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Abstract

This study analyzes the impact of mandatory calorie labeling on body weight and shows that implementation of the policy caused reductions in body mass index and the probability of obesity. The analysis also uncovers evidence of heterogeneity in the policy's impact on body weight. First, the policy had larger impacts in the upper half of the BMI distribution. Second, the impact of calorie labeling is concentrated among individuals with high propensities to eat fast food and to use nutrition information at restaurants. Heterogeneity in sensitivity to calorie information may explain the mixed evidence in previous studies on the policy's effectiveness.

Keywords

Calorie labeling, chain restaurants, body mass index, obesity

JEL Classification Codes

I12, I18

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I. Introduction

Obesity remains a major public health problem in the U.S. In 2009-2010, about one in three adults was classified as obese, and no state in the nation had met the *Healthy People 2010* objective of reducing the obesity rate among adults to 15% (Ogden *et al*. 2012). Obesity increases the risk of morbidity from hypertension, coronary heart disease, strokes, type 2 diabetes, and many other health conditions. Treating obesity-related illness is expensive and it imposes substantial healthcare costs on society. For example, 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).

Changes in the food environment and unhealthy eating habits are important to understanding the rise in obesity in the past half century.[1] For example, there has been a dramatic increase in the supply of, and demand for, food from restaurants, which tend to offer energy-dense and nutrient-poor food (Currie *et al*. 2010; Anderson and Matsa 2011). The consumption of food prepared away from home is often cited as a potential cause of increased body weight because the daily consumption of such foods has increased dramatically over time.[2] For example, recent data indicates that the share of daily calories consumed coming from restaurants and fast food establishments increased from 6% to 20% between 1977-78 and 2005-08 (Lin and Guthrie 2012).

While the provision of nutrition information on packaged foods has been mandated by the federal government since the passing of the Nutrition Labeling and Education Act (NLEA), restaurants were exempted from this requirement. A recent public policy response to the growing prevalence of obesity, and its association with the rising consumption of restaurant food, is to close the nutrition information gap that consumers face when purchasing

[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.* 2007).
[2] 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).

food from grocery stores and supermarkets versus restaurants. For example, localities throughout the U.S. have mandated chain restaurants to post calorie counts on menus in order to improve access to nutrition information at the point of purchase and to facilitate better informed and healthy menu item choices. The New York City (NYC) health department was the first to implement mandatory calorie labeling in July 2008 and six New York State county health departments quickly followed suit by also implementing the law in 2009 and 2010.[3]

The first contribution of this paper is that it provides the first estimates of the impact of mandatory calorie labeling in chain restaurants on body mass index (BMI) and the probability of obesity. Previous work has focused on examining purchasing behavior within chain restaurants in response to calorie counts posted on menus at the point of sale, *e.g.* by studying whether consumers choose lower calorie meals or buy fewer items (Bassett *et al.* 2008; Wisdom *et al.* 2010; Elbel *et al.* 2009; Bollinger *et al.* 2011). Evidence on whether mandatory calorie labeling is effective in reducing the amount of calories purchased at chain restaurants is mixed, with some studies finding no effect and others finding modest to sizeable reductions. However, behavioral changes may occur outside of chain restaurants as well. For example, individuals may use the calorie information they observe on menus to decide how much to eat later in the day after consuming a chain restaurant meal, they may substitute consumption towards non-chain restaurant meals, and there are many other potentially important behavioral responses. Also, many studies in the literature have focused on estimation of average effects of the policy on calorie consumption (Robert Wood Johnson Foundation 2013), which may mask important heterogeneity in the responsiveness and sensitivity to calorie information posted on menus in chain restaurants.

[3] NYC is composed of five counties: the Bronx, Kings, New York, Queens, and Richmond. Thus, a total of 11 of 62 counties in New York State implemented mandatory calorie labeling between 2008 and 2012. The law applies to all chain restaurants with 15 or more locations nationwide. In particular, the policy affects fast food as well as full-service or sit-down restaurants. Examples of restaurants that are affected by mandatory calorie labeling requirements include fast food restaurants such as McDonald’s and Burger King, and full-service restaurants such as Applebee’s and Denny’s.

This study employs a differences-in-differences empirical strategy, which uses within-county variation in the policy mandate and the differential timing of its implementation across New York State counties to identify the effect of calorie labeling on body weight. 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 the calorie information posted on menus in chain restaurants, both inside and outside of chains. Using the 2004 to 2012 waves of the Behavioral Risk Factor Surveillance System (BRFSS), the analysis reveals that implementation of mandatory calorie labeling has had its intended effects on body weight by causing reductions in BMI and the probability of obesity.

I estimate that, on average, implementation of calorie labeling reduced BMI by 0.4 units, and decreased the probability of being obese by 3 percentage points. Relative to the sample means, this is a reduction of 1.5% and 11%, respectively. These results are not sensitive to controlling for another health-related policy (bans on the use of trans fat containing oils in restaurants) that was rolled out by many counties around the same time as mandatory calorie labeling laws, various sensitivity and robustness checks including an event study analysis, and placebo regressions show that implementation of calorie labeling had no impact on health-related behaviors that are not related to diet or physical activity such as preventive health practices.

The analysis also uncovers heterogeneity in the policy's impact across the BMI distribution. In particular, results from quantile regressions indicate that the estimated impacts of calorie labeling are generally larger in the upper half of the BMI distribution. For example, I estimate that implementation of calorie labeling reduces BMI by 2.58% at the 0.8 quantile, while the corresponding estimate at the 0.4 quantile is a reduction of 0.79%. This finding may be viewed as consistent with the results of the study by Bollinger *et al.* (2011) who found that, in Starbucks, implementation of calorie labeling had a disproportionately larger effect on consumers who were high-calorie purchasers before the policy was implemented. In particular, they found that while, on average, calorie labeling caused a 6% reduction in calories purchased per transaction, the corresponding reduction for individuals who averaged more than 250 calories per transaction before calories were posted in Starbucks was 26%.

One interpretation of the finding that calorie labeling has larger impacts in the upper half of the BMI distribution is that the policy has been successful at disproportionately affecting the behavior of overweight individuals because they may be more sensitive to calorie information posted on menus in chain restaurants than non-overweight individuals. Another interpretation is that overweight individuals may be more likely than non-overweight individuals to be exposed to calorie information in chain restaurants if, for example, overweight individuals tend to visit such establishments on a more frequent basis.

To shed light on these two hypotheses, I also explore heterogeneity in the impact of mandatory calorie labeling on body weight by the likelihood that individuals are exposed to calorie information in chains and by the likelihood that individuals are sensitive to such information. To this end, I use the 2007-2008 wave of the National Health and Nutrition Examination Survey (NHANES), which has information on the frequency of fast food consumption, as well as information on the frequency with which individuals would use nutrition information to decide what to order if the information was readily available at fast food and sit-down restaurants. The first variable may be thought of as a proxy for potential exposure to calorie information in chains, while the latter two variables may be thought of as a proxy for sensitivity to it. I use these variables, together with demographic information common to the BRFSS and NHANES data sets, to estimate the propensity to be a (i) "regular fast food customer", (ii) "often user of nutrition information at fast food restaurants", and (iii) "often user of nutrition information at sit-down restaurants".

I find evidence that implementation of mandatory calorie labeling has strong impacts on the body weight outcomes of individuals who have above-median propensities to be (i), (ii), and (iii), and much weaker impacts on the body weight of those with below-median propensities. The estimated body weight impacts of mandatory calorie labeling are larger for individuals in the "above-median propensity" samples because these individuals are most likely to be "treated", *i.e.* they are more likely to be exposed to calorie information posted on menus in chains because of a relatively higher frequency of visits, or because they find nutrition information in restaurants to be useful in deciding what to order and their sensitivity to it is more pronounced. The latter finding highlights the importance of heterogeneity in sensitivity to nutrition information across consumers, and is consistent with evidence that implementation of NLEA, which improved the nutrition information set of consumers for packaged foods, was associated with a decrease in body weight for nutrition label users relative to nonusers (Variyam and Cawley 2006).

It is also important to know the timing of the impact of calorie labeling on body weight. On the one hand, it may take time after the implementation of mandatory calorie labeling for an effect on body weight to be observed because, for example, exposure to the new calorie information in chain restaurants grows over time. On the other hand, people may be most sensitive to calorie information when it is first learned, or initially made salient to them at the point of purchase, and sensitivity to the information may fade out over time. The analysis indicates that, on average, implementation of mandatory calorie labeling had its strongest impact on body weight within the first year of the law taking effect, and there is suggestive evidence that the effect of calorie labeling may be more persistent. The analysis also reveals evidence of heterogeneity in the length of time that calorie labeling has an impact on body weight. In particular, compared with individuals in the "below-median propensity" samples, I find evidence indicating that calorie labeling has a much more persistent effect on the body weight of individuals who have above-median propensities to use nutrition information at restaurants.

