Calorie Labeling in Chain Restaurants and Body Weight: Evidence from New York

Brandon J. Restrepo*

U.S. Food and Drug Administration

May 21, 2016

Abstract.—This study analyzes the impact of local mandatory calorie labeling laws implemented by New York jurisdictions on body weight. The analysis indicates that on average the point-of-purchase provision of calorie information on chain restaurant menus reduced body mass index (BMI) by 1.5% and lowered the risk of obesity by 12%. Quantile regression results indicate that calorie labeling has similar impacts across the BMI distribution. An analysis of heterogeneity suggests that calorie labeling has a larger impact on the body weight of lower income individuals, especially lower income minorities. The estimated impacts of calorie labeling on physical activity, smoking, and the consumption of alcoholic beverages, fruits, and vegetables are small in magnitude, which suggests that other margins of adjustment drive the body-weight impacts estimated here.

Keywords: Calorie labeling, chain restaurants, body mass index, obesity

JEL Classification Codes: H75, I12, I14, I18

* I would like to thank Jérôme Adda, David Blau, Anoshua Chaudhuri, Christian Dustmann, Javier Espinosa, Matthew Jones, Daeho Kim, Audrey Light, Trevon Logan, Corbin Miller, Matthew Neidell, Matthias Rieger, Soumyajit Sukul, Bruce Weinberg, seminar participants at Koç University, European University Institute, U.S. Food and Drug Administration, USDA Economic Research Service, and San Francisco State University, as well as conference participants at the 2015 Southern Economic Association and Agricultural & Applied Economics Association Annual Meetings for helpful comments and suggestions. And, finally, I would like to give special thanks to the EUI's Max Weber Program for providing excellent research facilities at Villa La Fonte and the Badia Fiesolana over the 2012-2014 period, where much of the preliminary research for this project was carried out. *Any opinions, findings, conclusions, or recommendations expressed are those of the author and do not necessarily reflect the views of the U.S. Food and Drug Administration*.

1. Introduction

Obesity remains a major public health problem in the U.S. In 2009-2010, one in three adults was classified as obese, and no state in the nation had met the *Healthy People 2010* objective of reducing the adult obesity rate to 15% (Ogden *et al*. 2012). Obesity increases the risk of morbidity and treating obesity-related illness imposes substantial healthcare costs on society. A recent study estimated that, in 2006, among Medicare and Medicaid beneficiaries, per capita medical spending was 36-47% higher for obese individuals than for non-obese individuals (Finkelstein *et al*. 2009). Cawley and Meyerhoefer (2012) estimated that obesity causes annual medical costs to rise by $3,022 (in 2008 dollars), which amounts to about 6% of median household income in 2008.

Changes in the food environment and unhealthy eating habits are important to understanding the recent rise in obesity.[1,2] For example, there has been a dramatic increase in the consumption of food from restaurants, which tend to offer energy-dense and nutrient-poor food (Currie *et al*. 2010; Anderson and Matsa 2011).[3] The estimated share of daily calories consumed coming from restaurants and fast-food establishments more than tripled between 1977 and 2008 (Lin and Guthrie 2012).

While the provision of nutrition information on packaged foods has been mandatory in the U.S. since the Nutrition Labeling and Education Act of 1990 (NLEA) took effect, foods sold or served in restaurants were exempted from this requirement. Recently, several

[1] It has been shown that increased caloric intake accounted for about 75% of the rise in adult obesity in the U.S. between 1990 and 2001 (Bleich *et al.* 2008).

[2] In an analysis of the impact of economic factors on obesity, Courtemanche *et al.* (2016a) found that changes in a host of economic factors explain 43% of the rise in obesity over the 1990-2010 period in the U.S., which, in large part, they found to be driven by factors related to the time costs of caloric intake (*e.g.* restaurant density).

[3] A recent review of the literature concluded that while causality is difficult to establish, there is a wealth of evidence indicating that the consumption of restaurant food is strongly associated with increased caloric intake and a higher risk of weight gain and obesity (Rosenheck 2008).

U.S. jurisdictions have mandated that chain restaurants post calorie counts on menus in order to improve access to nutrition information at the point of purchase and to facilitate better informed and healthier choices. The New York City (NYC) health department was the first to implement a local calorie labeling law in July 2008 and six New York (NY) county health departments quickly followed suit by implementing similar laws in 2009 and 2010.[4,5]

The first contribution of this study is that it provides the first estimates of the impact of calorie labeling laws on body mass index (BMI) and the probability of obesity. Previous work has focused on estimating the response of purchase behavior to calorie information posted on menus in restaurant settings, *e.g.* by studying whether consumers choose lower calorie meals or buy fewer items.[6] However, behavioral changes may occur outside the restaurant setting as well. For example, individuals may use the calorie information they observe on menus to decide how much to eat later in the day, they may substitute consumption towards non-chain restaurant meals, and there are many other potentially important margins of adjustment. And in addition to demand-side changes, supply-side responses to calorie labeling laws (*e.g.* the introduction of low-calorie menu items or reformulation to reduce the caloric content of existing products) could also have an impact on body weight.

[4] NYC is composed of 5 counties: the Bronx, Kings, New York, Queens, and Richmond. Thus, a total of 11 of 62 counties in NY implemented a calorie labeling law between 2008 and 2012. The local laws in NY apply to all chain restaurants with 15 or more locations nationwide, including fast-food and full-service restaurants. Not all restaurants are chains, but chains are responsible for a disproportionate fraction of restaurant traffic. For example, in 2007, only 10% of NYC's 23,000 restaurants were chains, but they accounted for 33% of all restaurant traffic (Farley *et al.* 2009).

[5] This study focuses its analysis on the impact of mandatory calorie labeling laws in NY because a subset of its counties has had regulations in place for longer than any other U.S. jurisdiction and there is substantial variation in the mandate across and within NY counties over the study period to exploit in estimation. Also, the legal requirements of calorie labeling laws in areas outside of NY differed from the law implemented in NY counties. For example, unlike NY jurisdictions, some other U.S. jurisdictions required a dietary statement be posted on menus along with calorie counts.

[6] See Littlewood *et al.* (2015) and Long *et al.* (2015) for recent reviews of this literature.

This study exploits within-county variation in the availability of calorie information posted on chain restaurant menus over time brought on by implementation of mandatory calorie labeling laws and the differential timing of implementation across NY counties to identify the effect of calorie labeling on BMI. This empirical approach allows estimation of the overall impact of calorie labeling on body weight, which may operate through a wide variety of behavioral responses to calorie information posted on menus, both inside and outside of chains, as well as supply-side responses. The analysis indicates that on average implementation of calorie labeling laws in NY led to economically important and statistically significant reductions in BMI and the risk of obesity.

The second contribution that this study makes to the literature is that it adds to the understanding of the channels through which calorie labeling affects consumer behavior, by analyzing whether calorie labeling induces changes in exercise, smoking, or dietary behavior as measured by a limited set of food and beverage items captured in the BRFSS. The estimated effects of calorie labeling on physical activity, smoking participation, and alcohol, fruit, and vegetable consumption are statistically insignificant and too small to explain the body-weight impacts of calorie labeling estimated here.

The third contribution of this study is that it sheds additional light on whether estimation of the average effect of calorie labeling masks heterogeneity in the responsiveness to calorie information posted on chain restaurant menus (Robert Wood Johnson Foundation 2009; 2013). Quantile regression point estimates are similar in size across the BMI distribution and are not significantly different across quantiles. While I find that the estimated effects of calorie labeling on body weight are larger for some groups relative to others (*e.g.* women versus men), the estimates from different pairs of subsamples are generally not significantly different from each other.[7] An important exception is suggestive evidence that calorie labeling has a larger impact on the body weight of lower income individuals, especially lower income minorities.

The rest of this paper is organized as follows. First, I review the literature on the effectiveness of calorie labeling on menus in chain restaurants. Second, I summarize the data sets used in the analysis. Third, I describe the empirical approach employed in the study, explain the results of the analysis, and explore several mechanisms that may drive the results. Lastly, I provide a discussion of the results and conclude.

2. Previous Literature

Many studies have examined whether calorie labeling induces individuals to make healthier choices in restaurant settings.[8,9] Elbel *et al.* (2009) found that calorie labeling had no impact on the calories purchased in several fast-food chain restaurants, despite the fact that 27% of those seeing calorie counts reported using them. Similarly, while Tandon *et al.* (2011) found that calorie labeling caused a significant increase in parents seeing nutrition information, they found no evidence that calorie labeling decreased calories purchased for either children or parents. Finkelstein *et al.* (2011) used transaction data from a Mexican fast-food chain and found that calorie labeling had no impacts on in-store or drive-through purchase behavior.

[7] It is important to note, however, that I may be lacking power in the subsample analyses to establish that the body-weight impacts of calorie labeling are larger for some groups than others.

[8] There are also many studies analyzing hypothetical menu item choices and purchase intentions. These studies used survey or laboratory experiment data and generally found evidence suggesting that calorie labeling decreases the calories of hypothetical purchases, decreases purchase intentions, and increases intentions to purchase lower calorie meals (Robert Wood Johnson Foundation 2013).

[9] A recent meta-analysis by Long *et al.* (2015) found that calorie labeling is associated with a statistically significant reduction of 18 calories ordered per meal; among controlled studies, however, calorie labeling is found to be associated with a statistically insignificant reduction of 8 calories per meal. Another recent meta-analysis (Littlewood *et al.* 2015) found that calorie labeling is associated with a statistically significant reduction of 78 calories ordered per meal.

Bollinger *et al.* (2011) found that calorie labeling in Starbucks resulted in a modest average reduction of 14 calories purchased per transaction, which was driven by changes in consumers' food choices and not beverage choices.[10] Wisdom *et al.* (2010) found that assigning calorie-labeled menus to diners at a fast-food sandwich chain caused them to order about 61 fewer calories—a reduction that was due to side-dish and drink choices and not sandwich choices. Ellison *et al.* (2013) found that, while assignment of menus with calorie counts alone in a full-service restaurant reduced entrée calories, it did not significantly reduce calories from other sources such as drinks and desserts.[11]

The studies discussed above suggest that the impact of calorie labeling on calories ordered may depend on the menu items or type of establishments under consideration, which creates some ambiguity regarding the overall impact of calorie labeling laws. Compensatory behavior may also have important implications for the overall impact of providing calorie information. For example, Roberto *et al.* (2010) found that, in an experiment that took place in a university classroom, diners assigned a calorie-labeled menu ordered fewer calories during a study meal but offset this calorie reduction by consuming more calories later in the day.[12]

There is also evidence that supply-side responses to calorie labeling laws may have a beneficial impact on the nutrient content of restaurant foods. Namba *et al.* (2013) found that

[10] They also found that calorie labeling had larger impacts on the purchase behavior of women and individuals who were high-calorie purchasers before calories were posted on menus.

