	(18.759)	(23.516)	(23.516)	(10.515)	(10.515)
2010 Year Dummy	-5.643	-5.643	15.404	15.404	-21.047	-21.047
	(35.298)	(35.298)	(46.042)	(46.042)	(19.796)	(19.796)
newyork_2009	-4.825	-4.825	-0.153	-0.153	**-4.671***	**-4.671***
	(5.563)	(5.563)	(5.297)	(5.297)	**(2.173)**	**(2.173)**
newyork_2010	-0.115	-0.115	9.796	9.796	**-9.911***	**-9.911***
	(12.912)	(12.912)	(13.024)	(13.024)	**(5.393)**	**(5.393)**
new york_PostCP		-4.940		9.643		**-14.582****
		(17.669)		(17.898)		**(6.309)**
Constant	-3,882.254	-3,882.254	854.620	854.620	-4,736.872	-4,736.872
	(17,497.725)	(17,497.725)	(18,785.109)	(18,785.109)	(9,126.836)	(9,126.836)
Observations	64	64	64	64	64	64
R-squared	0.885	0.885	0.712	0.712	0.920	0.920
Adj. R-Squared	0.638	0.638	0.094	0.094	0.749	0.749

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty
These regressions also control for county-specific time trends

Table 9: Impact of Legislation on Obese and Overweight (by separated NYC counties)

	(1)	(1)	(2)	(2)	(3)	(3)
Dependent Variable:	Overweight/Obese	Overweight/Obese	Overweight	Overweight	Obese	Obese
2006 Year Dummy	-6.148	-6.148	-21.732	-21.732	15.584	15.584
	(35.172)	(35.172)	(42.505)	(42.505)	(21.521)	(21.521)
2007 Year Dummy	-2.196	-2.196	-10.013	-10.013	7.817	7.817
	(17.474)	(17.474)	(20.488)	(20.488)	(10.776)	(10.776)
2009 Year Dummy	-3.533	-3.533	7.678	7.678	-11.211	-11.211
	(18.466)	(18.466)	(25.133)	(25.133)	(11.819)	(11.819)
2010 Year Dummy	-7.517	-7.517	15.605	15.605	-23.122	-23.122
	(35.181)	(35.181)	(49.773)	(49.773)	(23.420)	(23.420)
kings_2009	**-9.603***	**-9.603***	-2.942	-2.942	-6.660	-6.660
	(5.244)	**(5.244)**	(6.065)	(6.065)	(4.164)	(4.164)
kings_2010	-1.831	-1.831	6.969	6.969	-8.801	-8.801
	(11.537)	(11.537)	(10.585)	(10.585)	(5.648)	(5.648)
kings_PostCP		-11.434		4.027		**-15.461***
		(15.750)		(15.737)		**(8.056)**
newyorkcounty_2009	-4.222	-4.222	0.969	0.969	**-5.190***	**-5.190***
	(6.112)	(6.112)	(7.404)	(7.404)	**(2.753)**	**(2.753)**
newyorkcounty_2010	-13.101	-13.101	0.736	0.736	-13.837	-13.837
	(18.961)	(18.961)	(24.690)	(24.690)	(11.166)	(11.166)
newyorkcounty_PostCP		-17.323		1.705		-19.028
		(23.769)		(30.961)		(13.250)
queens_2009	-4.945	-4.945	-1.188	-1.188	-3.758	-3.758
	(5.045)	(5.045)	(5.497)	(5.497)	(2.252)	(2.252)
queens_2010	-0.359	-0.359	11.019	11.019	-11.378	-11.378
	(15.347)	(15.347)	(17.316)	(17.316)	(7.303)	(7.303)
queens_PostCP		-5.304		9.831		-15.1354
		(20.319)		(22.628)		(9.260)
Constant	-8,789.206	-8,789.206	-2,086.659	-2,086.659	-6,702.547	-6,702.547
	(21,101.656)	(21,101.656)	(24,391.137)	(24,391.137)	(10,762.950)	(10,762.950)
Observations	64	64	64	64	64	64
R-squared	0.909	0.909	0.746	0.746	0.928	0.928
Adj. R-Squared	0.640	0.640	-0.001	-0.001	0.715	0.715

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty
These regressions also control for county-specific time trends

Table 10: Falsification (by aggregrated NYC Counties)