The second contribution that I make to the literature is to add to the understanding of the channels through which calorie labeling might affect consumer behavior. Analyzing purchasing behavior within chain restaurants is important for understanding how the policy works at the point of purchase, but there are other potentially important margins of adjustment. I explore whether calorie labeling improves health-related behaviors, such as following a healthier diet and engaging in more physical activity. I do not find evidence that calorie labeling causes individuals to follow a more active lifestyle or a more healthy diet, as measured by greater physical activity, lower alcohol consumption, and greater fruit and vegetable consumption. The estimated effects of calorie labeling on alcohol, fruit, and vegetable consumption do imply a net reduction in total daily calories consumed, but it is too small to explain the body weight impacts of calorie labeling estimated here.

While the analysis reveals that changes in physical activity or changes in a select set of diet-related behaviors do not explain the results in this study, the analysis does suggest that food-away-from-home consumption is an important underlying mechanism. For example, the evidence indicating that the impact of calorie labeling on body weight is concentrated among individuals with a high propensity to eat fast food implies that changes in the consumption of food away from home may be an important margin of adjustment. I performed a back-of-the-envelope calculation based on the intensive margin of consumption of food away from home in order to quantify the magnitude of the change necessary to account for the results in this study. Todd *et al.* (2010) estimate that each additional meal away from home substituting for a meal at home on a given day adds an average of 134 calories to that day's caloric intake. Using this estimate, one meal per week fewer eaten away from home for a year would result in a 1 kg or 2 lb loss in weight, which is slightly lower than the average estimated impact on body weight (about 1.2kg) of calorie labeling found in this study. Also, as I discuss in greater detail below, the estimated body weight impacts found here are in line with the predicted impact of calorie labeling on body weight provided by Bollinger *et al.* (2011), which is based on the estimated average reduction in calories purchased per transaction in Starbucks applied to all chain restaurants.

The rest of this paper is organized as follows. First, I provide some background information on mandatory calorie labeling in New York State counties and briefly summarize the relevant literature on the effectiveness of calorie labels on menus in chain restaurants. Second, I describe and summarize the data sets used in the analysis. Third, I describe the empirical approach employed in this study and discuss the results of the analysis. Fourth, I investigate potential mechanisms that might drive the estimated impacts of calorie labeling on body weight. Lastly, I provide an overall discussion of my analysis and conclude.

II. Background and Previous Literature

Consumers are able to make informed and healthy decisions over food purchases by reviewing the caloric content and other nutrition information on “Nutrition Facts” labels of packaged products in grocery stores and supermarkets, which has been mandated by the federal government since the passing of the Nutrition Labeling and Education Act (NLEA) of 1990. Restaurant patrons across the nation were not afforded a similar opportunity with the passing of NLEA because it exempted restaurants from providing nutrition information at the point of purchase. Many restaurants provide information on the nutritional content of menu items on their websites or in on-site brochures and posters, but very few consumers report using this nutrition information. For example, while a study conducted in 2004 found that 54% of the 287 largest chain restaurants made nutrition information for standard menu items available for consumers (Wootan and Osborn

2006), another study found that less than 1% of consumers used on-site nutrition information before making a purchase (Roberto *et al*. 2009).

In 2008, New York City's (NYC) Department of Health was the first to implement mandatory calorie labeling in chain restaurants, and between 2009 and 2010 six county health departments in New York State also implemented calorie labeling. Each county health department mandates that chain restaurants with 15 or more locations nationwide post calorie information on standard menu items on menus and menu boards in a font and format that is at least as prominent as menu item prices. Not all restaurants are chains, but chains are responsible for a disproportionate fraction of restaurant traffic. For example, in 2007, only ten percent of NYC's 23,000 restaurants were chain restaurants, but they accounted for one-third of all restaurant traffic (Farley *et al.* 2009).

It is a priori unclear how consumers will respond to calorie counts posted on menus in chain restaurants. Consumers who care a lot about calories may be well-informed about the calories in the food and beverage items they typically choose to buy. Thus, there may be no impact of improving access to calorie information in chain restaurants on the purchasing behaviors of these consumers. For less well-informed consumers, the element of surprise will be important for understanding whether they choose to consume a lower number of calories when the information is available at the point of purchase. On the one hand, consumers who underestimate the amount of calories in a given chain restaurant meal may opt to purchase another meal with fewer calories. On the other hand, calorie information in chain restaurants may lead to greater calorie consumption among consumers who routinely overestimate the amount of calories in chain restaurant meals. That said, the available evidence indicates that 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). Also, a survey of dieticians found that even welltrained nutrition experts routinely and substantially underestimate the number of calories in restaurant meals (Backstrand *et al.*, 1997).

The average response of consumers to calorie information in chain restaurants is ultimately an empirical question. The focus of the relevant literature has been to examine whether the provision of calorie information at the point of purchase induces individuals to make healthier choices, such as choosing lower calorie meals or purchasing fewer items.[4] Evidence from field studies using data on transactions to analyze the effect of calorie labeling on the amount of calories purchased within chain restaurants is mixed.[5] Using information on receipts from 14 fast food restaurants from 4 chains (McDonald's, Burger King, Wendy's, and KFC), Elbel *et al.* (2009) found that calorie labeling had no impact on the amount of calories purchased in NYC, despite the fact that 27% of those seeing labels reported using them. Dumanovksy *et al.* (2011) randomly selected 168 locations from the top 11 fast food chains in NYC, and did not find a significant difference between the amount of calories purchased before and after mandatory calorie labeling was implemented. However, they did find reductions ranging from 44 to 80 calories per transaction at three chains, which accounted for 42% of their sample.[6] This finding suggests that the effect of calorie labeling on the calories purchased in chain restaurants may vary by chain. Bollinger *et al.* (2011) used detailed transactions data from Starbucks, and found that calorie posting in NYC locations resulted in an average reduction of 14 calories purchased per transaction. They found that

[4] There are also many studies analyzing hypothetical menu item choices and purchase intentions. These studies use survey or laboratory experiment data and generally find 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). Also, I focus my discussion on relevant studies that use data from New York State. However, studies drawing on data from outside New York State also report mixed evidence (Robert Wood Johnson Foundation 2013).

[5] Bassett *et al.* (2008) provide early evidence of the potential for calorie information at the point of purchase to influence purchases. Subway was posting calorie information at the point of purchase before mandatory calorie labeling was implemented in NYC. They found that Subway customers who saw calorie information purchased 52 fewer calories than did other customers. Wisdom *et al.* (2010) found that providing calorie information to diners at an undisclosed fast food sandwich chain caused them to order about 61 fewer calories.

[6] An important caveat is that this study did not make use of a control group, *i.e.* locations that were not affected by calorie labeling, and so interpreting their results as causal is difficult.

about 75% of this reduction was due to customers purchasing fewer items, and the remainder was due to customers choosing lower calorie items. They also found that calorie labeling had larger impacts on calories purchased per transaction among women and individuals who were high-calorie purchasers before calories were posted on menus.

In sum, there is evidence in the literature that calorie labeling reduces the amount of calories purchased per transaction in chain restaurants. This study, however, is the first to evaluate whether calorie labeling affects the targeted outcome of the policy—body weight—and the results shed light on whether it has the potential to curb the obesity epidemic. The strength of the empirical approach used here is that it allows measurement of the overall impact of calorie labeling on body weight outcomes, which may operate through purchasing choices made within chain restaurants, as some of the evidence above suggests is the case, or through a variety of other choices made outside of chains. The literature also suggests that the impact of calorie labeling on consumers may not be uniform, which motivates the analysis of heterogeneity in the impact of calorie labeling on body weight shown below. Also, as I discuss in greater detail below, I investigate the importance of several potential mechanisms in order to shed light on whether there is evidence of behavioral effects of the policy that have not been fully explored in the literature.

III. Data

The main analysis draws on data from the 2004-2012 Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a nationally representative survey established in 1984 by the Centers for Disease Control and Prevention, and it is conducted in collaboration with state health departments to track health conditions and health-related behaviors of adults aged 18 and over in the United States. The BRFSS is especially useful for the present analysis because it is rich in demographic and health-related information, and the public-use data set contains county identifiers. County identifiers are crucial to the analysis because within-county variation and the differential timing of the implementation of mandatory calorie labeling laws across New York State (NYS) counties is used to identify the effects of calorie labeling on measures of body weight.

Self-reported height and weight are part of the core information that is collected by the BRFSS, and it is used to calculate an individual's body mass index (BMI). BMI based on self-reported and measured height and weight has been found to be highly correlated (Cawley 1999). However, people tend to under-report their weight and over-report their height, which causes BMI based on self-reports to be measured with error. Cawley (1999) developed a correction for this reporting error, which requires a data set with information on height and weight that is based on self-reports and body measurements. 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). Nonetheless, following Cawley (1999), I also examine the sensitivity of my results to correcting for reporting error in height and weight, using the National Health and Nutrition Examination Survey (NHANES). The NHANES is representative of the U.S. non-institutionalized civilian population, but is not representative of NYS, which is why I chose not to employ this correction in the main analysis.

I obtained county-specific information on legislation regarding mandatory calorie labeling laws from the Center for Science in the Public Interest. The adoption and effective dates of these laws were verified using documentation on local laws retrieved from county health department websites. Figure 1 illustrates the timing of adoption and the effective dates. New York City (NYC) led the way by implementing mandatory calorie labeling in July 2008. Six counties in New York State also implemented a calorie labeling law in 2009 and 2010.[7]

[7] Nassau county adopted a mandatory 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 have learned that no enforcement actions were taken during the short time that the mandatory calorie

In the analysis below, the main variable of interest is a dummy variable taking a value of one if a county has implemented mandatory calorie labeling (and zero otherwise), which is assigned according to the exact date of an interview because interview day, month, and year are identified in the data set.