[11] In addition, they found that, among diners assigned a calorie-labeled menu, the reduction in calories ordered was larger for those who were less "health conscious" compared with those who were more "health conscious". In similar studies, Ellison *et al.* (2014a; 2014b) found that random assignment of calorie-labeled menus did not significantly reduce total calories ordered but the addition of a symbolic traffic light did significantly reduce total calories ordered.

[12] A third group of diners was assigned a menu with calorie information and a statement about the recommended daily caloric intake for an average adult. These diners also ordered fewer calories than those who were assigned a menu with no calorie information, but this reduction was not offset by increases in calorie consumption later in the day.

implementation of local calorie labeling laws caused a 5% increase in what they refer to as "healthier adult entrées" on fast-food chain restaurant menus.[13] And in a survey of NYC chain restaurant managers, Bollinger *et al.* (2010) found that, among managers that reported changing their menus at least once a year, the probability of managers indicating that a low-calorie option was added to their menu in the past 6 months was higher for NYC chains that were required to comply with calorie labeling requirements (chains with 15-20 locations nationwide versus those with 10 to 14).

In sum, evidence that calorie labeling reduces the amount of calories purchased in chain restaurants is mixed.[14] Unlike previous studies that focus on the first-stage impact of calorie labeling, this study evaluates whether calorie labeling laws lead to a reduction in body weight. The strength of the empirical approach used here is that it allows measurement of the overall impact of calorie labeling on body weight, which may operate through a variety of demand-side and supply-side responses. To complement the body-weight analysis, I also investigate the importance of mechanisms related to dietary behavior, smoking, and physical activity. The literature suggests that the impact of calorie labeling on consumers may not be

[13] Bleich *et al.* (2015a) and Bleich *et al.* (2016) found that in recent years large chain restaurants have significantly reduced the number of calories in newly introduced menu items, which they argue may be in anticipation of the federal menu labeling regulations. Bleich *et al.* (2015b) found that restaurants that voluntarily posted calorie information had lower average per-item calorie content than those that did not. Bruemmer *et al.* (2012) found that, among menu items that were on menus 6 and 18 months after calorie labeling requirements were implemented in King County WA, there were improvements in the nutrient content of chain restaurant entrées.

[14] A closely related literature examines whether the provision of nutrition information on packaged foods has beneficial impacts on health as measured by body weight. The findings in this literature are also mixed. Using a differences-in-differences estimation approach that compares nutrition label users to non-users, Variyam and Cawley (2006) found that that implementation of NLEA was associated with a decrease in BMI among only one group—non-Hispanic white females. Drichoutis *et al.* (2009) employ a propensity score matching approach and found no evidence that nutrition labeling affects body weight. And Loureiro *et al.* (2012) estimate switching regression models and found that nutrition labeling reduces the body weight of both men and women, but has a larger impact on the body weight of women.

uniform across individuals, which motivates an analysis of heterogeneity in the impact of calorie labeling on body weight.

3. Data

The main analysis draws on data from selected state files of the 2004-2012 Behavioral Risk Factor Surveillance System (BRFSS). The analysis sample is composed of individuals who reside in NY counties and counties in the NY-NJ-PA Metropolitan Statistical Area (MSA) that did not implement a calorie labeling law over the study period. The total number of observations in the 2004-2012 BRFSS for these counties is 136,471. I drop 6,109 observations because county information could not be identified.[15] Self-reported height and weight are used to calculate an individual's BMI.[16] I drop 7,080 observations due to missing information on BMI. To address the concern that outliers are driving the results, I drop 127 observations for which BMI is below 10 or above 60.[17] The main regression analysis controls for the following individual-level information: age, gender, race/ethnicity, educational attainment, family income, the number of children, and marital status. The main estimation sample consists of 103,220 individuals, for whom information on county of residence, BMI, and all the above-mentioned demographics is available.

I obtained county-level information on the timing of calorie labeling laws from the Center for Science in the Public Interest. The adoption and effective dates of these laws were

[15] The county identifier is suppressed for BRFSS respondents who reside in a county with fewer than 50 respondents or adult populations less than or equal to 10,000 residents.

[16] Cawley (1999) developed a procedure to address empirical problems associated with self-reported height and weight data. Studies that have employed this correction have found that coefficient estimates in regressions involving measures of body weight as a dependent variable are not sensitive to using the correction (Gruber and Frakes 2006; Lakdawalla and Philipson 2002). Below, I also examine the sensitivity of my results to correcting for reporting error in height and weight, using the NHANES. I choose not to employ this correction in the main analysis because the NHANES is representative of the U.S. non-institutionalized civilian population and not representative of NY state.

[17] Dropping these individuals does not affect the results of the analysis.

verified using local law documentation retrieved from county health department websites. Figure 1 shows the law adoption and effective dates by county.[18] Policy variables in the analysis are coded according to the exact date of a respondent's interview.

Previous work has documented a relationship between economic conditions and BMI (*e.g.* Ruhm 2005). For this reason, county unemployment rates are controlled for throughout the regression analysis. County-level unemployment rates were obtained from the Bureau of Labor Statistics, and were merged with the BRFSS analysis sample by month and year.

All the NY counties that implemented a calorie labeling law over the study period are metropolitan counties, which might be a cause for concern with respect to differences between counties that did and did not implement a law over the sample period.[19] For example, time-varying differences in a county's urbanicity, sentiments toward healthy behavior, or availability of healthy food may be related to body weight and a county's decision to implement a calorie labeling law. I address this concern by controlling for the following county-level information from the County Business Patterns in the analysis: the number of fitness and recreation centers, fast-food restaurants, full-service restaurants, grocery stores and supermarkets, convenience stores, and specialty food outlets. And, finally, I control for other county or state policies that may affect body weight: smoke-free laws, cigarette taxes, beer taxes, and soda taxes. Information on these policies was drawn from

[18] Nassau County adopted a calorie labeling law in October 2009, which became effective in April of 2010, and was repealed in May of 2010. In a personal communication with the Nassau County Department of Health, I learned that no enforcement actions were taken during the short time that the calorie labeling law was in effect. In my analysis, I consider Nassau County to be a "treated county" for the short period of time the calorie labeling law was in effect.

[19] For a county's metropolitan status, I used the 2004 County Typology Codes provided by the United States Department of Agriculture's Economic Research Service. A county is classified as metropolitan or non-metropolitan based on categories of economic dependence and policy-relevant themes. Examples of economic factors that contribute to a county's metropolitan status include its manufacturing- and services-dependence, and examples of policy-relevant factors include the fraction of a county's low-educated population and population loss. These codes may be accessed here: www.ers.usda.gov/data-products/county-typology-codes.aspx (last accessed May 14, 2016).

Americans for Nonsmokers' Rights, The Tax Burden on Tobacco, Brewer's Almanac, and Robert Wood Johnson Foundation, respectively. Table I shows summary statistics for the full sample and by law implementation status.[20]

4. Methods and Results

4.1. Main Analysis

An important concern is that differing BMI trajectories between treatment and control groups leading up to the period over which jurisdictions began to implement calorie labeling laws may cause overestimation or underestimation of treatment effects. I examine this by plotting BMI means by treatment county and year of implementation. Figure 2 shows that in the years leading up to implementation years, BMI trends for treatment counties and the control group tend to be similar.[21] While the control group's BMI is generally increasing over the sample period, BMI tends to shift downward for treatment counties in implementation years—although the duration of the policy effect appears to vary by county. And in some cases, there are anticipatory patterns that could be due to the fact that some chains were posting calories prior to a county's effective date or that BMI may respond to a neighboring county's implemented policy. Below, I further explore these trends by examining the average duration and timing of policy effects, as well as the importance of policy spillover effects.

The pre-implementation trends by and large lend credibility to the identification assumption of parallel trends between treatment and control groups made in the empirical analysis below and the post-implementation trends suggest that implementation of calorie

[20] In Appendix Table I, I also show additional sample summary statistics for subsets of the control group that I make use of in the robustness section.

[21] It is important to note that there is greater sampling variation around BMI means among small counties, which, in some cases, makes it more difficult to establish that BMI was trending in a similar fashion in treatment and control counties. After presenting the main results, in the robustness section, I carefully investigate the implications of this issue by examining how the estimated effect of calorie labeling on body weight changes after excluding from the regression sample respondents with relatively few other respondents in a county-year.

labeling laws lead to reduced body weight. To estimate the effect of calorie labeling on body weight while also controlling for other potentially important observed and unobserved factors, a panel regression model of the following form is estimated,

$$Y_{ict} = \beta_0 + X'_{ict}\beta_1 + Z'_{ct}\beta_2 + \beta_3 \mathrm{CL}^{e}_{ct} + \beta_4 \mathrm{CL}^{a}_{ct} + \gamma_c + \gamma_t + \gamma_c * t + \varepsilon_{ict}, \quad (1)$$

where *Y* is either BMI or an indicator for whether an individual *i* residing in county *c* at time *t* has a BMI greater than or equal to 30; *X* is a vector of individual-level characteristics; *Z* is a vector of county-specific characteristics; CL^{e} is an indicator for whether a respondent's county of residence *c* has implemented a calorie labeling law as of time *t*; CL^{a} is an indicator for whether a respondent's county of residence *c* has adopted but not implemented a calorie labeling law as of time *t*;[22] γ_c is a county fixed effect; γ_t is a time fixed effect; $\gamma_c * t$ are county-specific linear time trends; and ε is an idiosyncratic error term. This model nets out secular trends in body weight across time, all time-invariant heterogeneity across counties, and also controls for unobserved factors that move in a linear fashion over time and vary by county.[23,24] The coefficient of interest is β_3, which measures the overall impact of implementation of calorie labeling laws on body weight.

[22] I include a law adoption policy variable in the regression model because, for some treatment counties, exposure to calorie counts in chain restaurants began before effective dates of local laws. Chain restaurants were notified 6-12 months before effective dates about the adoption of a local calorie labeling law, and were asked to comply before or on the effective date to avoid fines and penalties. In personal communications with representatives of county health departments, I learned that some chain restaurants were posting calorie counts on menus before effective dates. For example, a representative from Albany's Department of Health indicated that about 15% of chain restaurants were in compliance before its law's effective date. Also, while NYC's mandatory calorie labeling law became effective in July 2008, Bollinger *et al.* (2011) report that Starbucks locations in NYC began posting calorie counts on menus in April 2008.

[23] For ease of interpretation and to maintain consistency across specifications with continuous and binary dependent variables, all main models are estimated using Ordinary Least Squares. The results are not sensitive to changes in specification or alternative estimation procedures. For example, unreported results from models in which the log of BMI is used instead of BMI in levels are similar to those shown in the main analysis. In models of obesity, results from estimation of linear probability models shown here are also very similar to unreported results from probit/logit models.