	(1)
Dependent Variable:	Diabetesduetopregnancy
2006 Year Dummy	-0.160
	(0.523)
2007 Year Dummy	0.144
	(0.313)
2009 Year Dummy	-0.001
	(0.208)
2010 Year Dummy	-0.052
	(0.203)
newyork_2009	-0.328
	(0.316)
newyork_2010	0.100
	(0.386)
Constant	-104.976**
	(36.756)
Observations	64
R-squared	0.645
Adj. R-Squared	0.302

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty

Table 11: Falsification (by separated NYC counties)

	(1)
Dependent Variable:	Diabetesduetopregnancy
2006 Year Dummy	-0.062
	(0.718)
2007 Year Dummy	0.201
	(0.411)
2009 Year Dummy	-0.002
	(0.237)
2010 Year Dummy	-0.039
	(0.235)
kings_2009	0.150
	(0.245)
kings_2010	0.097
	(0.326)
newyorkcounty_2009	-0.783
	(0.502)
newyorkcounty_2010	0.018
	(1.043)
queens_2009	-0.395
	(0.271)
queens_2010	0.147
	(0.574)
Constant	-86.180
	(61.602)
Observations	64
R-squared	0.662
Adj. R-Squared	0.239

*** p<0.01, ** p<0.05, * p<0.1

Robust Standard Errors in ( )

SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty

Table 12: Falsification (by aggregrated NYC Counties)

	(1)
Dependent Variable:	Diabetesduetopregnancy
2006 Year Dummy	-2.081
	(6.222)
2007 Year Dummy	-0.759
	(2.821)
2009 Year Dummy	1.250
	(3.343)
2010 Year Dummy	2.388
	(6.441)
newyork_2009	-0.580
	(0.567)
newyork_2010	-0.262
	(0.857)
Constant	1,091.669
	(2,477.083)
Observations	64
R-squared	0.754
Adj. R-Squared	0.225

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty
These regressions also control for county-specific time trends

Table 13: Falsification (by separated NYC Counties)

	(1)
Dependent Variable:	Diabetesduetopregnancy
2006 Year Dummy	-1.660
	(7.112)
2007 Year Dummy	-0.542
	(3.342)
2009 Year Dummy	1.258
	(3.689)
2010 Year Dummy	2.437
	(7.099)
kings_2009	-0.039
	(0.637)
kings_2010	-0.425
	(0.925)
newyorkcounty_2009	-1.185
	(0.971)
newyorkcounty_2010	0.173
	(2.257)
queens_2009	-0.442
	(0.592)
queens_2010	0.221
	(1.457)
Constant	1,855.063
	(2,618.748)
Observations	64
R-squared	0.789
Adj. R-Squared	0.169

*** p<0.01, ** p<0.05, * p<0.1
Robust Standard Errors in ( )
SE's clustered by county

These regressions control for county fixed effects, exercise, health coverage, race, age, gender, education, HH Income, average income of households below poverty
These regressions also control for county-specific time trends