The total number of observations in the 2004-2012 BRFSS files for New York State is 63,761. I drop 6,109 observations because county information could not be identified and 2,820 observations due to missing information on BMI. To address the concern that outliers are driving the results, I drop 48 observations for which BMI is below 10 or above 60.[8] 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 from the BRFSS New York State file consists of 45,939 individuals, for whom information on county of residence, BMI, and all of the above-mentioned demographic information is available.

Previous work has documented a relationship between economic conditions and body weight (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/year.

All of the counties that implemented calorie labeling are metropolitan counties, which might be a cause for concern with respect to differences between counties that did and did not implement calorie labeling over the sample period.[9] For example, time-varying differences in a county's urbanicity, sentiments toward healthy behavior, availability of healthy food, or restaurant environment may be related to body weight and a county's decision to implement

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 was in effect.

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

[9] 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.

mandatory calorie labeling. I address this concern by obtaining the following county-level information from the 2004-2011 County Business Patterns (CBP): the number of fitness and recreation centers, fast food restaurants, full-service restaurants, grocery stores and supermarkets, convenience stores, and specialty food outlets. Information on these variables is not yet available for 2012. Four New York State counties implemented calorie labeling in 2010, and two did so in late 2010 (see Figure 1). To maximize the usefulness of the duration analysis described below, I use the 2004-2012 waves of the BRFSS in the analysis. Information for the year 2012 on the above-mentioned county-level variables was extrapolated using the 2004-2011 CPB.

Table 1 shows weighted 2004-2012 BRFSS sample summary statistics for the full sample and by whether counties implemented calorie labeling over the study period. Counties that implemented calorie labeling over the study period, on average, have a higher percentage of minorities, a lower percentage of individuals whose highest level of education completed was high school, a higher percentage of individuals with a college degree or more, and individuals with a higher family income. They also have a greater availability of fitness and recreation centers, healthy food, and unhealthy food.[10]

To examine the impact of mandatory calorie labeling on the body weight of individuals who are likely to be affected by the law, *e.g.* regular customers of chain restaurants, information on the frequency of consumption at such restaurants is needed. The BRFSS does not contain such data. However, the 2007-2008 NHANES contains information on the frequency of meals from fast food restaurants.[11] The 2007-2008 NHANES also has

[10] As shown below, the results are not sensitive to the choice of control group. In Appendix Table 1, I also show additional sample summary statistics for subsets of the control group that I make use of in the robustness section.

[11] The following questions were asked: (1) "Next I'm going to ask you about meals. By meal, I mean breakfast, lunch and dinner. During the past 7 days, how many meals did you get that were prepared away from home in places such as restaurants, fast food places, food stands, grocery stores, or from vending machines?"; and (2) "How many of those meals did you get from fast-food or pizza places?"

information on the frequency with which individuals would use nutrition information to decide what to order if it was readily available at fast food and sit-down restaurants.[12] Appendix Table 2 shows the summary statistics for the NHANES sample that is used to estimate the propensity to be a (i) "regular fast food customer", (ii) "often user of nutrition information at fast food restaurants" and (iii) "often user of nutrition information at sit-down restaurants" in the BRFSS data set.[13] This analysis used NHANES data on individuals who were aged 18 and over in order to match the age range of individuals in the BRFSS data set. Of course, this analysis makes two important assumptions. First, it assumes transportability, or that the relationship between demographics and the three variables of interest is the same in both data sets. Second, it assumes that the propensities do not change over time.

The summary statistics show that, on average, Americans eat two fast food meals per week, about 45% of Americans report having had two fast food meals in the last week, and 26% and 27% of Americans would use nutrition information to decide what to order if it was available at fast food restaurants and sit-down restaurants, respectively. A caveat with the analysis based on NHANES data, as mentioned above, is that the NHANES is representative of the U.S., and not of New York State. I am unable to carry out a comprehensive comparison between the data from the NHANES and BRFSS because comparable data do not exist for the measures used in the analysis. However, the 2012 BRFSS data reveal that about 7.59% of New Yorkers indicate that they do not eat at fast food or chain restaurants;[14] the 2007-2008

[12] The following questions were asked: (1) "If nutrition or health information were readily available in fast food or pizza places, would you use it often, sometimes, rarely, or never, in deciding what to order?" (2) "If nutrition information were readily available in restaurants with a waiter or waitress, would you use it often, sometimes, rarely, or never, in deciding what to order?"

[13] I chose to use the 2007-2008 NHANES because it is the earliest wave for which information to construct these three variables is available, and is the latest wave before localities and states in the U.S. began to implement mandatory calorie labeling laws.

[14] Information on the extensive margin of fast food consumption in the BRFSS is derived from a question that is available only in the 2012 BRFSS, which is described in greater detail below. The 2012 BRFSS also has information on whether survey respondents find calorie information useful. I find that individuals living in counties with calorie labeling are 6 percentage points more likely than other individuals to report that calorie information is always useful in deciding what to order (see Appendix Table 3).

NHANES data reveal that about 9.05% of Americans reported not buying food from fast food or pizza places in the past year. These measures are not the same, but a comparison of the two figures suggests that the consumption of fast food on the extensive margin is similar in NYS and the U.S. as a whole.

IV. Empirical Analysis, Methods, and Results

A. Main Regression Analysis

To estimate the impact of calorie labeling on body mass index (BMI) and the probability of being obese,[15] I estimated the following model:

$$Y_{ict} = \beta_0 + \mathbf{X}'_{ict}\beta_1 + \beta_2 CL_{ct} + \beta_3 TFB_{ct} + \gamma_c + \gamma_t + \boldsymbol{\lambda}(c,t) + \varepsilon_{ict,} \qquad (1)$$

where Y is either BMI or a dummy variable equal to one if an individual *i* residing in county *c* at time *t* has a BMI greater than or equal to 30 (and zero otherwise); X is the vector of individual-level characteristics such as gender and race/ethnicity that may be related to the response of body weight to calorie labeling, which were summarized in Table 1; CL is a dummy variable equal to 1 if a respondent's county of residence *c* has implemented calorie labeling as of time *t*, and zero otherwise; TFB is a dummy variable equal to 1 if a respondent's county of residence *c* has implemented a trans fat ban as of time *t*, and zero otherwise γ_c is a county fixed effect; γ_t is a time fixed effect, which includes both month and year dummies; $\lambda(c, t)$ is county-specific information including the unemployment rate and county-specific linear time trends; and ε is an idiosyncratic error term. This empirical model delivers an "intention-to-treat" estimate. Nonetheless, this is an important policy parameter and $\hat{\beta}_2$ will measure the overall impact of calorie labeling on body weight.

This model nets out statewide secular trends in body weight across time, all

[15] Appendix Figure 1 shows that both treatment and control groups followed similar body weight trends prior to the period over which a subset of counties in New York State began to implement calorie labeling. After adoption and implementation of mandatory calorie labeling, there is a clear widening in the BMI gap between counties that did and did not implement calorie labeling, with average BMI falling over this period for treatment counties. The graphs lend credibility to the identification assumption of parallel trends between treatment and control counties that is made in the empirical analysis.

time-invariant heterogeneity across counties, and also allows for county-specific unobserved slow-moving trends in body weight that might affect a county's decision to adopt nutrition-related policies, such as calorie labeling. For ease of interpretation and to maintain consistency across specifications with continuous and binary dependent variables, all models are estimated using Ordinary Least Squares.[16] Standard errors are clustered at the county level to allow for arbitrary correlation among observations in the same county, and BRFSS sample weights are used in the regression analysis to account for the sampling design of the BRFSS.

A potential concern is that counties that implemented calorie labeling also implemented other nutrition-related policies that could confound the estimated effect of calorie labeling on BMI and the probability of obesity. Indeed, one policy—a ban on the use of artificial trans fat in restaurants—was implemented in 9 of the 11 county health departments that also implemented calorie labeling over the study period. [17] Some county health departments implemented the ban on trans fat over two 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. Laws regarding bans on trans fat apply to all food service establishments that require a permit to serve food from a county health department, not only chain restaurants with 15 or more locations nationwide.

While there is a strong link between trans fat intake and heart disease, there is

[16] 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. Similarly, in models of obesity, results from estimation of linear probability models shown here are very similar to unreported results from probit or logit models.
[17] See Appendix Table 4 for the timing of the trans fat bans.

very little evidence linking trans fat consumption to weight gain or obesity (Scientific Advisory Committee on Nutrition 2007).[18] However, it is possible that restaurants in counties that banned the use of artificial trans fat in food preparation made other substitutions that were not required by the law. For example, restaurants may have reformulated their products in a way that substituted unhealthy ingredients in menu items with healthier ones. Thus, throughout the regression analysis, as shown in equation (1), I control for the trans fat ban dummy variable, which is coded according to a county's earliest implementation date.