In Table II, I present results from the specification shown in equation 1. The analysis indicates that on average implementation of calorie labeling laws reduced BMI by 0.4 units and decreased the probability of obesity by 3 percentage points. Relative to sample means in 2007, the regression estimates indicate that on average calorie labeling caused BMI to fall by 1.5% and the risk of obesity to fall by 12%. In contrast, while the coefficient estimates of the impacts of the adoption of calorie labeling laws on body weight are also negative, they are much smaller in magnitude and statistically insignificant.[25] Taken together, the results indicate that on average implementation of calorie labeling laws in NY—after which all rather than a subset of affected chain restaurants were posting calorie counts on menus—caused an economically important and statistically significant reduction in body weight.

4.2. Robustness Checks

Before turning to analyses that investigate the timing of the policy's impact, the importance of several mechanisms, and whether there is heterogeneity in the impact of calorie labeling on body weight across individuals, I conduct a battery of robustness checks.

First, there may be policy spillovers to neighboring counties when a calorie labeling law takes effect. If residents of neighboring control counties commute to treatment counties on a regular basis, for example, not accounting for commuting patterns could cause underestimation of the effect of calorie labeling on body weight. I examine this by estimating a model where a separate indicator variable is included to designate a neighboring but not implementing county. Inclusion of this indicator produces slightly smaller calorie-labeling implementation effect estimates (row 1 of Table III), suggesting that policy spillovers do not

[24] Standard errors are clustered at the county level to allow for arbitrary correlation among observations in the same county over time, and BRFSS sampling weights are used in the regression analysis to account for the sampling design of the BRFSS.

[25] These findings persist throughout the analysis. To save space, I do not present the estimates of the policy adoption variable, but it is controlled for throughout the regression analysis.

cause significant attenuation in estimation.[26] Interestingly, the coefficient estimates of the neighboring indicator variable are negative, which is suggestive of beneficial policy spillovers, but the estimates are small and imprecise.

Second, one may be concerned that treatment and control counties are insufficiently similar because, for example, all the local jurisdictions that implemented calorie labeling laws in NY are metropolitan counties. Instead of using all the counties that never implemented calorie labeling over the study period as the control group (as in Table II), I test for sensitivity of the results to changing the composition of the control group by using three subsets of these counties: 1) only NY counties 2) only metropolitan counties in NY and 3) counties that are in the NY-NJ-PA MSA and in NY regions that contain at least one implementing county.[27] Rows 2-4 of Table III show that the estimates from regressions that use these alternative control groups are similar—albeit somewhat larger in magnitude—to those in the main analysis. This suggests that issues related to geographical clustering of policies and urbanicity are not a problem for the analysis.

Third, business cycles have been shown to affect health outcomes including BMI (*e.g.* Ruhm 2005). I have controlled for unemployment rates throughout the analysis, but it is possible that the impact on health of economic conditions varies across counties in ways that affect a county's policy environment. In row 5 of Table III, I present results from a model that allows the effect of unemployment rates on body weight outcomes to vary by county. Allowing for heterogeneous impacts of local economic conditions by county causes only small changes in the estimated effects of calorie labeling on body weight, suggesting that

[26] In an unreported analysis I also excluded neighboring counties from the regression analysis, which produced similar results.

[27] Appendix Table I contains summary statistics for the alternative control groups.

issues related to economic conditions—such as the 2008 financial crisis—and the timing of county-level implementation of calorie labeling laws do not drive the results.

Fourth, one might be concerned that time-changing unobserved factors that vary by county may be nonlinear, and thus not well captured by county-specific linear time trends. In row 6 of Table III, I show results from a specification that includes county-specific quadratic time trends. The results are similar to the main results and suggest that, for example, nonlinear trends between upstate and downstate NY, which were differentially affected by calorie labeling laws, are unlikely to account for the results.

Fifth, because BMI is based on self-reported height and weight data, I show results from analyses that employ a correction for reporting bias in self-reports of height and weight (row 7 of Table III).[28] The main results are similar to those obtained when the correction is used, which is consistent with the findings of other studies that have employed this correction (Gruber and Frakes 2006; Lakdawalla and Philipson 2002).

Sixth, one may be concerned about the potential for policy endogeneity. For example, 9 of the 11 county health departments that implemented a calorie labeling law also implemented a law restricting the use of partially hydrogenated oils (PHOs) in restaurants ("trans fat bans").[29] In addition, NYC engaged in other initiatives that might have influenced

[28] Following Cawley (1999), I used the 2007-2008 National Health and Nutrition Examination Survey (NHANES), and regressed measured height (weight) on self-reported height (weight), separately by gender and race/ethnicity. Estimates from these regressions were then multiplied by the self-reported measures of height and weight in the BRFSS data set.

[29] While there is a strong link between trans fat intake and cardiovascular disease (CVD), there is very little evidence linking trans fat consumption to weight gain or obesity (*e.g.* see Scientific Advisory Committee on Nutrition 2007). Also, while Restrepo and Rieger (2016) found evidence indicating that implementation of trans fat bans in NY counties led to an important reduction in CVD mortality rates, changes in obesity rates did not explain the CVD mortality reduction. Some county health departments implemented PHO restrictions over 2 phases where, generally, Phase I allowed the use of trans-fat-containing oils in some foods while in Phase II the ban applied to oils in all foods. The trans fat ban policy variable is coded according to a county's earliest implementation date (see Restrepo and Rieger [2016] for information on the timing of the trans fat bans).

body weight at around the same time that it implemented its calorie labeling law.[30] To reduce the risk of policy endogeneity, I present results from regressions in which I control for county-level trans fat bans (row 8 of Table III) and results from dropping NYC from the analysis (row 9 of Table III). Both sets of results are similar to the results in the main analysis, which suggests that policy endogeneity is unlikely to account for the results.

Seventh, I conduct a placebo test. Implementation of calorie labeling laws may have impacts on health behaviors such as those related to diet and exercise, but it should not have any meaningful impacts on other health behaviors such as vaccinations. Row 10 of Table III shows that the estimated impact of calorie labeling on the probability of obtaining a flu shot is small in magnitude and statistically insignificant, which lends further credibility to the body-weight analysis.[31]

Eighth, I perform a lead-lag policy analysis to examine the timing of the policy's impact on body weight.[32] The results are summarized in Figure 3. The regression coefficients prior to the implementation period are small in magnitude and are not jointly significant at conventional levels (p-value 0.148). In contrast, regression estimates in the post-implementation period are larger and jointly significant at the 10% level (p-value 0.076). The policy's impact on body weight, however, appears to be concentrated in the first year of the law's implementation. While the second and third year's estimated impacts are economically

[30] For example, the NYC Department of Transportation built about 30 miles of protected bicycle lanes since 2007 (see http://www.nyc.gov/html/dot/downloads/pdf/2014-09-03-bicycle-path-data-analysis.pdf, last accessed May 14, 2016). And the NYC Department of Health implemented its "Green Cart Initiative" in 2009, which offered 1,000 permits for a new street class of mobile fruit and vegetable vendors in underserved areas (see http://www.nyc.gov/html/doh/downloads/pdf/epi/databrief48.pdf, last accessed May 14, 2016).

[31] The sample mean in 2007 for obtaining a flu shot in the past 12 months is 0.43.

[32] In an unreported event study analysis I restricted the sample to include only treatment counties, which produced a similar pattern of results.

important, I cannot reject the null hypothesis that they are jointly equal to zero (p-value 0.168).

Finally, the BRFSS is not designed to be representative of counties and, in some cases, the number of respondents in a county-year is small. This explains the greater variance around BMI means for the smaller counties shown in Figure 2. I examine whether the results are sensitive to setting different thresholds for the minimum number of respondents in a county-year, which, as shown in Appendix Table II, affects the sampling variance around the (county-year) mean BMI of the observations used in the regression analysis. In columns 2-6 of Appendix Table II, I show that steadily increasing the minimum number of respondents in a county-year produces estimates that hover around -0.4, which is similar to the main estimate (reproduced in column 1 of Appendix Table II).[33] This exercise suggests that using all counties in the analysis rather than honing in on only the largest counties, which are subject to less sampling variance in the dependent variable over time, does not substantively alter the results.[34]

4.3. Heterogeneity in the Effect of Calorie Labeling on Body Weight

I have focused on estimating the average effect of calorie labeling on BMI, but I investigate two potentially important sources of heterogeneity in the policy's impact across individuals.

[33] Dropping all observations from counties—instead of dropping a subset of observations—that have fewer than 250 respondents in any year over the study period from the analysis produces similar results (coef. -0.359, s.e. 0.131).

[34] The concern regarding sampling variance around the mean is further alleviated in an analysis that restricts attention to only the largest counties in the regression sample. In Appendix Figure 3, I show BMI trends for NYC as a whole, each county in NYC individually, and the control counties in the NY-NJ-PA MSA. The BMI trends are similar leading up to NYC's 2008 calorie labeling law and BMI in NYC generally falls after its implementation and remains below its pre-implementation BMI throughout the sample period. In a regression analysis that uses the main specification, I find that the estimated effect of calorie labeling on BMI in this sample is -0.425 (s.e. 0.186) [p-value adjusted using a wild cluster bootstrap-t procedure is 0.028], which is similar to the estimates shown in Table II and Appendix Table II.

First, the effect of calorie labeling on body weight may vary across the BMI distribution if, for example, overweight individuals are more responsive to calorie labeling than normal-weight individuals. Table IV shows quantile regression estimates across a wide range of the BMI distribution. The point estimates are similar in size across the BMI distribution and are not significantly different across quantiles. For example, I cannot reject the null hypothesis that the estimated impacts at the 0.1, 0.25, 0.5, 0.75, and 0.9 quantiles are equal to each other (p-value 0.954).

Second, I analyze whether the effect of calorie labeling on body weight varies by gender, race/ethnicity, income, and education.[35] Panel A of Table V shows that the estimates are larger for women relative to men, larger for minorities relative to non-Hispanic whites, larger for below-median income individuals relative to higher income individuals, and larger for individuals with some college or more relative to those with less education. For each pair of subsamples, except for the two income groups, I cannot reject the null hypothesis that the estimated impacts are equal across regression models. The estimates for the two income groups are significantly different from each other at the 10% level (p-value 0.086).

To further investigate the heterogeneity by income, I explore heterogeneity in the estimated body-weight impacts on subsets of the lower income group of respondents. The estimated body-weight impacts for men and women are similar in magnitude and are not significantly different from each other. And while the estimated body-weight impact of calorie labeling among individuals with a high school degree or less is only about 60% as large as the estimated impact among more educated individuals, the estimates are not significantly different from each other. The estimated body-weight impact of calorie labeling is over 7 times larger for minorities than for non-Hispanic whites—both in terms of

[35] It is important to note, however, that stratification produces smaller sample sizes that often lead to less precise estimates, which limits my ability to make comparisons across groups.

differences in coefficient estimates and relative to 2007 sample means—and these estimates are significantly different from each other at the 10% level (p-value 0.063).