Figure 1: Menu Changes, Before and After

2007 Drive-thru Menu:

2010 Drive-thru Menu:

Figure 2. Obesity Trends

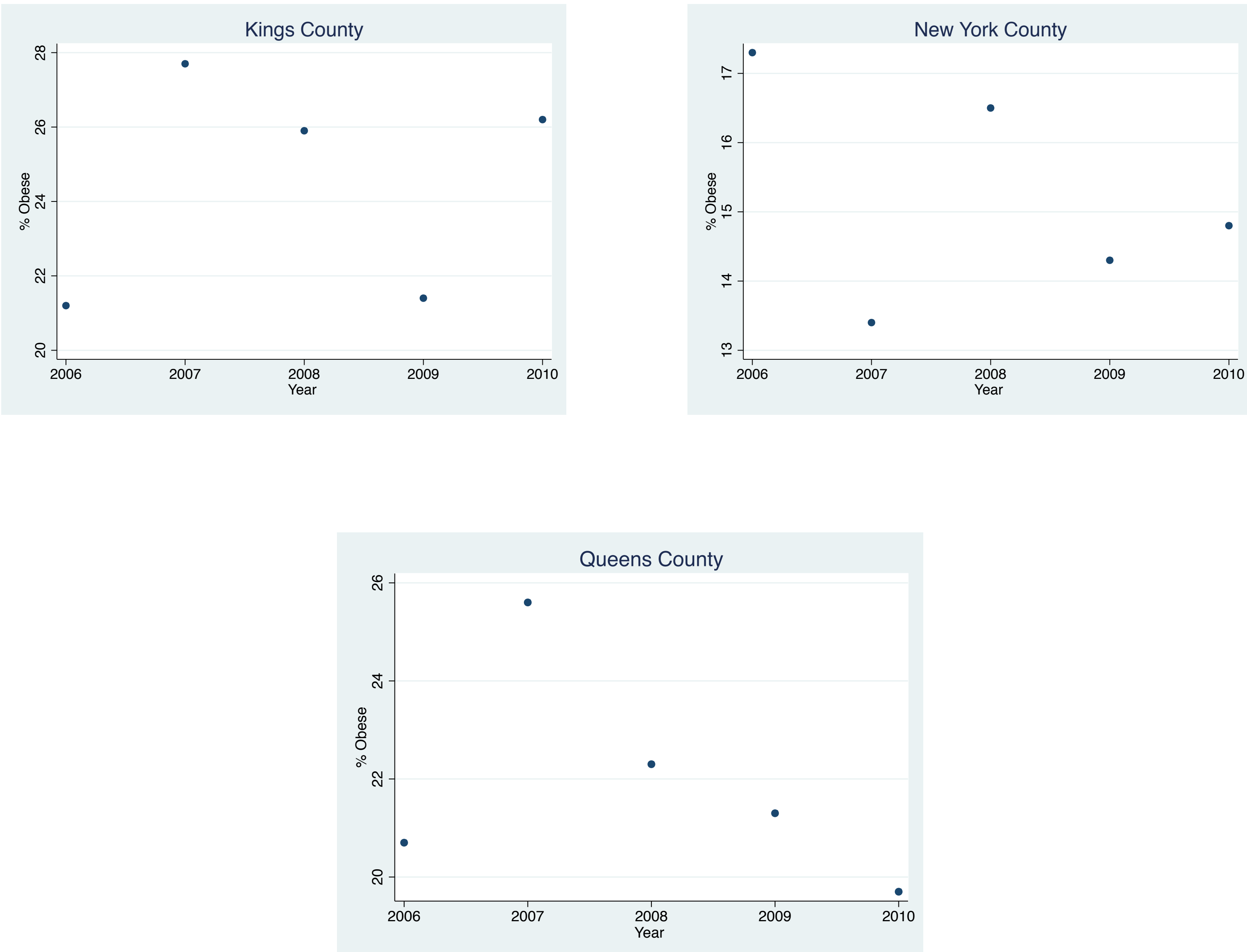
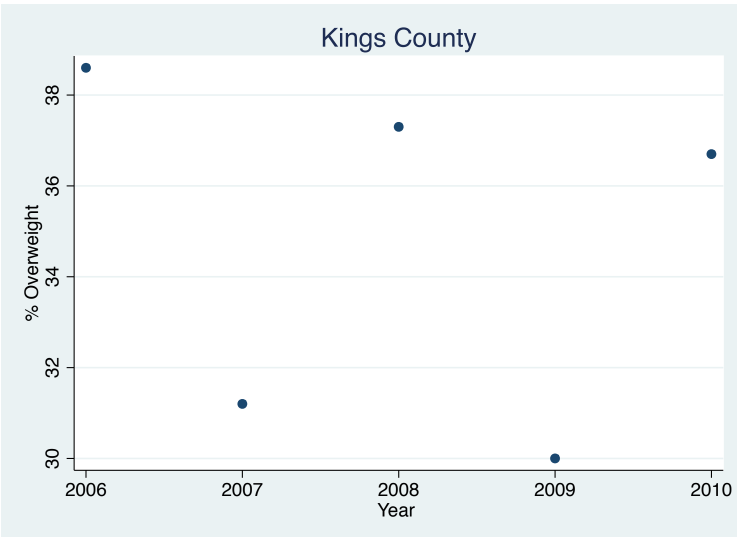
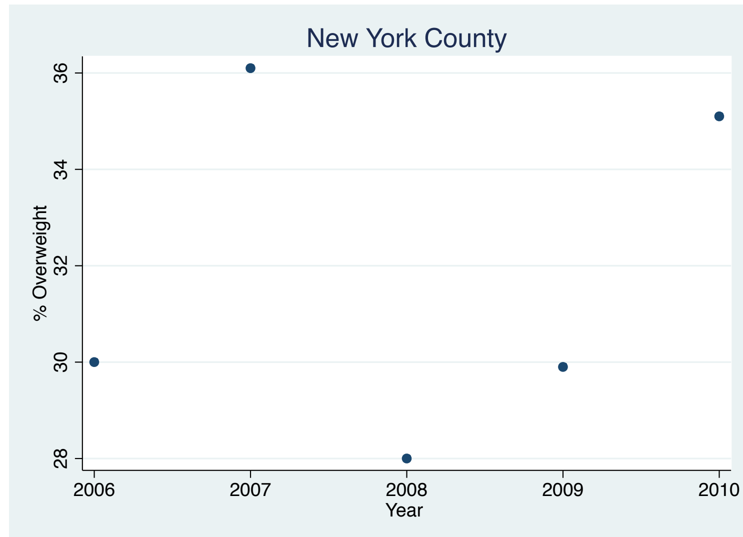
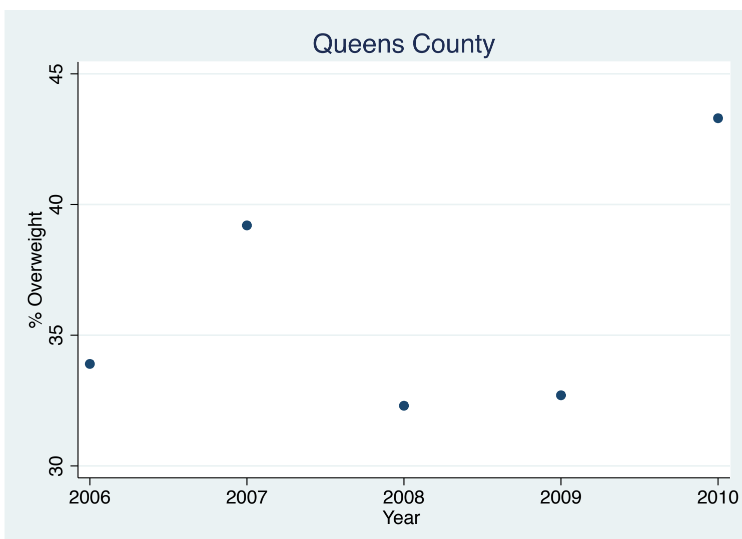