In column 1 of Table 2, I present the results from a specification that includes the policy dummies for calorie labeling and trans fat ban, as well as county, month, and year fixed effects. The estimates indicate that calorie labeling reduced BMI by about 0.4 units and decreased the probability of being obese by about 3 percentage points, which is a reduction of 1.3% and 11% from the sample mean, respectively. In column 2 of Table 2, I show that adding all of the control variables listed in Table 1 to the model causes the estimated effects to decrease somewhat in magnitude. The estimated BMI reduction relative to the sample mean is about 1% and the reduction in the probability of obesity is estimated to be about 7%. In column 3, I present results from the full specification shown in equation (1), which includes county dummies interacted with a linear time trend or county-specific linear time trends.[19] Regression estimates using the full specification indicate that mandatory calorie labeling caused BMI to fall by about 1.5% and the probability of being obese to fall by 11%. This is my preferred specification, which is used throughout the remainder of the analysis. Coefficient estimates of the impact of trans fat bans on body weight are always small in magnitude and statistically insignificant, which is a finding that persists throughout the

[18] Restrepo and Rieger (2014) find evidence indicating that implementation of trans fat bans in New York State counties led to an important reduction in mortality caused by heart disease, and that changes in obesity rates over time do not explain the reduction in heart disease mortality.
[19] Estimates for all the explanatory variables included in the model estimated in column 3 of Table 2 can be found in Appendix Table 5.

analysis. To save space, I do not present estimates of the trans fat ban dummy variable, but it is also controlled for in all regressions in the analysis.

B. Event Study Analysis and Other Robustness Checks

As a check on the validity of the identification strategy employed above, I conduct an event study analysis. The event study addresses the concern that there are trends in body weight that are correlated with the implementation of calorie labeling laws, which are not well captured by county-specific linear time trends. Using the subsample of counties that implemented calorie labeling over the sample period, a model of the following form is estimated,

$$Y_{ict} = \beta_0 + \mathbf{X}'_{ict}\beta_1 + \sum_{\substack{j=-7 \\ j\neq -2}}^{6} \gamma_j 1(\tau_{ct} = j) + \gamma_c + \gamma_t + \boldsymbol{\lambda}(c,t) + \varepsilon_{ict,} \tag{2}$$

where τ_{ct} is the event half-year, which is defined so that $\tau_{ct} = 0$ is the first 6-month block of time after the exact date of implementation of calorie labeling for each county. The coefficients γ_j are estimated relative to an omitted event time category, $\tau_{ct} = -2$, or the time period 6 months to 1 year before calorie labeling was implemented. Identification of the impact of calorie labeling on BMI comes from the differential timing of the policy's implementation across counties.

Figure 2 plots regression coefficients (*i.e.* γ_j for j=-7,-6,…,-3,-1,…,6) and the corresponding 95% confidence interval bands from estimated versions of equation (2) against event time half-years. There is no clear pattern in calorie labeling regression coefficients prior to the implementation date. The regression coefficients for event half-years in the pre-implementation periods jump around zero, and none are statistically significant at conventional levels. However, there is a clear trend break in the 6-month block of time after the implementation date. All of the regression estimates after the implementation date are negative, with statistical significance being achieved in period 0 at the 10% level and in period 1 at the 5% level.

The event study analysis shows that the trend break in BMI occurred after county health departments implemented mandatory calorie labeling. This analysis lends credibility to the identification strategy employed in this study because potential confounders would have to mimic the timing of mandatory calorie labeling laws for them to account for the results.

I have also subjected the main analysis to a series of other sensitivity and robustness checks. In Appendix Table 6, I show that the results are robust to the following analyses: changing the coding of the policy variable to reflect the policy's adoption date instead of the implementation date; changing the composition of the control group to address issues related to geographical clustering of preferences and treatment spillovers; omitting data from 2012 to avoid using extrapolated 2012 county-level information; allowing for the impact of unemployment rates to vary by county to address the potential concern that the timing of menu labeling laws coincided with the financial crisis, which may have affected the relative consumption of unhealthy food differently across counties; and correcting BMI for self-reporting error using the procedure proposed by Cawley (1999). I also show that the impact of menu labeling on BMI is operating through changes in weight and not height and, finally, that implementation of menu labeling laws had small and statistically insignificant effects on health-related behaviors that should have been little (if at all) affected by exposure to calorie information in chain restaurants.

C. Heterogeneous Effects of Calorie Labeling on Body Weight

i. Impacts across the BMI Distribution

Exposure to calorie information in chains and sensitivity to it is not uniform. I have focused on the average impact of calorie labeling on body weight, but it is important to examine whether there is heterogeneity in its impact across individuals. First, I examine whether the effect of calorie labeling varies across the BMI distribution, by running quantile regressions. Second, I examine whether there are heterogeneous impacts of calorie labeling across various subsamples, which are composed of individuals with different estimated propensities to eat at restaurants and to use nutrition information available at restaurants.

In Figure 3, I show plotted estimated effects of calorie labeling on BMI and corresponding 95% confidence interval bands across a wide range of the BMI distribution. The estimated effects of calorie labeling are sizeable across BMI quantiles, but they are generally larger in magnitude at the upper end of the BMI distribution. For example, while the impact of calorie labeling is estimated to reduce BMI by about 0.436 units at the median of the BMI distribution (p-value 0.076), the corresponding reduction is about 0.774 units at the 0.8 quartile (p-value 0.042). Relative to corresponding quantile means, the former is a reduction of about 1.70% and the latter is a reduction of about 2.58%. These estimates are not, however, statistically different from each other (p-value = 0.432). I come closest to rejecting the null hypothesis that the estimated effects at different quartiles are equal to each other when comparing the estimates from the 0.4 and 0.8 quartiles (p-value = 0.138).

The upper half of the BMI distribution corresponds to individuals who are overweight, which suggests that calorie labeling was successful at disproportionately affecting the behavior of the most overweight individuals. However, overweight individuals may visit chain restaurants that are required to post calorie counts more frequently than do non-overweight individuals. I now turn to an analysis that aims to shed more direct light on whether the impact of calorie labeling on body weight is larger among individuals who are most likely to be exposed to, and to use, calorie information in chain restaurants.

ii. Impacts by Likelihood of Treatment

The impact of calorie information at the point of sale on consumers is expected to be more pronounced among individuals who visit restaurants frequently because they are exposed to it more often than others. Following Anderson *et al.* (2011), I define a regular fast food customer as an individual who reports having had two or more meals in the past seven days at fast food restaurants. Appendix Table 2 shows the summary statistics for the NHANES sample that is used to estimate the propensity to be a (i) "regular fast food customer", (ii) "often user of nutrition information at fast food restaurants" and (iii) "often user of nutrition information at sit-down restaurants" in the BRFSS data set.

I construct and then regress dummy variables for (i), (ii), and (iii) on the demographic information listed in Appendix Table 2, and results from this regression are shown in Appendix Table 7.[20] In column 1, I show that the probability of being a regular fast food customer generally decreases with age, individuals with a college education, or more, are less likely than high school dropouts to be regular fast food customers, males are more likely than females to be regular fast food customers, and blacks are more likely than whites to have had two fast food meals in the past week. Generally, the patterns are similar in columns 2 and 3. For example, males are less likely than females, and individuals with a college education, or more, are more likely than high school dropouts to report that they would use nutrition information often if it was readily available at fast food or sit-down restaurants.

Using all of the estimates shown in Appendix Table 7, I predict the propensity

[20] The results in Table 4 are reported with standard errors clustered by county. In unreported regressions, I have also estimated standard errors using a bootstrapping procedure with 1000 replications in addition to clustering on county to address the potential importance of the generated regressor problem. While standard errors generally increase slightly when using a bootstrapping procedure, the unreported results are very similar to those shown here.

to be (i), (ii), and (iii) in the BRFSS analysis sample.[21] In Table 3, I present the results from estimating equation (1) on two subsamples for (i), (ii), and (iii): (a) those with an above-median propensity ("high propensity") and (b) those with a below-median propensity ("low propensity"). The "high propensity" sample probably includes individuals who are most likely to be treated within treatment counties because (a) they are more exposed to calorie information that is available in chain restaurants because of their relatively high frequency of visits or (b) they are most likely to use nutrition information to decide what to order if it is readily available in chain restaurants.

In general, Table 3 shows that the estimated effects of calorie labeling on BMI in the "high propensity" samples are much larger in magnitude than the corresponding ones in the "low propensity" samples.[22,23] This set of results conforms to the expectation that the impact of calorie labeling should be larger among individuals who are most likely to be exposed to calorie information in chain restaurants and to use nutrition information to help them decide what to order. Interestingly, the most pronounced difference in estimated effects between the two samples occurs in Panel C, which involves sample splits between individuals who differ in their propensity to use nutrition information if it was readily available at sit-down restaurants. While there is some evidence in the literature regarding the impact of calorie labeling on calorie consumption at sit-down restaurants, this literature is much more limited than that examining the corresponding impact on the consumption behavior of fast food restaurant patrons.[24]

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[21] The set of demographic information used in section (g) is the same as the one used throughout the analysis except for the number of children, because this variable is unavailable in the NHANES data.

[22] The estimated effects in the low versus high propensity samples are generally not statistically different from each other at conventional levels. However, I can reject the null that the estimated effects in Panel C in Table 3 are statistically equal to each other (p-value 0.027).