The impact of calorie labeling on body weight may be larger among lower income minorities because they are either more exposed to calorie information in chain restaurants, or, because they are more responsive to the information. The former might result from more frequent visits to chain restaurants and the latter might result if calorie labeling produced a stronger shock to the nutrition information sets of lower income minorities relative to non-Hispanic white counterparts.[36] Another possible explanation is that there could have been supply-side responses to calorie labeling laws that impacted the offerings of restaurants most visited by lower income minorities.

4.4. The Effect of Calorie Labeling on Dietary Behavior, Physical Activity, and Smoking Participation

As discussed above, most studies have analyzed how on-site purchase behavior responds to calorie information posted on menus, but there are many other potential margins of adjustment. I explore whether calorie labeling induces individuals to change their smoking habits, physical activity, or some dietary behaviors.[37,38] The results are summarized in Table

[36] The BRFSS lacks the necessary information to shed light on these issues, but information from the 2007-2008 NHANES provides some support for these interpretations. For example, I estimate that, in a sample of NHANES respondents with a family income of below $63,793 (to match the median family income in the BRFSS analysis sample), minorities on average report having more fast-food meals in the past week (2.4) than do non-Hispanic whites (1.9). Minorities in this lower income sample are on average also more likely to report that they would often use nutrition information (0.39) to decide what to order if it were readily available in restaurants than are non-Hispanic whites (0.34). These patterns may be taken to suggest that calorie labeling laws may have caused a greater reduction in body weight among lower income minorities because of their more pronounced exposure or intention to use nutrition information in chains.

[37] Information on exercise on the extensive margin of exercise and alcohol consumption is available for the full sample period, but information on the intensive margin of exercise, fruit, and vegetable consumption is available only for 2005, 2007, 2009, and 2011.

[38] In 2007-2009, BRFSS respondents whose weight changed between the time of their interview and a year prior to their interview were asked whether the change in weight was intentional. The effect of calorie labeling on the probability of a respondent responding in the affirmative is imprecisely estimated but it is economically important (coef 0.055, se. 0.058). Relative to the 2007 sample mean, this is an increase of about 13%. The

VI. There is no evidence that physical activity responded to implementation of calorie labeling laws. The estimated effect of calorie labeling on the extensive margin of exercise is small in magnitude—indicating about a 0.7% decrease in exercise participation relative to the 2007 sample mean—and statistically insignificant (column 1 in Table VI). And the estimate presented in column 2 in Table VI—which captures the combined calorie-labeling effect on exercise participation and intensity—is statistically insignificant and, relative to the 2007 sample mean, translates into an increase in physical activity of about 30 minutes per week. Increasing physical activity by 30 minutes burns about 130 calories, so this estimated impact is the equivalent of an increase in caloric expenditure of 19 calories per day.[39]

I also find small and statistically insignificant impacts on fruit/vegetable and alcohol consumption (columns 3-4 in Table VI). Relative to 2007 sample means, the estimated effects indicate a reduction of 0.1 units of fruit and vegetable servings a day and an increase of 0.01 units of alcohol per day. The estimated impact of calorie labeling is equivalent to a reduction of about 5 calories in fruit and vegetable consumption, and an increase of 1 calorie from alcohol.[40] To the extent that people smoke to control their weight,[41] it is possible that calorie labeling could affect smoking behavior. However, in column 6 of Table VI, I show

estimated effect of calorie labeling is larger among those who lost weight (coef 0.087, s.e. 0.057) than among those who gained weight (coef 0.037, s.e. 0.072). These results may be viewed as suggestive evidence that, at least for the subgroup considered in this subsample, calorie labeling induced demand-side changes.

[39] This estimate is based on an increase in the most popular form of exercise (walking). According to WebMD (see http://www.webmd.com/diet/healthtool-fitness-calorie-counter, last accessed May 14, 2016), for a person of average weight in my sample, walking on a level surface for 30 minutes burns about 130 calories.

[40] These are based on my calculations of average calories in a serving of fruit, vegetables, and a unit of alcohol. I obtained calorie information for the 20 most frequently consumed raw fruits and vegetables from the U.S. Food and Drug Administration, and calculated the average over all of these fruits and vegetables (see http://www.fda.gov/food/ingredientspackaginglabeling/labelingnutrition/ucm063367.htm, last accessed May 14, 2016). An average serving of fruit contains 68.25 calories, and an average serving of vegetables contains 33.5 calories. On average, one beer contains 150 calories, one glass of wine contains 120 calories, and 1.5 ounces of liquor contain 100 calories (Nielsen *et al.* 2012).

[41] Recent work indicates that the demand for cigarettes is derived from the demand for weight loss (Cawley *et al.* 2016) and that smoking has a causal impact on BMI (Courtemanche *et al.* 2016b).

that the impact of calorie labeling on smoking participation is also small and statistically insignificant.[42]

5. Discussion

5.1 Plausibility of Estimated Effect Sizes

Using a specification similar to the one shown in the main analysis (equation 1 with weight as a dependent variable and adding height as an explanatory variable), I find that on average calorie labeling reduces body weight by -1.23 kg [95% confidence interval (-2.10, -0.36)]. This reduction in body weight can be explained by a persistent average daily energy imbalance gap between intake and expenditure of about 45 calories per day for a year.[43] Relative to the average daily energy intake in the U.S., this is a reduction of about 1.8%.[44]

While the effects are imprecisely estimated, it is useful to calculate the implied body-weight effects of calorie labeling on physical activity and the dietary behaviors discussed above. The diet-related estimates (columns 3-4 in Table VI) imply a net reduction in caloric intake of about 4 calories per day and the exercise-related estimate (column 2 in Table VI) implies an increase in caloric expenditure of about 19 calories per day. Assuming that the net effect of these behavioral changes is equivalent to a reduction in caloric intake of 23 calories per day, I estimate that, holding all else constant, for an average person in my sample, a persistent reduction in caloric intake of 23 calories per day for a year would reduce weight by

[42] Similarly, I find that the estimated effects of calorie labeling on someday (coef -0.009, s.e. 0.007) and everyday smoking (coef 0.006, s.e. 0.012) participation are small and statistically insignificant.

[43] This estimate accounts for dynamic physiological adaptations that occur with decreases in body weight à la Hall *et al.* (2011).

[44] In 2010, USDA's Economic Research Service estimated that on average Americans consume about 2,544 calories per day (see http://www.ers.usda.gov/data-products/food-availability-%28per-capita%29-data-system/summary-findings.aspx, last accessed May 14, 2016).

about 0.6 kg.[45] This exercise suggests that such changes in physical activity and diet related to the consumption of alcoholic beverages, fruits, and vegetables would explain less than half of the body-weight effects estimated here.[46]

To get a better sense of the magnitude of the estimated effect of calorie labeling on body weight, I perform another back-of-the-envelope calculation, which uses the implied body-weight impact estimate from a study (Bollinger *et al.* 2011) that analyzes the effect of calorie labeling on calories purchased in chain restaurants. Their study is perhaps the best one to use for this purpose because they analyzed detailed transaction-level data for all Starbucks locations in a city that was affected by the policy and their data span a lengthy period of time (10 months) after the policy was implemented. They estimated that calorie labeling caused a 6% reduction in calories purchased per transaction.

If we assume that calorie labeling caused calories purchased to fall by 6% in all chain restaurants in NY counties that implemented calorie labeling laws, then the estimated reduction in total calorie consumption would amount to 38 calories per day.[47] This exercise indicates that such a change in chain restaurant consumption for a year would explain about 84% of the average body-weight effect of calorie labeling estimated here. As discussed above, in addition to demand-side changes, supply-side responses to calorie labeling laws may also explain a portion of the estimated impact of calorie labeling on body weight.

[45] This estimated weight-loss calculation is also based on the work of Hall *et al.* (2011). Hall *et al.* (2011) point out that an increase in physical activity will not necessarily lead to the same weight loss resulting from an energy-equivalent decrease in caloric intake because the energy expenditure that results from greater physical activity is proportional to body weight.

[46] I also conducted an (unreported) analysis of the exercise and dietary behaviors by demographic subgroup and I reached a similar conclusion—changes in these behaviors in response to implementation of calorie labeling laws do not explain the patterns shown in Table V.

[47] This calculation is based on the following additional assumptions: (1) 25% of an average American's calorie consumption comes from chain restaurants; (2) reductions in calorie consumption are not offset by increases in other meals; and (3) the average daily intake is 2,544 calories.

5.2. The Impacts of Local Calorie Labeling Laws and NLEA on Body Weight

A closely related study by Variyam and Cawley (2006) found that, while implementation of NLEA on average did not reduce body weight, it was associated with a decrease in BMI among non-Hispanic white females. It is unclear why implementation of NLEA significantly reduced the body weight of only one segment of the population. Why might calorie labeling laws lead to a stronger average response of body weight?

Packaged food labels contain much more nutrition information than do point-of-purchase chain restaurant menus, which may reduce the impact of calorie information on calories purchased.[48] The NYC Health Department, for example, considered mandating chain restaurants to post additional nutrition information (*e.g.* saturated fat and sodium), but decided to mandate the posting of only calories because posting other nutrition information "risked reducing the impact of the calorie information on obesity" (Farley *et al.* 2009).[49]

Relatedly, it is possible that the shock to the average consumers' nutrition information set generated by calorie labeling laws is more impactful for body-weight regulation than the corresponding shock generated by NLEA. Most consumers underestimate the number of calories contained in meals prepared away from home and underestimation of calories tends to be greatest for high-calorie menu items (Robert Wood Johnson Foundation 2009). Even well-trained nutrition experts routinely and substantially underestimate the number of calories in restaurant meals (Backstrand *et al.* 1997).

5.3. Study Limitations

[48] The "Nutrition Facts" panel of a packaged food label lists the amount of calories, fat, cholesterol, sodium, carbohydrates, protein, and some other nutritional information.

[49] A recent study sheds light on the relative impacts of NLEA on dietary outcomes. Variyam (2008) analyzed the impact of nutrition labeling on nutrient intakes and found that, for example, nutrition labeling increases the intakes of fiber and iron but has no impact on calorie intake.

This study has several limitations. First, while some mechanisms have been ruled out, the analysis does not pin down the mechanisms that drive the body-weight impacts estimated here. Second, the BRFSS does not contain a measure of total caloric intake and the dietary data captured in the BRFSS account for about 15% of total energy intake (Block 2004), so I am unable to provide a complete picture of the effects of calorie labeling on dietary behavior. Third, the BRFSS lacks information on where the consumption of the food and beverage items captured in the data took place, so it is not possible to separately identify calories consumed at home versus away from home. Fourth, since the individuals who are actually "treated" in treatment counties cannot be identified in the data, I am unable to estimate effects on the treated and make an internal comparison of treatment-on-the-treated effects to the intention-to-treat effects estimated here. Fifth, BMI measures are based on self-reported rather than measured height and weight, which would allow for more accurate healthy and unhealthy body weight categorizations.