Figure 3. Overweight Trends







7. Appendix: CHS Across Neighborhoods

The results using CHS demonstrate no statistically significant change in BMI after the Legislation. This finding presumes the Legislation impacted all neighborhoods in the same way. Should the postings impact some neighborhoods more than others, it would be useful to analyze the individual-level data taking advantage of each individual's distinct neighborhood classification. I do this by categorizing neighborhoods: 1) neighborhoods where the Legislation would impact resident BMIs and 2) neighborhoods where the Legislation would not impact resident BMIs. Presumably, neighborhoods within the first category would contain a large number of treated restaurants. Treated restaurants are those chains that have 15 locations nationally, and thus must comply with the Legislation.

I employ a linear regression model to better estimate the effect of the Legislation on BMI over time for those areas in New York City that had a high density of treated restaurants. I use a proxy to measure the number of treated restaurants in each neighborhood. The proxy variable, "Big 4," denotes the ratio McDonald's, KFC, Wendy's, and Burger King establishments to total establishments. The proxy variable, "Subway," denotes the number of Subway establishments to total establishments in each neighborhood. I include the Subway estimates because I want to test if the Legislation would have different effects on BMI for residents in a neighborhood with high concentrations of Subways than in a neighborhood with high concentrations of Big 4. The BMJ group's research, which highlights the differences in behavioral outcomes of individuals sampled in Big chains vs. Subways, shows that individuals frequenting Big chain restaurants lower calorie intake after the Legislation while individuals frequenting

Subway do not. I hypothesize that residents of a neighborhood with many Subways will see no change in BMI due to the Legislation because Subway clearly informed customers of calories before the Legislation. Conversely, I hypothesize that residents of neighborhoods with high concentrations of Big 4 establishments will have a significantly lower BMI after the Legislation because Big 4 establishments did not clearly display calories to its customers prior to the Legislation.