[23] See Appendix Table 8 for results when the dependent variable is a dummy for obesity.

[24] For example, see Pulos and Leng (2010), Holmes *et al.* (2012), and Ellison *et al.* (2013). The study by Pulos and Leng (2010) evaluated the impact of a voluntary menu labeling program on calorie consumption in full-service restaurants; the study by Holmes et al. (2012) analyzed the impact of menu labeling on the choice of

While Binkley (2008) found that differences in the caloric content of meals at fast food and full-service restaurants are not large, Stewart *et al.* (2004) found that, in 2002, the share of away-from-home food sales at full-service restaurants was larger than the corresponding share at fast food restaurants.[25] The demographic composition of diners differs across chain types and, in general, there is likely to be much more time to decide between menu items at sit-down restaurants than at fast food restaurants. Thus, more research on the impact of calorie labeling on consumer purchasing behavior in sit-down or full-service restaurants seems warranted.

D. The Timing of the Policy's Impacts on Body Weight

The main regression results indicate that mandatory calorie labeling has had its intended effect of reducing body weight, but it is important to know when the policy has its greatest effect and whether the policy's effect on body weight is long-lasting. To examine the amount of time it takes body weight to respond to calorie labeling, and the duration of its impact on BMI and the probability of being obese, I estimate a model similar to the one shown in equation (1). However, instead of including only one dummy variable that takes a value of one if mandatory calorie labeling is effective in a county at a particular point in time, I include three dummy variables in the model, which turn on at different points in time after the law takes effect in a county.[26] The first takes a value of 1 if calorie labeling has been in effect in a county for more than 0 months but less than or equal to 12 months (and zero otherwise); the second takes a value of 1 if calorie labeling has been in effect for more than

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children's meals; and, finally, the study by Ellison et al. (2013) studied the impact of menus with different amounts of calorie information on calorie consumption in one restaurant on the Oklahoma State University campus.

[25] Also, while spending at both types of restaurants is expected to grow over time, the largest increase is expected to occur at full-service restaurants. Interestingly, they also found that rising income is the major predictor of increased spending at full-service restaurants in the future, and that rising income's effect on full-service restaurant spending is larger than the corresponding one on spending at fast food restaurants.

[26] Among treatment counties, the average and median number of months after implementation of mandatory calorie labeling in chain restaurants is 24.

12 months but less than or equal to 24 months (and zero otherwise); and the third takes a value of 1 if calorie labeling has been in effect for more than 24 months but less than or equal to 53 months (and zero otherwise).[27] Note that 53 months is the maximum number of months that a law was effective in treatment counties over the study period.

Table 4 shows results from an analysis of the timing of the impact of calorie labeling on BMI using the full sample and, separately, by using the high and low propensity samples analyzed in Table 3.[28] The estimates from a regression on the full sample (Panel A in Table 4) show that the impact of calorie labeling was concentrated within the first year of implementation. The estimated impacts for later time periods after implementation are economically significant, but not statistically significant at conventional levels. However, I fail to reject the null hypothesis that all of the estimated effects are jointly equal to zero (p-value 0.089). Thus, taken together, a conservative interpretation is that the policy had its strongest impact on body weight in the first year of implementation, and may have persisted afterwards.

There is, however, evidence of heterogeneity in the size and duration of the body weight impact of calorie labeling across the high and low propensity subsamples. In general, as the evidence in Table 3 revealed, I find that implementation of calorie labeling has larger impacts on individuals with high propensities to eat at fast food restaurants and to use nutrition information at fast food and sit-down restaurants. More interestingly, I find evidence that the body weight impacts tend to grow over time and are longer-lasting for the subsamples involving individuals who have high propensities to use nutrition information to decide what to order if it was readily available at fast food and sit-down restaurants.

[27] The policy dummies for counties that never implemented mandatory calorie labeling are always zero.

[28] See Appendix Table 9 for results when the dependent variable is a dummy for obesity.

The evidence in Tables 3 and 4 revealed important evidence on the heterogeneity of the impact of mandatory calorie labeling on body weight. As one might expect, the body weight impact is largest among individuals who are most likely to be exposed to calorie counts in chain restaurants through frequent visits to such establishments, as well as individuals who often use such nutrition information to decide what to order. These results imply that estimation of *average* estimated effects of mandatory calorie labeling, which are the focus of much the literature thus far (Robert Wood Johnson Foundation, 2009; 2013), are likely to be masking important heterogeneity in responsiveness and sensitivity to calorie information across individuals.

V. Discussion

Most studies have focused on purchasing behavior in chain restaurants in response to calorie labels, but there are many other potential margins of adjustment. I explored various other mechanisms that might explain the effects of calorie labeling on body weight, such as whether there is evidence that calorie labeling induces individuals to adopt healthier lifestyles by following a healthier diet and getting more exercise. In Appendix Table 10, I show estimates of the impact of calorie labeling on physical activity, and on a limited set of food and beverage items. The analysis indicates that implementation of calorie labeling had small and generally statistically insignificant impacts on these behaviors. The estimates do imply a net reduction of about 2.4 calories per day, but this daily reduction in calories is very small relative to the average daily recommended caloric intake of 2000 calories. Thus, changes in physical activity levels or changes in diet related to the consumption of alcohol, fruits, and vegetables are not the main driver in explaining the body weight effects I estimate.

The analysis reveals no evidence that calorie labeling induces healthier eating and exercise behaviors. However, the analysis does reveal that the impact of calorie labeling is concentrated among individuals who have a high propensity to be a regular fast food customer. Taken together, one interpretation the evidence in this study is that changes in the consumption of food away from home are important for understanding the body weight impacts estimated here.

Previous work has shown that changes in the extensive and intensive margins of chain restaurant consumption are potentially important margins of adjustment. For example, Bollinger *et al.* (2011) found that about three-fourths of the reduction in food calories purchased per transaction in Starbucks caused by calorie labeling was due to individuals being less likely to purchase a food item (extensive margin) and the remainder was due to individuals substituting towards lower calorie items (intensive margin).

To get a better sense of the magnitude of the estimated effect of calorie labeling on BMI found in this study, I performed a back-of-the envelope calculation for the reduction in the number of meals away from home that could explain it. The main analysis revealed that implementation of mandatory calorie labeling caused an average reduction in BMI of about 0.4 units. For a man of average height and weight in the U.S., this roughly translates into a 1.4 kg or 3 lb loss in weight. (The corresponding estimate for women is a 1 kg or 2 lb loss in weight.) Researchers from the USDA's Economic Research Service have compared the average caloric value of meals at home to those away from home, using 2 days of dietary intake data from two national surveys (Todd *et al.* 2010). They estimate that each additional meal or snack substituted toward food away from home on a given day adds an average of 134 calories on that day. Assuming that this added caloric intake from food away from home across the nation applies to meals from chain restaurants in New York State—and assuming all else is constant—the average estimated reduction in BMI in this study can be explained by the consumption of 1 to 1.5 fewer meals from chain restaurants each week for a year.[29] In

[29] These calculations are based on a 52-week year, where 1 lb equals 3,500 calories. For example, for an average U.S. man to lose 3 lbs over the course of a year, he would have to achieve a net calorie expenditure of 10,500

other words, the average estimated reduction in body weight could be explained by a substitution of between 5 to 7% of food-away-from home meals with meals prepared at home for a year, assuming that individuals eat 21 meals per week.

Another way to compare the plausibility of my estimates of the reduction in body weight caused by calorie labeling is to compare them to the ones implied by the estimated reduction in calories purchased in chains caused by calorie labeling in the literature. The study by Bollinger *et al.* (2011) is perhaps the best one to use for this purpose because it analyzed detailed transaction level data for an establishment that was affected by the policy and the data used span a lengthy period of 10 months after the policy was implemented. They calculated that a 6% decrease in average calories purchased per transaction in Starbucks—under various assumptions—implies a reduction in total daily calorie consumption of about 1.5% or 30 calories per day.[30] They also argue that a permanent 1.5% reduction in daily caloric intake would decrease long-run body weight by no more than 1%. In the preferred specification of the main analysis (column 3 of Table 2), the results indicate that the 95% confidence interval of the estimated effect of calorie labeling on BMI is (-0.762, -0.054). For a man of average height and weight in the U.S., these are estimated reductions in body weight of between 0.19% and 2.7%. (The corresponding range of estimated reductions for a woman of average height and weight in the U.S. is about the same.) These are very rough comparisons based on many assumptions, but the impact of calorie labeling on body weight estimated here is in line with the estimate provided by Bollinger *et al.* (2011).

calories. Holding everything else constant, he could achieve this by eating 10,500 ÷ (52*134) or 1.51 fewer meals away from home per week.

[30] This calculation is based on the following assumptions: (1) 25% of an average American's calorie consumption comes from chain restaurants (2) calorie consumption also falls by 6% in all other chain restaurants as a result of calorie labeling (3) reductions in calorie consumption are not offset by increases in other meals and (4) the average daily intake is 2,000 calories.