6. Conclusion

This study sheds light on whether mandatory calorie labeling laws have the potential to curb the obesity epidemic. The analysis indicates that on average the local NY jurisdictions that implemented a mandatory calorie labeling law were successful in reducing BMI and the risk of obesity. The analysis also suggests that the mandate may have had a larger impact on the body weight of lower income individuals, especially lower income minorities. The results here apply to NY, but an important policy implication of this study is that federal menu labeling regulations may help to reduce body weight throughout the U.S. and may be more impactful among some groups. That said, if the average body-weight impact of federal menu labeling regulations across U.S. states is similar to the relatively modest average body-weight impact of local calorie labeling laws rolled out in NY counties, menu labeling alone is unlikely to be sufficient to reverse the obesity epidemic.

7. References

Anderson M and Matsa D. (2011). “Are Restaurants Really Supersizing America.” *American Economic Journal: Applied Economics*, 3(1): 152-88.

Backstrand J, Wootan MG, Young LR, and Hurley J. (1997). “Fat Chance: A survey of dietitians’ knowledge of the calorie and fat in restaurant meals.” Washington, DC: Center for Science in the Public Interest.

Bleich S, Cutler D, Murray C, and Adams A. (2008). “Why Is the Developed World Obese?” *Annual Review of Public Health*, 29: 273-295.

Bleich SN, Woldfson JA, and Jarlenski MP. (2015a). “Calorie changes in chain restaurant menu items: implications for obesity and evaluations of menu labeling.” *American Journal of Preventive Medicine*, 48(1): 70–75.

Bleich SN, Woldfson JA, and Jarlenski MP. (2016). “Calorie Changes in Large Chain Restaurants: Declines in New Menu Items but Room for Improvement.” *American Journal of Preventive Medicine*, 50(1): e1-8.

Bleich SN, Wolfson JA, Jarlenski MP, and Block JP. (2015b). “Restaurants With Calories Displayed On Menus Had Lower Calorie Counts Compared To Restaurants Without Such Labels.” *Health Affairs*, 34(11): 1877-84.

Block G. (2004). “Foods contributing to energy intake in the US: data from NHANES III and NHANES 1999–2000.” *Journal of Food Composition and Analysis*, 17(3-4): 439–447.

Bollinger B, Leslie P, and Sorensen A. (2011). “Calorie Posting in Chain Restaurants.” *American Economic Journal: Economic Policy*, 3(1): 91-128.

Bruemmer B, Krieger J, Saelens BE, and Chan N. (2012). “Energy, Saturated Fat, and Sodium Were Lower in Entrées at Chain Restaurants at 18 Months Compared with 6 Months Following the Implementation of Mandatory Menu Labeling Regulation in King County, Washington.” *Journal of the Academy of Nutrition and Dietetics*, 112(8): 1169-76.

Cawley J. (1999). “Rational addiction, the consumption of calories, and body weight.” *Ph.D. Dissertation*. University of Chicago, Chicago, IL.

Cawley, J. Dragone, D, and Von Hinke Kessler Scholer, S. (2016). “The Demand for Cigarettes as Derived from the Demand for Weight Loss: A Theoretical and Empirical Investigation.” *Health Economics*, 25(1): 8-23

Cawley J and Meyerhoefer C. (2012). “The medical care costs of obesity: an instrumental variables approach.” *Journal of Health Economics*, 31(1): 219-30.

Chou S, Grossman M, and Saffer H. (2004). “An economic analysis of adult obesity: results from the Behavioral Risk Factor Surveillance System.” *Journal of Health Economics*, 23(3): 565-87.

Courtemanche, CJ, Pinkston, JC, Ruhm, CJ, and Wehby, GL. (2016a). “Can Changing Economic Factors Explain the Rise in Obesity?” *Southern Economic Journal*, 82(4): 1266-1310.

Courtemanche, CJ, Tchernis, R, and Ukert, B. (2016a). “The Effect of Smoking on Obesity: Evidence from a Randomized Trial.” *NBER Working Paper* No. 21937.

Currie J, Della Vigna S, Moretti E, and Pathania V. (2010). “The Effect of Fast-food restaurants on Obesity and Weight Gain.” *American Economic Journal: Economic Policy*, 2(3): 32-63.

Drichoutis, AC, Nayga, RM, and Lazaridis, P. (2009). “Can Nutritional Label Use Influence Body Weight Outcomes?” *Kyklos*, 62(4): 500-525.

Elbel B, Kersh R, Brescoll V, and Dixon L. Beth. (2009). “Calorie Labeling and Food Choices: A First Look at the Effects on Low-Income People in New York City. *Health Affairs*, 28(6): w1110–21.

Ellison B, Lusk J, and David D. (2013). “Looking at the label and beyond: the effects of calorie labels, health consciousness, and demographics on caloric intake in restaurants.” *International Journal of Behavioral Nutrition and Physical Activity*, 10:21.

Ellison B, Lusk J, and David D. (2014a). “The Impact of Restaurant Calorie Labels on Food Choice: Results from a Field Experiment.” *Economic Inquiry*, 52(2): 666–681.

Ellison B, Lusk J, and David D. (2014b). “The Effect of Calorie Labels on Caloric Intake and Restaurant Revenue: Evidence from Two Full-Service Restaurants.” *Journal of Agricultural and Applied Economics*, 46(2): 173-191.

Farley T, Caffarelli A, Bassett M, Silver L, and Frieden T. (2009). “New York City’s Fight Over Calorie Labeling. *Health Affairs*, 28(6): w1098-w1109.

Finkelstein EA, Strombotne KL, Chan NL, and Krieger J. (2011). “Mandatory menu labeling in one fast-food chain in King County, Washington.” *American Journal of Preventive Medicine*, 40(2):122-7.

Finkelstein EA, Trogdon JG, Cohen JW, and Dietz W. (2009). “Annual Medical Spending Attributable to Obesity: Payer and Service-Specific Estimates”. *Health Affairs*, 28(5): w822-w831.

Gruber J and Frakes M. (2006). “Does falling smoking lead to rising obesity?” *Journal of Health Economics*, 25(2): 183–197.

Hall KD, Sacks G, Chandramohan D, Chow CC, Wang YC, Gortmaker SL, and Swinburn BA. (2011). “Quantification of the effect of energy imbalance on bodyweight.” *Lancet*, 378(9793): 826-37.

Lakdawalla D and Philipson T. (2002). “The Growth of Obesity and Technological Change: A Theoretical and Empirical Examination”. *NBER Working Paper* No. 8946.

Lin B, and Guthrie J. (2012). “Nutritional Quality of Food Prepared at Home and Away From Home, 1977-2008.” EIB-105, USDA, Economic Research Service.

Littlewood JA, Lourenço S, Iversen CL, and Hansen GL. (2015). “Menu labelling is effective in reducing energy ordered and consumed: a systematic review and meta-analysis of recent studies.” *Public Health Nutrition*, 30: 1-16.

Long MW, Tobias DK, Cradock AL, Batchelder H, and Gortmaker SL. (2015). “Systematic review and meta-analysis of the impact of restaurant menu calorie labeling.” *American Journal of Public Health,* 105(5): e11-24.

Loureiro ML, Yen ST, and Nayga RM. (2012). “The effects of nutritional labels on obesity.” *Agricultural Economics,* 43(3): 333-342.

Namba A, Auchincloss A, Leonberg BL, and Wootan MG. (2013). “Exploratory analysis of fast-food chain restaurant menus before and after implementation of local calorie-labeling policies, 2005-2011.” *Preventing Chronic Disease*, 10: 120224.

Nielsen SJ, Kit BK, Fakhouri T, Ogden CL. (2012) “Calories consumed from alcoholic beverages by U.S. adults, 2007–2010.” NCHS Data Brief, No. 110. Hyattsville, MD: National Center for Health Statistics.

Ogden CL, Carroll MD, Kit BK, Flegal KM. “Prevalence of obesity in the United States, 2009–2010.” (2012). NCHS Data Brief, No. 82. Hyattsville, MD: National Center for Health Statistics.

Restrepo B and Rieger M. (2016). “Trans Fat and Cardiovascular Disease Mortality: Evidence from Bans in Restaurants in New York.” *Journal of Health Economics*, 45: 176-96.

Robert Wood Johnson Foundation. (2009). “Menu Labeling: Does Providing Nutrition Information at the Point of Purchase Affect Consumer Behavior?”

Robert Wood Johnson Foundation. (2013). “Impact of Menu Labeling on Consumer Behavior: A 2008-2012 Update.”

Roberto CA, Larsen PD, Agnew H, Baik J, and Brownell KD. (2010). “Evaluating the Impact of Menu Labeling on Food Choices and Intake.” *American Journal of Public Health*, 100(2): 312-318.

Rosenheck R. (2008). “Fast food consumption and increased caloric intake: a systematic review of a trajectory towards weight gain and obesity risk.” *Obesity Reviews*, 9(6): 535–54.

Ruhm C. (2005) “Healthy Living in Hard Times.” *Journal of Health Economics*, 24(2): 341–363.

Scientific Advisory Committee on Nutrition. (2007). “Update on trans fatty acids and health.” The Stationary Office, London, U.K.

Tandon PS, Zhou C, Chan NL, Lozano P, Couch SC, Glanz K, Krieger J, and Saelens BE. “The impact of menu labeling on fast-food purchases for children and parents.” *American Journal of Preventive Medicine,* 41(4): 434-8.

Variyam JN. (2008). “Do nutrition labels improve dietary outcomes?” *Health Economics*, 17(6): 695-708.

Variyam JN and Cawley J. (2006). "Nutrition Labels and Obesity." *NBER Working Paper* No. 11956.

Wisdom J, Downs J, and Loewenstein G. (2010). "Promoting Healthier Food Choices: Information versus Convenience." *American Economic Journal: Applied Economics*, 2(2): 164-78.