7.1. Dataset

I use the same CHS dataset that I previously used in Section 4., and compliment it with the Big 4 and Subway ratios. I obtain the numerator of the ratios on Subway, McDonald's, KFC, Wendy's, and Burger King corporate websites, tallying number of establishments per zip code. I then aggregate the numbers up to each corresponding neighborhood using the United Hospital Fund (UHF) classification. UHF is the same classification that CHS uses to assign individuals to a distinct neighborhood. I calculate the denominator of the ratio using counts of total establishments per zip code from the United States Census Bureau website.[25] I also aggregate this number to the neighborhood level using the UHF classification. The proxies for density of treated restaurants in each neighborhood, thus, are the count of Big 4 or Subway restaurants divided by the total restaurants in each respective neighborhood. Numbers of Big 4 and Subway establishments are current 2013 estimates, while the count for total establishments are 2007 estimates.

[25] Counts include full-service restaurants (industry code 722110), limited-service restaurants (industry code 722211), and cafeteria grills and buffets (industry code 722212).

7.2. Equation Structure

I run regressions using the same equation structure as in Section 4., and again observe the direction and significance on the coefficient for years 2009, 2010, and the combined two years, “PostCP”. I, however, run the regressions on subsets of neighborhoods with the following dummies. One dummy variable indicates neighborhoods containing above 2.2% of Subway restaurants and another dummy variable for neighborhoods containing above 3.3% of Big 4 establishments. I choose cut-off values as the median ratio for all neighborhoods in the survey.

7.3. Results

Table 14 displays the results of the Legislation’s impact on BMI based on neighborhood classifications. The regression in Columns 1 includes residents of neighborhoods that have a higher concentration of Big 4 establishments than the rest of the data, and Columns 2 only include residents of neighborhoods that have a higher concentration of Subways than the rest of the data.

There is no evidence of significant changes in individuals BMIs after the Legislation in areas with greater than 3.3% of Big 4 restaurants per neighborhood. The same holds true for individuals in neighborhoods that have greater than 2.2% of Subway restaurants.

7.4. Discussion and Limitations

At first glance the subset of results seems inconsistent with expectations; presumably in areas with a higher concentration of treated restaurants, residents would have greater exposure to calorie labels and consequently alter their choices. However, the fact that the residents of certain neighborhoods show no difference compared to the full sample (from Section 4.) could be because of measurement error.

A limitation of this analysis is the structure of my equations. I perform the regression on a subset of the population instead of on the entire population with interaction terms. This is because performing a difference-in-difference model is not possible when the ratios of restaurant concentration in each neighborhood are fixed over time (i.e. restaurants opening or closing is ignored). It would be more useful to use the difference-in-difference model and thus test if the BMI outcomes varied more for the high-density neighborhoods versus all other neighborhoods. In addition, because the ratios consist of data for two different time periods, they may not accurately account for true density of Big 4 and Subway restaurants. This last concern, however, is minor because the legislation should have affected all chains in the same manner. The probability of chain restaurants closing due to costs would then be equal in each neighborhood – and the net effect of any change in ratios over time would be null.

Table 14: Impact of Legislation on BMI, by Neighborhood Category

Dependent Variable: BMI	(1)	(1)	(2)	(2)
For subset:	big4>3.3%	big4>3.3%	Subway>2.2%	Subway>2.2%
2006 Year Dummy	-0.142	-0.142	-0.214	-0.214
	(0.118)	(0.118)	(0.133)	(0.133)
2007 Year Dummy	-0.036	-0.036	-0.065	-0.065
	(0.095)	(0.095)	(0.069)	(0.069)
2009 Year Dummy	-0.067	-0.067	-0.064	-0.064
	(0.118)	(0.118)	(0.151)	(0.151)
2010 Year Dummy	0.102	0.102	0.259	0.259
	(0.162)	(0.162)	(0.156)	(0.156)
PostCP		0.034		0.195
		(0.236)		0.250
Constant	16.469***	16.469***	16.515***	16.515***
	(0.849)	(0.849)	(0.651)	(0.651)
Observations	20,404	20,404	20,708	20,708
R-squared	0.079	0.079	0.058	0.058
Adj. R-Squared	0.078	0.078	0.057	0.057

*** p<0.01, ** p<0.05, * p<0.1

Robust Standard Errors in ( )

SE's clustered by neighborhood

These regressions control for neighborhood fixed effects, race, sex, education, poverty, age, and age^2