VI. Conclusion

The results in this study indicate that the New York State counties that implemented mandatory calorie labeling in chain restaurants achieved their objective of reducing BMI and decreasing in the probability of obesity. The analysis reveals relatively larger impacts at the upper end of the BMI distribution, and that the impact of the policy is concentrated among individuals who have a high propensity to eat at fast food restaurants and to use nutrition information to decide what to order if it was readily available at fast food and sit-down restaurants. The analysis also reveals no evidence that calorie labeling causes individuals to increase their physical activity or to increase their consumption of a select set of healthy foods such as fruits and vegetables. On balance, these results suggest that changes in the consumption of food away from home are important for understanding the body weight reduction caused by the mandatory provision of calorie information on menus in chain restaurants.

The analysis shows that, on average, the policy's impact on body weight is strongest within the first year after implementation. However, the evidence indicates that the body weight reduction caused by calorie labeling tends to grow over time and is more persistent for individuals with a high propensity to eat fast food and to use nutrition information at restaurants. This suggests that, for at least some people, sensitivity to calorie information at the point of purchase in chain restaurants may diminish over time. If the effect of the policy on body weight were permanent, then the results in this study imply that the reduction in obesity prevalence would be substantial. Policies that raise awareness of calorie information in chain restaurants may be helpful in prolonging the impact of calorie labeling on body weight. The results here apply to New York State, but an important policy implication of this study is that pending federal legislation regarding mandatory calorie labeling in chain restaurants may help to address the obesity problem throughout the U.S.

There are a couple of important limitations of the analysis in this study, which should be addressed by future research. First, an analysis of detailed data on food consumption is important for understanding how mandatory calorie labeling caused a reduction in body weight. The food consumption data I observe do not distinguish between foods consumed at home and foods consumed away from home. Distinguishing between (and within) the two food categories is important for understanding potentially important substitution behaviors, which may shed light on how the provision of calorie information in chain restaurants led to a reduction in body weight. Consumption data based on transactions in fast food versus sit-down restaurants would be especially useful because the composition of patrons and the average length of time that patrons have to review calorie information are likely to vary by chain type. Second, the data set used in this study is rich in information on adults aged 18 and over, but it contains no information on children and adolescents. While this study has important policy implications for programs that aim to reduce the prevalence of adult obesity, it is silent on whether mandatory calorie labeling has an impact on the probability of child obesity. Child obesity is also prevalent in New York and across the country, so investigating whether mandatory calorie labeling affects child weight outcomes is an important avenue for future research.

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Table 1: Sample Summary Statistics

	(1) All Counties (No. Counties = 61)[a]		(2) CL Implemented Over Sample Period (No. Counties = 11)		(3) CL Not Implemented Over Sample Period (No. Counties = 50)	
2004-2012 BRFSS	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Body Mass Index (BMI)	27.120	5.563	26.790	5.396	27.608	5.766
1 if Obese (BMI≥30)	0.245		0.225		0.275	
Age	46.925	17.082	46.364	16.929	47.752	17.273
1 if Male	0.499		0.498		0.501	
1 if Black	0.164		0.224		0.075	
1 if Other Race	0.116		0.158		0.053	
1 if Hispanic	0.136		0.193		0.053	
1 if HGC is High School Deg	0.260		0.234		0.298	
1 if HGC is Some College	0.256		0.238		0.283	
1 if HGC is >= 4 Year College Deg	0.389		0.427		0.332	
Log(Family Income in $2012)	10.707	0.646	10.715	0.661	10.694	0.624
Number of Children	0.755	1.117	0.754	1.101	0.755	1.139
1 if Married	0.542		0.513		0.584	
County-Level Information						
County Unemployment Rate	6.664	2.160	6.715	2.284	6.588	1.962
Fast Food Restaurants[b]	9.488	3.274	10.192	3.939	8.450	1.351
Full Service Restaurants[b]	9.295	5.361	9.722	6.718	8.665	1.971
Fitness and Recreation Centers[b]	1.160	0.648	1.211	0.772	1.086	0.387
Supermarkets and Grocery Stores[b]	4.287	2.102	5.543	1.792	2.433	0.659
Convenience Stores[b]	0.992	0.380	0.994	0.385	0.989	0.371
Specialty Stores[b]	1.663	0.851	2.157	0.726	0.934	0.351
N	45,939		25,067		20,872	

Note: These weighted summary statistics are for the Table 2 regression sample. Individual-level information was drawn from the 2004-2012 Behavioral Risk Factor Surveillance System (BRFSS). 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 & recreation centers, fast food and full-service restaurants, supermarkets and grocery stores, and specialty food stores was drawn from the 2004-2011 County Business Patterns; information for 2012 was extrapolated.

aThere are 62 counties in New York State, but Hamilton County is not represented in the BRFSS.

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

Table 2: The Effect of Calorie Labeling on Body Weight (2004-2012 BRFSS)

	(1)	(2)	(3)
Panel A			
Dep Var	BMI	BMI	BMI
1 if County Has Implemented Trans Fat Ban	0.061	0.014	-0.095
	(0.110)	(0.099)	(0.104)
1 if County Has Implemented Calorie Labeling Law	-0.365***	-0.248**	-0.408**
	(0.129)	(0.108)	(0.177)
R-squared	0.016	0.08	0.081
% Impact Relative to Sample Mean	-1.346	-0.914	-1.504
% Impact Relative to CL=0 Sample Mean	-1.322	-0.898	-1.478
Panel B			
Dep Var	1 if Obese	1 if Obese	1 if Obese
1 if County Has Implemented Trans Fat Ban	0.006	0.007	-0.002
	(0.010)	(0.009)	(0.011)
1 if County Has Implemented Calorie Labeling Law	-0.028***	-0.018**	-0.027**
	(0.008)	(0.008)	(0.013)
R-squared	0.011	0.045	0.045
Percent Impact Relative to Sample Mean	-11.429	-7.347	-11.020
Percent Impact Relative to CL=0 Sample Mean	-10.182	-6.545	-9.818
Sample Size		45,869	
County, Month, and Year FE	x	x	x
Control Variables	x	x	x
County Dummies × Year			x

Note: Controls included but not shown in (2) and (3): 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, and log of family income. 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, and # of specialty stores.
Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: The Impact of Calorie Labeling on BMI by Likelihood of Treatment

	Predicted Value from NHANES	
	< Median	> Median
Panel A: Predicted Likelihood of Being Regular Fast Food Customer		
1 if County Has Implemented Calorie Labeling Law	-0.195	-0.520**
	(0.290)	(0.235)
R-squared	0.071	0.087
Sample Size	23,029	22910
Panel B: Predicted Likelihood of Being Often User of Fast Food Nutrition Info		
1 if County Has Implemented Calorie Labeling Law	-0.258	-0.672***
	(0.319)	(0.172)
R-squared	0.080	0.104
Sample Size	22,976	22,963
Panel C: Predicted Likelihood of Being Often User of Sit Down Nutrition Info		
1 if County Has Implemented Calorie Labeling Law	-0.161	-0.820***
	(0.241)	(0.269)
R-squared	0.082	0.109
Sample Size	22,964	22,975
County, Month, and Year FE	x	x
Control Variables	x	x
County Dummies × Year	x	x

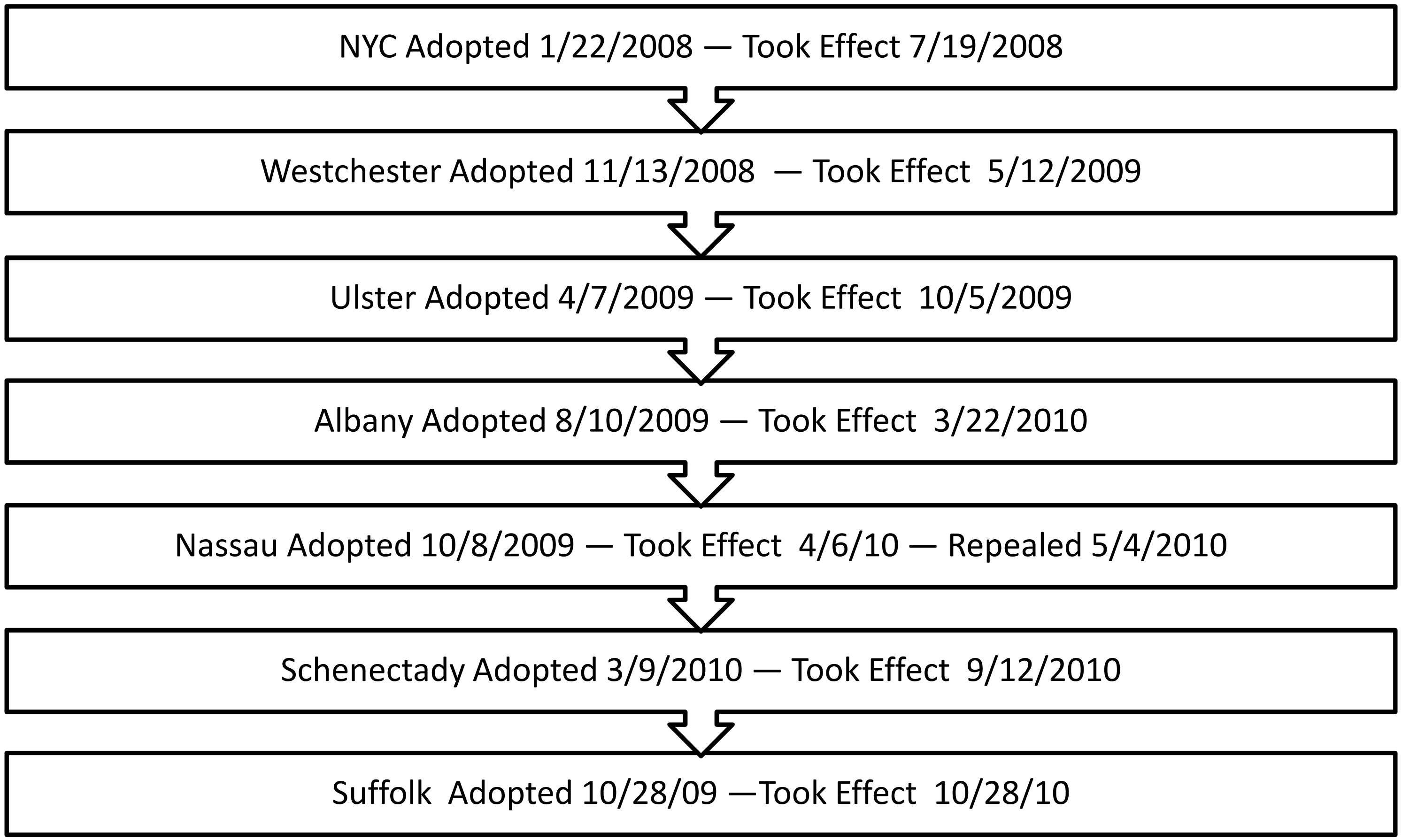
Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race, and ethnicity dummies (black, other race, hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county has a trans fat ban. 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, and # of specialty stores. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: The Timing of the Impact of Calorie Labeling on BMI