Table I: Sample Summary Statistics

	All Counties (No. Counties = 74)		CL Implemented Over Sample Period (No. Counties = 11)		CL Not Implemented Over Sample Period (No. Counties = 63)	
2004-2012 BRFSS	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Body Mass Index (BMI)	27.129	5.492	26.732	5.427	27.256	5.507
1 if Obese (BMI≥30)	0.245		0.221		0.252	
Age	53.245	16.372	52.814	16.698	53.383	16.264
1 if Male	0.412		0.408		0.414	
1 if Black	0.115		0.172		0.097	
1 if Other Race	0.088		0.087		0.089	
1 if Hispanic	0.095		0.118		0.088	
Number of Children	0.603	1.052	0.571	1.126	0.613	1.027
1 if Married	0.523		0.467		0.542	
1 if HGC is High School Deg	0.257		0.222		0.269	
1 if HGC is Some College	0.237		0.219		0.242	
1 if HGC is >= 4 Year College Deg	0.441		0.493		0.424	
Log(Family Income in $2012)	10.752	0.632	10.749	0.648	10.753	0.627
County-Level Information						
County Unemployment Rate	6.719	2.285	6.644	2.126	6.743	2.333
Fast-Food Restaurants[a]	7.224	1.791	8.055	2.955	6.958	1.070
Full-Service Restaurants[a]	8.276	3.961	10.422	7.051	7.589	1.690
Fitness and Recreation Centers[a]	1.359	0.622	1.308	0.781	1.376	0.560
Supermarkets and Grocery Stores[a]	3.448	1.679	5.476	1.866	2.799	0.932
Convenience Stores[a]	1.300	0.457	1.001	0.378	1.395	0.438
Specialty Stores[a]	1.514	0.642	2.153	0.752	1.309	0.436
1 if 100% Smoke-free Law	0.871		1		0.829	
Cigarette Tax (per pack in $2012)	2.967	0.884	3.696	1.273	2.734	0.538
Beer Tax (per gallon in $2012)	0.150	0.048	0.209	0.066	0.131	0.012
Soda Sales Tax Rate	5.481	1.330	4.055	0.104	5.93716	1.21428
N	103,220		25,025		78,195	

Note: These summary statistics are for the Table II regression sample. Individual-level information was drawn from the 2004-2012 Behavioral Risk Factor Surveillance System. County-level unemployment rates were drawn from the 2004-2012 Local Area Unemployment Statistics series of the Bureau of Labor Statistics. County-level information on fitness and recreation centers, fast-food and full-service restaurants, supermarkets and grocery stores, and specialty food stores was drawn from the 2004-2012 County Business Patterns. Information on smoke-free laws, cigarette taxes, beer taxes, and soda taxes was drawn from Americans for Nonsmokers' Rights, The Tax Burden on Tobacco, Brewer's Almanac, and Robert Wood Johnson Foundation, respectively. [a]These figures are per 10,000 persons in the county.

Table II: Estimated Effects of Calorie Labeling on BMI and Risk of Obesity

Dep Var	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.396***	-0.031**
	(0.138)	(0.013)
1 if County Has Adopted But Not Implemented CL Law	-0.051	-0.011
	(0.181)	(0.018)
1 if Aged 25 to 34	2.171***	0.110***
	(0.156)	(0.010)
1 if Aged 35 to 44	2.726***	0.131***
	(0.183)	(0.012)
1 if Aged 45 to 54	3.307***	0.166***
	(0.143)	(0.010)
1 if Aged 55 to 59	3.545***	0.181***
	(0.123)	(0.009)
1 if Aged 60 to 64	3.530***	0.174***
	(0.146)	(0.010)
1 if Aged 65 and Over	2.432***	0.105***
	(0.124)	(0.008)
1 if Male	1.048***	0.022**
	(0.141)	(0.009)
1 if Black	1.542***	0.086***
	(0.147)	(0.010)
1 if Other Race	-0.877***	-0.058***
	(0.121)	(0.011)
1 if Hispanic	0.792***	0.038***
	(0.119)	(0.009)
Number of Children	0.040	0.002
	(0.040)	(0.003)
1 if Married	0.025	0.003
	(0.065)	(0.006)
1 if High School Graduate	-0.266	-0.021*
	(0.184)	(0.011)
1 if Some College	-0.336*	-0.022*
	(0.186)	(0.012)
1 if Four Years of College or More	-1.348***	-0.098***
	(0.200)	(0.011)
Log(Family Income)	-0.322***	-0.023***
	(0.054)	(0.004)
County Unemployment Rate	-0.011	0.004
	(0.104)	(0.011)

Fast-Food Restaurants Per 10,000 Persons	0.107	0.001
	(0.109)	(0.008)
Full-Service Restaurants Per 10,000 Persons	-0.005	-0.007
	(0.129)	(0.010)
Fitness and Recreation Centers Per 10,000 Persons	0.294	-0.002
	(0.349)	(0.024)
Supermarkets and Grocery Stores Per 10,000 Persons	0.133	0.006
	(0.201)	(0.014)
Convenience Stores Per 10,000 Persons	0.150	0.017
	(0.213)	(0.016)
Specialty Stores Per 10,000 Persons	-0.566*	-0.079***
	(0.317)	(0.023)
1 if 100% Smoke-free Law	0.331	0.011
	(0.203)	(0.017)
Cigarette Tax	-0.098	0.010
	(0.123)	(0.009)
Beer Tax	4.666	0.440
	(8.704)	(0.893)
Soda Sales Tax Rate	-0.266	-0.033**
	(0.191)	(0.014)
Constant	27.812***	0.624***
	(2.109)	(0.184)
R-squared	0.082	0.046
Sample Size	103,220	
County, Month, and Year FE	x	x
Control Variables	x	x
County Dummies × Year	x	x

Note: Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. Individuals 18 and older are included in these regressions. All regressions used sampling weights. *,**, and, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table III: Robustness Checks

	BMI	1 if Obese
(1) Testing for Policy Spillover Effects (N = 103,220)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.363***	-0.024**
	(0.113)	(0.010)
1 if Neighboring County to County that Has Implemented CL Law	-0.068	-0.010
	(0.175)	(0.019)
(2) Counties in NY as Control Group (N = 45,870)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.394**	-0.038**
	(0.155)	(0.015)
(3) Metropolitan Counties in NY as Control Group (N = 41,247)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.457***	-0.045***
	(0.152)	(0.016)
(4) Counties in NY-NJ-PA MSA and Selected NY Regions as Control Group (N = 86,540)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.492***	-0.041**
	(0.156)	(0.016)
(5) Allowing County-Specific Effects of UR (N = 103,220)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.444***	-0.032**
	(0.123)	(0.013)
(6) Including County-Specific Quadratic Time Trends (N = 103,220)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.403**	-0.028*
	(0.166)	(0.014)
(7) Correcting BMI for Self-Reporting Error (N = 103,220)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.461***	-0.037***
	(0.146)	(0.013)

(8) Controlling for Trans Fat Bans (N = 103,220)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.365**	-0.034**
	(0.143)	(0.014)
1 if County Has Implemented TFB	-0.072	0.007
	(0.088)	(0.009)
(9) Dropping NYC from the Analysis (N = 85,926)	BMI	1 if Obese
1 if County Has Implemented CL Law	-0.412*	-0.040***
	(0.229)	(0.012)
(10) Placebo Test (N = 105,282)	1 if Flu Shot	
1 if County Has Implemented CL Law	0.007	
	(0.018)	
County, Month, and Year FE	x	x
Control Variables	x	x
County Dummies × Year	x	x

Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race and ethnicity dummies (black, other race, Hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county's calorie labeling law has been adopted but not implemented. Also included but not shown: unemployment rate, # of fast-food restaurants, # of full-service restaurants, # of fitness and recreation centers, # of supermarkets and grocery stores, # of convenience stores, # of specialty stores, cigarette taxes, beer taxes, soda taxes, and a dummy for whether a county has a 100% smoke-free law. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sampling weights. *, **, and,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table IV: Heterogeneity in the Effect of Calorie Labeling across the BMI Distribution

Quantile	0.1	0.25	0.5	0.75	0.9
1 if County Has Implemented CL Law	-0.213*	-0.330**	-0.291*	-0.308	-0.251
	(0.121)	(0.129)	(0.155)	(0.210)	(0.266)
R-Squared	0.035	0.052	0.065	0.066	0.055
P-value of Test of Equality of Estimated Coefficients			0.954		
County, Month, and Year FE	x	x	x	x	x
Control Variables	x	x	x	x	x
County Dummies × Year	x	x	x	x	x

Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race and ethnicity dummies (black, other race, Hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county's calorie labeling law has been adopted but not implemented. The following county-level information is also included but not shown: unemployment rate, # of fast-food restaurants, # of full-service restaurants, # of fitness and recreation centers, # of supermarkets and grocery stores, # of convenience stores, # of specialty stores, cigarette taxes, beer taxes, soda taxes, and a dummy for whether a county has a 100% smoke-free law. Sample size is 103,220. Standard errors are clustered at the county level, and are in parentheses below QR coefficients. *,**, and, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table V: Heterogeneity in the Effect of Calorie Labeling on BMI, by Demographic Sub-Group

Panel A

	Female	Male
1 if County Has Implemented CL Law	-0.551**	-0.330
	(0.258)	(0.273)
R-squared	0.105	0.076
P-value of Test of Equality of Coefficients	0.624	
Sample Size	60,679	42,541
	Minority	Non-Hisp White
1 if County Has Implemented CL Law	-0.748**	-0.227*
	(0.354)	(0.131)
R-squared	0.099	0.086
P-value of Test of Equality of Coefficients	0.195	
Sample Size	26,117	77,103
	< Median Inc	> Median Inc
1 if County Has Implemented CL Law	-0.759***	-0.147
	(0.230)	(0.244)
R-squared	0.070	0.109
P-value of Test of Equality of Coefficients	0.086	
Sample Size	51,610	51,610
	≤ HS Grad	≥ Some College
1 if County Has Implemented CL Law	0.083	-0.664***
	(0.355)	(0.241)
R-squared	0.058	0.092
P-value of Test of Equality of Coefficients	0.151	
Sample Size	33,307	69,913

Panel B	**< Median Inc**	
	Female	Male
1 if County Has Implemented CL Law	-0.809	-0.816*
	(0.543)	(0.480)
R-squared	0.094	0.075
P-value of Test of Equality of Coefficients	0.994	
Sample Size	33,043	19,331
	Minority	Non-Hisp White
1 if County Has Implemented CL Law	-1.291**	-0.171
	(0.519)	(0.291)
R-squared	0.092	0.071
P-value of Test of Equality of Coefficients	0.063	
Sample Size	17,621	34,753
	≤ HS Grad	≥ Some College
1 if County Has Implemented CL Law	-0.607	-1.004***
	(0.412)	(0.275)
R-squared	0.057	0.087
P-value of Test of Equality of Coefficients	0.465	
Sample Size	25,534	26,840
County, Month, and Year FE	x	x
Control Variables	x	x
County Dummies × Year	x	x