Panel A: Using the Full Sample		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.450**	
	(0.195)	
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.351	
	(0.269)	
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	-0.473	
	(0.344)	
	Predicted Value from NHANES	
	< Median	> Median
Panel B: Predicted Likelihood of Being Regular Fast Food Customer		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.249	-0.571**
	(0.307)	(0.256)
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.097	-0.494
	(0.333)	(0.441)
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	-0.037	-0.703
	(0.374)	(0.508)
Panel C: Predicted Likelihood of Being Likely User of Fast Food Nutrition Info		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.238	-0.817***
	(0.332)	(0.199)
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.067	-0.820***
	(0.344)	(0.306)
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	0.136	-1.397***
	(0.446)	(0.372)
Panel D: Predicted Likelihood of Being Likely User of Sit Down Nutrition Info		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.117	-0.987***
	(0.257)	(0.307)
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	0.012	-0.924**
	(0.314)	(0.378)
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	0.403	-1.671***
	(0.400)	(0.477)
County, Month, and Year FE	x	x
Control Variables	x	x
County Dummies × Year	x	x

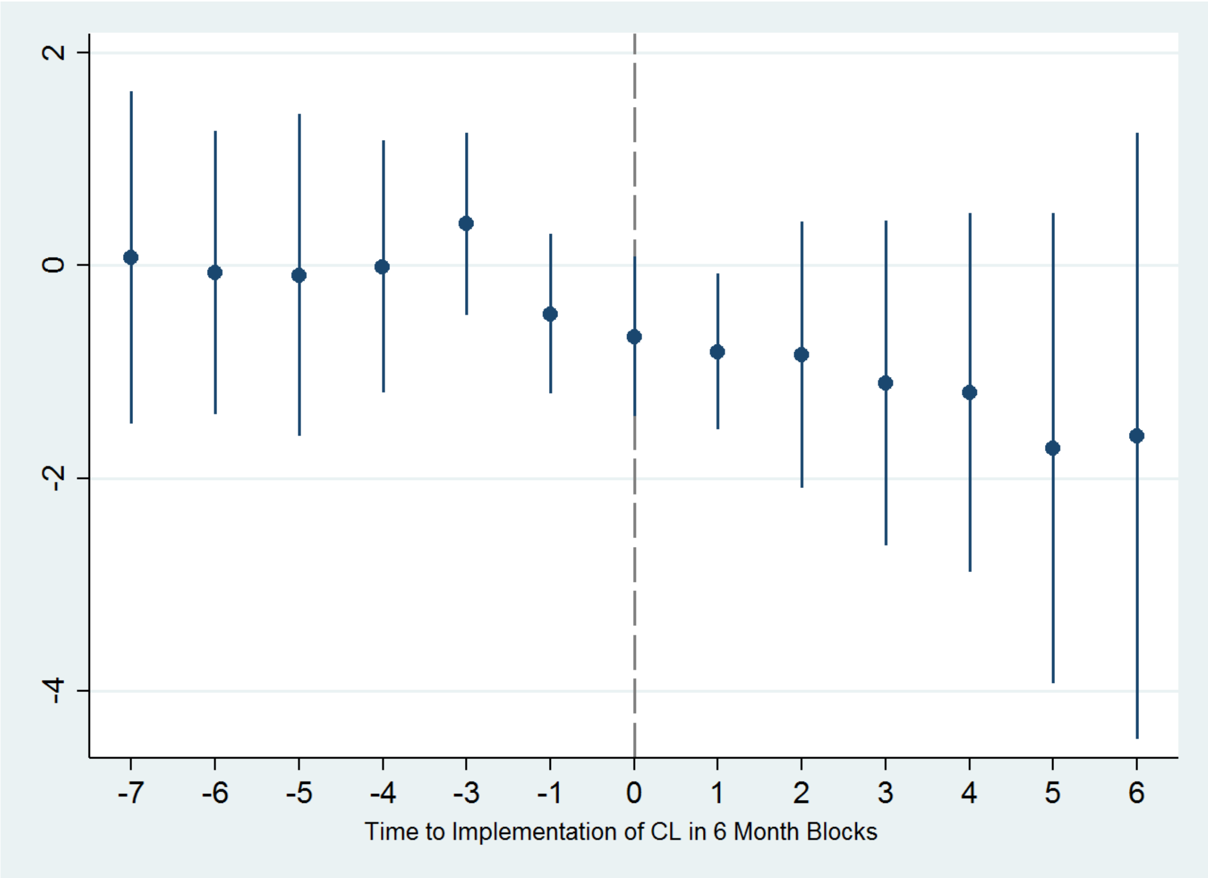
Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race, and ethnicity dummies (black, other race, hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county has a trans fat ban. 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, and # of specialty stores. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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



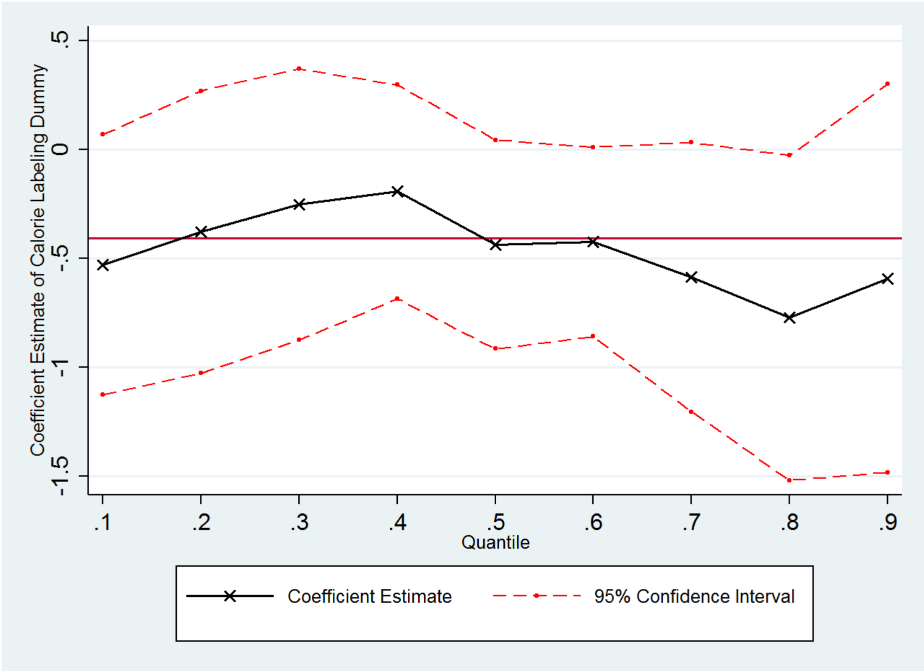
Note: The NYC Department of Health initially adopted mandatory calorie labeling in chain restaurants on 12/05/2006. However, after a couple of legal challenges, a revised mandatory calorie labeling law was adopted on 1/22/2008.

Figure 2: Estimates of the Effect of Calorie Labeling on BMI from an Event Study Analysis



Note: These are estimated event time regression coefficients from a regression using the subsample of counties that implemented calorie labeling over the sample period. The time of the implementation 6-month block is normalized to period zero. The omitted time block is 1 year to 6 months before the calorie labeling law takes effect. Thus, period zero corresponds to the period between the exact effective date and 6 months after, period one corresponds to the period between 6 months after the effective date and one year after, and so on. Sample size is 22, 211. This specification controls for the same variables shown in column 3 of Table 2. The difference-in-difference regression estimate of calorie labeling on this sample is -0.388 (p-value 0.045).