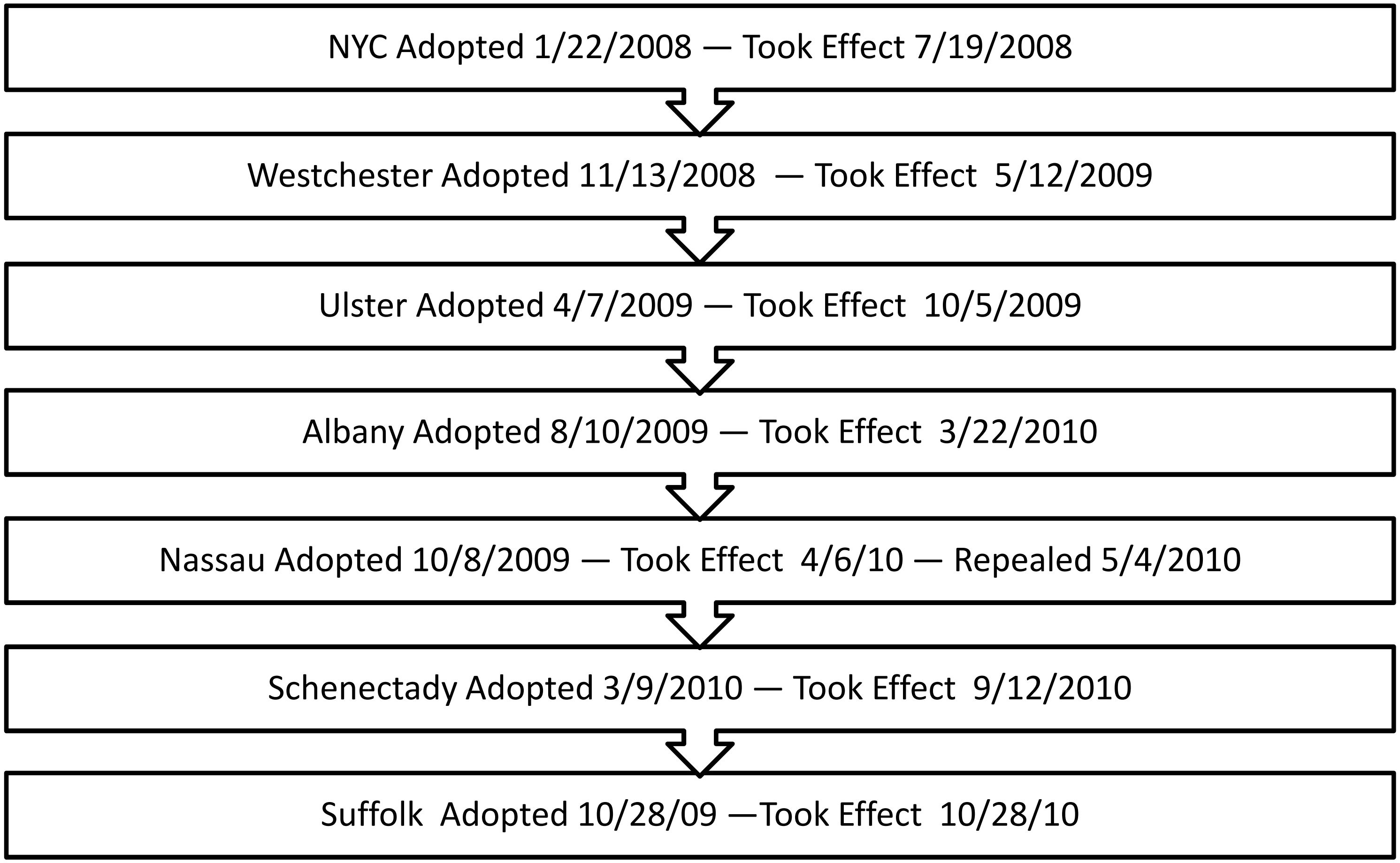
Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race and ethnicity dummies (black, other race, Hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county's calorie labeling law has been adopted but not implemented. Also included but not shown: unemployment rate, # of fast-food restaurants, # of full-service restaurants, # of fitness and recreation centers, # of supermarkets and grocery stores, # of convenience stores, # of specialty stores, cigarette taxes, beer taxes, soda taxes, and a dummy for whether a county has a 100% smoke-free law. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sampling weights. *, **, and,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table VI: Estimated Effects of Calorie Labeling on Physical Activity, Dietary Behavior, and Smoking

Dep Var	1 if Any Exercise in Past Month	Ln(Mins of Exercise per Week + 1)	Ln(Fruit &Veg Serv per Day +1)	Ln(Alcohol Units/Day + 1)	1 if Current Smoker
Sample Mean in 2007	0.756	358.528	2.915	0.353	0.166
1 if County Has Implemented CL Law	-0.005 (0.025)	0.088 (0.069)	-0.026 (0.032)	0.017 (0.010)	-0.003 (0.013)
R-squared	0.079	0.188	0.083	0.107	0.077
Sample Size	106,704	38,343	44,664	103,979	106,826
County, Month, and Year	x	x	x	x	x
Control Variables	x	x	x	x	x
County Dummies × Year	x	x	x	x	x

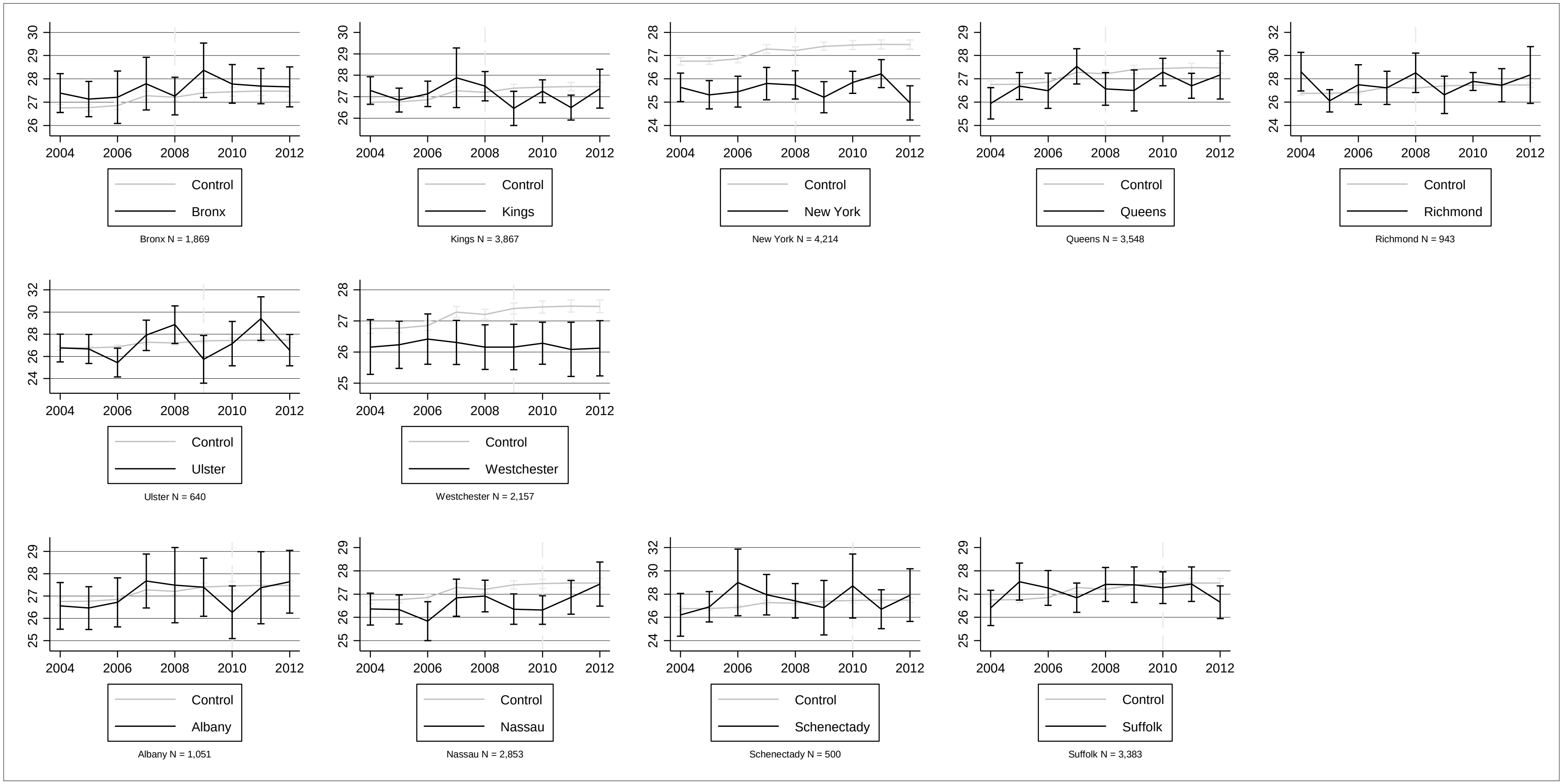
Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race and ethnicity dummies (black, other race, Hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county's calorie labeling law has been adopted but not implemented. The following county-level information is also included but not shown: unemployment rate, # of fast-food restaurants, # of full-service restaurants, # of fitness and recreation centers, # of supermarkets and grocery stores, # of convenience stores, # of specialty stores, cigarette taxes, beer taxes, soda taxes, and a dummy for whether a county has a 100% smoke-free law. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sampling weights. *,**, and, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 1: Timeline of Adoption and Implementation Dates of Calorie Labeling Laws in New York



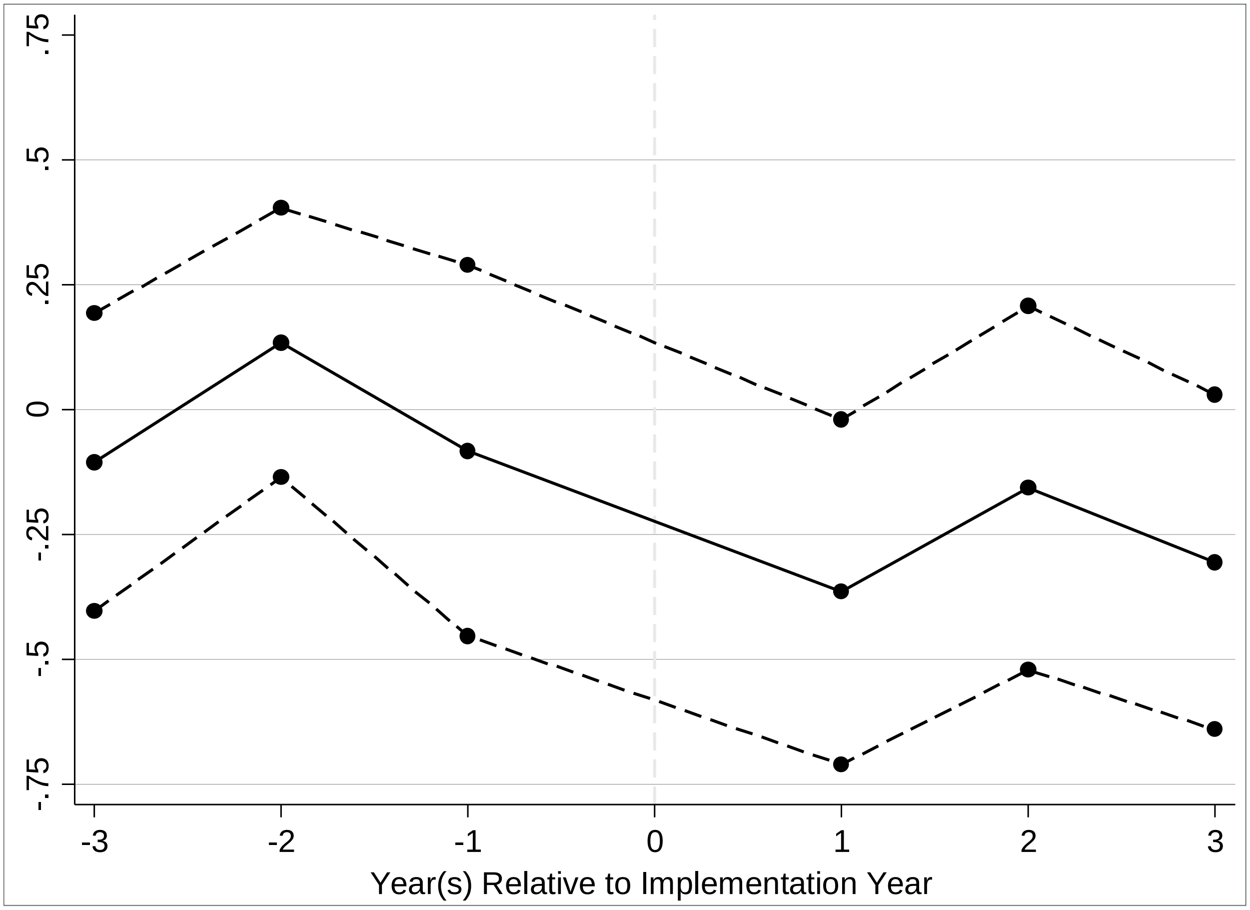
Note: The NYC Department of Health initially adopted mandatory calorie labeling on 12/05/2006. However, after a couple of legal challenges, a revised mandatory calorie labeling law was adopted on 1/22/2008.

Figure 2: Trends in BMI, by Treatment Group and County



Note: These are plotted county-specific BMI means and their corresponding 95% confidence intervals for the Table II regression sample. The x-axis corresponds to the BRFSS sample year and the y-axis corresponds to the average BMI for BRFSS respondents residing in a given county. The vertical dashed line corresponds to the treatment county's year of implementation. For every year, the BMI of all respondents residing in counties with no effective calorie labeling law are included in the control group—including those residing in counties that implement a law in a later year. The control group's sample size is 90,812.

Figure 3: Estimates of the Effect of Calorie Labeling on BMI from a Lead-Lag Analysis



Note: These are estimated coefficients and their corresponding 95% confidence interval bands from the main regression specification, except for the addition of leads and lags of the policy variable. A test of joint significance of policy leads yields a p-value of 0.148. The p-value from a test of joint significance of the first, second, and third year of calorie labeling effects is 0.076, while the p-value from a test of joint significance of the second and third year of calorie labeling effects yields a p-value of 0.168.

Appendix Table I: Summary Statistics for Alternative Control Groups

	Counties That Did Not Implement CL Over Sample Period					
	NY (No. Counties = 50)		Metro NY[a] (No. Counties = 25)		Selected NY Regions & NY-NJ-PA MSA[b] (No. Counties = 25)	
2004-2012 BRFSS	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Body Mass Index (BMI)	27.685	5.814	27.566	5.744	27.113	5.392
1 if Obese (BMI≥30)	0.283		0.275		0.243	
Age	54.684	16.483	54.518	16.432	52.996	16.155
1 if Male	0.405		0.404		0.416	
1 if Black	0.043		0.052		0.112	
1 if Other Race	0.025		0.026		0.107	
1 if Hispanic	0.024		0.025		0.107	
Number of Children	0.546	1.011	0.556	1.018	0.636	1.036
1 if Married	0.531		0.531		0.546	
1 if HGC is High School Deg	0.303		0.288		0.257	
1 if HGC is Some College	0.271		0.270		0.234	
1 if HGC is >= 4 Year College Deg	0.358		0.379		0.445	
Log(Family Income in $2012)	10.640	0.634	10.676	0.628	10.791	0.619
County-Level Information						
County Unemployment Rate	6.606	1.834	6.289	1.732	6.757	2.453
Fast-Food Restaurants[c]	6.567	1.069	6.797	0.911	7.056	1.030
Full-Service Restaurants[c]	8.667	2.007	8.338	1.821	7.339	1.502
Fitness and Recreation Centers[c]	1.075	0.387	1.189	0.320	1.459	0.574
Supermarkets and Grocery Stores[c]	2.436	0.663	2.377	0.626	2.935	0.959
Convenience Stores[c]	0.970	0.366	1.004	0.357	1.516	0.373
Specialty Stores[c]	0.917	0.339	0.964	0.324	1.422	0.396
1 if 100% Smoke-free Law	1		1		0.783	
Cigarette Tax (per pack in $2012)	2.817	0.974	2.741	0.97876	2.715	0.330
Beer Tax (per gallon in $2012)	0.133	0.010	0.133	0.010	0.130	0.012
Soda Sales Tax Rate	4.046	0.097	4.053	0.102	6.450	0.801
Sample Size	20,845		16,222		61,515	

Note: These summary statistics are for the alternative control groups used in Table III.

[a]I use 2004 County Typology Codes provided by the Economic Research Service to assign metropolitan county status.

[b]These include counties in NY-NJ-PA MSA and NYS regions with a county that implemented CL over the sample period.

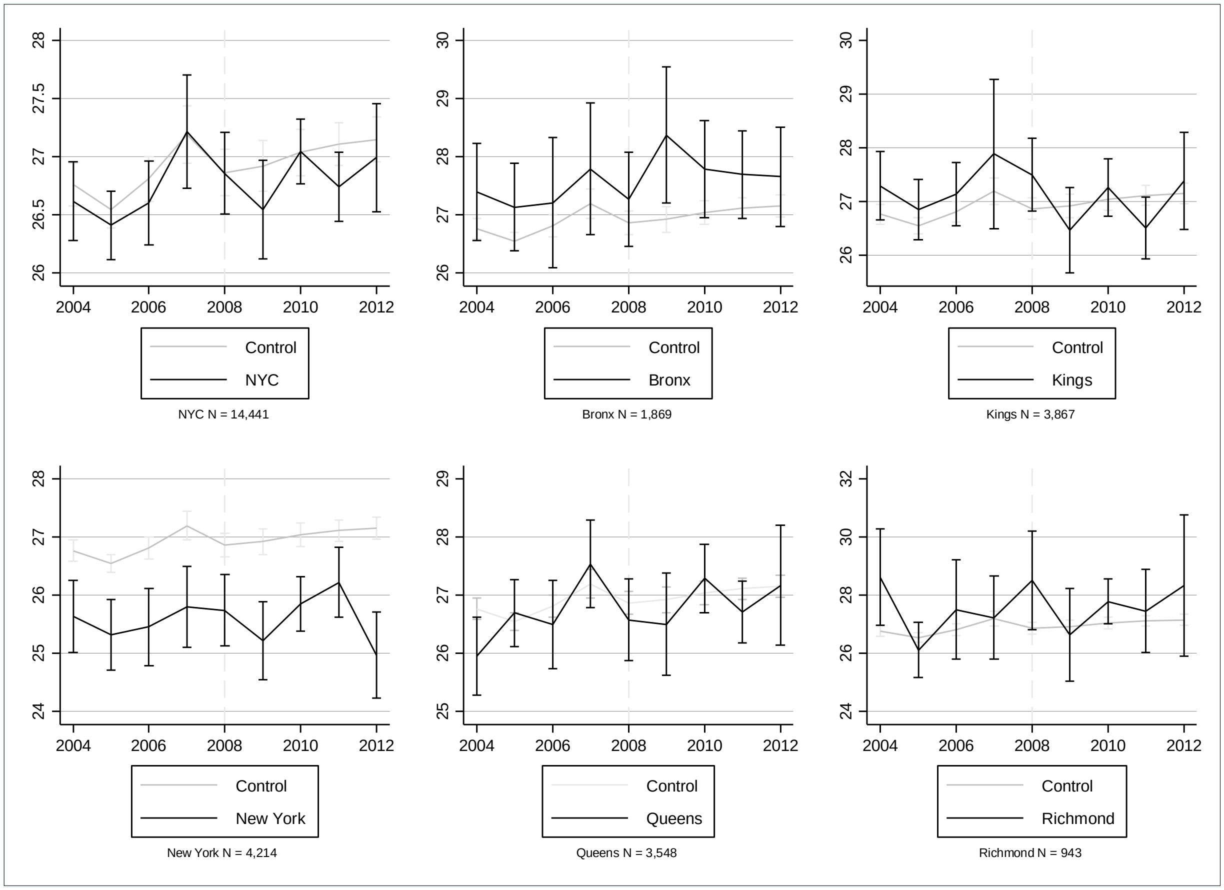
[c]These figures are per 10,000 persons in the county.

Appendix Table II: Sensitivity in the Estimated BMI Effect of Calorie Labeling to Raising Minimum County-Year Respondent Size

	(1)	(2)	(3)	(4)	(5)	(6)
1 if County Has Implemented CL Law	-0.396***	-0.388**	-0.452***	-0.382**	-0.432**	-0.457***
	(0.138)	(0.144)	(0.149)	(0.146)	(0.155)	(0.136)
	[0.030]	[0.046]	[0.028]	[0.052]	[0.036]	[0.014]
R-Squared	0.082	0.082	0.082	0.085	0.086	0.086
Number of Clusters	74	44	31	24	22	22
Minimum *i* respondents in County *c* in Year *t*	None	50	100	150	200	250
Mean County-Year BMI Relative Standard Error	1.238%	1.083%	0.965%	0.927%	0.909%	0.894%
Range County-Year BMI Relative Standard Error	[0.52%, 18.41%]	[0.52%, 3.56%]	[0.52%, 2.19%]	[0.52%, 1.78%]	[0.52%, 1.49%]	[0.52%, 1.39%]
Sample Size	103,220	97,408	89,427	85,751	83,063	80,090
Treatment County-Year Information Dropped	None	None	Schenectady Ulster	Schenectady Ulster Albany	Schenectady Ulster Albany Richmond	Schenectady Ulster Albany Richmond
County, Month, and Year FE	x	x	x	x	x	x
Control Variables	x	x	x	x	x	x
County Dummies × Year	x	x	x	x	x	x

Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race and ethnicity dummies (black, other race, Hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county's calorie labeling law has been adopted but not implemented. The following county-level information is also included but not shown: unemployment rate, # of fast-food restaurants, # of full-service restaurants, # of fitness and recreation centers, # of supermarkets and grocery stores, # of convenience stores, # of specialty stores, cigarette taxes, beer taxes, soda taxes, and a dummy for whether a county has a 100% smoke-free law. Sample size is 103,220. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. P-values adjusted using a wild cluster bootstrap-t procedure are in brackets. All regressions used sampling weights. *,**, and, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix Figure 1: Trends in BMI in NYC versus NY-NJ-PA MSA Counties



Note: These are plotted county-specific BMI means and their corresponding 95% confidence intervals for a regression sample (N = 74,409) including BRFSS respondents residing in NYC and NY-NJ-PA MSA counties. The vertical dashed line corresponds to the treatment county's year of implementation. The x-axis is the BRFSS sample year and the y-axis is the average BMI for all BRFSS respondents residing in a given county. The control group's sample size is 59,968.