Figure 3: Heterogeneity in the Effect of Calorie Labeling Across the BMI Distribution



Note: These are plotted regression estimates and 95% confidence interval bands. The specification used here is the same as the main specification shown in column 3 of Table 2 estimated by OLS, and the horizontal solid line is the corresponding estimated effect of calorie labeling.

“Appendix”

A. Do Individuals Find Calorie Information Useful?

It is important to know whether individuals living in New York State counties with calorie labeling find calorie information in chain restaurants useful.[1] In 2012, New York State participated in a new optional BRFSS module, which asks survey respondents about whether they find calorie information useful.[2] Using this variable, I estimate an ordered probit regression on a dummy variable equal to one if a respondent lives in a county with a mandatory calorie labeling law (and zero otherwise) and the demographic information listed above. I restrict my analysis here to respondents who have seen calorie information in restaurants, *i.e* individuals who answer the question with one of the following responses: Never, Sometimes, About Half the Time, Most of the Time, or Always.[3]

In Appendix Table 3, I show ordered probit coefficients. In computations not shown I find that individuals living in counties with calorie labeling are 6 percentage points more likely than other individuals to report that calorie information is always useful. This result suggests that calorie labeling in New York State counties increases the probability that individuals find calorie information useful in deciding what to order.[4]

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[1] Unfortunately, this question is not specific enough for us to learn exactly how respondents found the information useful. That is, we do not know whether calorie information in chain restaurants helped respondents choose fewer items, choose lower calorie items, ask for fewer condiments, *etc*.

[2] The exact wording of the question is the following: “The next question is about eating out at fast food and chain restaurants. When calorie information is available in the restaurant, how often does this information help you decide what to order?”

[3] These are the responses that are *read to* respondents, and I limit the analysis in Appendix Table 3 to individuals who selected one of these responses. However, other volunteered answers include the following: Never Noticed or Never Looked for Calorie Information, Usually Cannot Find Calorie Information, and Do Not Eat at Fast Food or Chain Restaurants. The results are very similar to those presented here if I include respondents who gave one of these responses to the above question.

[4] In column 2 of Appendix Table 3, I add county fixed effects to control for, for example, fixed preferences over the caloric content in food or health across counties. I find evidence of heterogeneity by gender, marital status, education, and income. In computations not shown I find that, for example, males are 12 percentage points less likely than females to report that calorie information always helps them decide what to order; married individuals are 2.8 percentage points more likely than unmarried individuals to report that calorie information always helps them with their menu item choice; and relative to individuals with less than a high school degree, individuals with some college, and college or more, are 5 and 7 percentage points more likely to always find the calorie information helpful, respectively.

B. Parallel Trends Assumption

I examine whether counties in New York State that implemented calorie labeling over the study period ("treatment counties") have trends in BMI that were similar to those of counties that never implemented calorie labeling ("control counties"), leading up to the period over which counties began to implement mandatory calorie labeling. In Appendix Figure 1, I present plotted weighted means of BMI by treatment status and time relative to the first year of implementation (or adoption) of mandatory calorie labeling, which has been normalized to zero.

Counties that never implemented calorie labeling have BMI trending upward in a roughly linear fashion. In Appendix Figure 1a, the graph shows that treatment counties and control counties followed very similar trends prior to the first year of the law's implementation in treatment counties. For treatment counties, BMI trends downward slightly in the year before the first year of implementation, but the steepest downward shift in BMI occurs during the first year after the law is implemented. As described in greater detail in the paper, the slight downward shift in BMI for treatment counties occurring in the year before implementation of mandatory calorie labeling may be due to the fact that some chains began posting calorie counts on menus well before they were required to do so according to the effective date of the law. For comparison, in Appendix Figure 1b, I present plotted weighted means of BMI by treatment status and time relative to the first year of the law's adoption. This graph shows that the trend break occurs after the law is adopted. Average BMI falls within the first year after the law is adopted and further still within the second year after the law's adoption, which generally corresponds to the first year after the law is implemented.

In sum, the yearly means in BMI show that both treatment and control groups followed similar body weight trends prior to the period over which a subset of counties in New York State began to implement calorie labeling. After adoption and implementation of mandatory calorie labeling, there is a clear widening in the BMI gap between counties that did and did not implement calorie labeling, with average BMI falling over this period for treatment counties. The graphs lend credibility to the identification assumption of parallel trends between treatment and control counties that is made in the empirical analysis. Analysis of the means alone suggests that mandatory calorie labeling caused a reduction in body weight.

C. Additional Robustness Checks

I conduct several other robustness checks. In the main analysis, I coded the calorie labeling policy variable according to its effective date. However, chain restaurants were notified between 6 and 12 months before the effective date about the adoption of mandatory calorie labeling, 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 have learned that some chain restaurants complied with the mandate and were posting calorie counts on menus before the implementation date. [5,6] Bollinger *et al.* (2011) also report that chain restaurants started posting calorie counts on menus before the law took effect. For example, Starbucks was in full compliance with NYC's mandatory calorie labeling law in April 2008, which was much earlier than the effective date of July 2008. Compliance rates, and thus exposure to calorie information in chain restaurants before the effective date of mandatory calorie labeling laws, may vary by county. In row 1 of Appendix Table 6, I show

[5] I contacted county health departments that implemented calorie labeling to learn about the process of notifying restaurants of the adoption of the law and expectations regarding compliance. Standard protocol appears to be that chain restaurants were informed of the mandatory requirements regarding posting calorie counts on menus and menu boards soon after the adoption date. Some chain restaurants started the process of compliance immediately after being notified of the future effective date. While I do not have compliance rates over time for counties, a representative from Albany indicated that about 15% of chain restaurants began compliance efforts early and were in compliance before its March 22, 2010 effective date.

[6] Anecdotal evidence suggests that efforts to comply quickly were especially made by big chains, perhaps because they are better able to carry out the necessary steps (*e.g.* nutrient analysis of menu items, purchasing new menus and menu boards, *etc.*). This may be because (a) the steps necessary to comply with mandatory calorie labeling had been completed prior to calorie labeling; (b) they can better afford to conduct the costly steps to full compliance and perhaps do not need as much time as smaller chains to carry out these steps; or (c) customer expectations regarding provision of nutrition information are higher for big chain restaurants, and these chains make an effort to meet customer expectations as quickly as possible.

that coding the policy variable according to its adoption date produces results that are similar to the results from the main analysis shown in Table 2, which codes the policy variable according to its implementation or effective date.

In row 2 of Appendix Table 6, I estimate equation (1), using only the 2004 to 2011 waves of the BRFSS, to examine whether the results are sensitive to using the extrapolated data for the county-level variables used throughout the main analysis. The results are very similar to those shown in column 3 of Table 2, which suggests that using the extrapolated data in the analysis is not a problem for the analysis.

As Appendix Figure 2 shows, counties that implemented calorie labeling over the study period are geographically clustered in the mid-to-lower part of New York State, suggesting that, for example, attitudes toward healthy eating may be geographically clustered. Also, all of the counties that implemented calorie labeling are metropolitan counties. More importantly, commuting between treatment and control counties may result in treatment spillovers. For example, if residents of neighboring control counties commute to treatment counties on a regular basis, this may attenuate the effect of calorie labeling on body weight. I test the sensitivity of the estimated effects on body weight of calorie labeling to changing the composition of the control group. In rows 3-4 of Appendix Table 6, instead of using all of the counties that never implemented calorie labeling over the study period as the control group, I use two subsets of these counties: 1) counties that are not geographically adjacent to counties that implemented calorie labeling and 2) only metropolitan counties. The results of the analysis using all of the counties that never implemented calorie labeling as the control group (column 3 of Table 2) are similar to the results when I use either of the two subsets of counties as an alternative control group. This suggests that issues related to geographical clustering of policies, treatment spillovers, and urbanicity are not a problem for the analysis.

Business cycles have been shown to affect health, including health as measured by BMI (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. For example, bad economic times might affect the relative consumption of healthy versus unhealthy food, which is a policy target of mandatory calorie labeling in chain restaurants. This could be important in the analysis conducted here since the financial crisis occurred during the study period and all county health departments implemented the policy after the financial crisis began. In row 5 of Appendix Table 6, 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 little change in the estimated effects of calorie labeling on body weight, suggesting that issues related to economic conditions—such as the financial crisis—and the timing of county-level implementation of calorie labeling are not a problem for the analysis.

In row 6 of Appendix Table 6, I show results from estimating equation (1), using as a dependent variable BMI and an obesity indicator that is corrected for reporting bias in self-reports of height and weight. Following Cawley (1999), I used the 2007-2008 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. Coefficient estimates of calorie labeling are barely affected when I correct for self-reporting bias, which is consistent with other studies that have employed this correction (*e.g.* Gruber and Frakes 2006).

In row 7 of Appendix Table 6, I examine whether the estimated effect of calorie labeling is driven by changes in height or weight, the two components that are used to calculate BMI. I find that calorie labeling has no impact on height, and that calorie labeling reduces weight by about 1.2 kg or 2.6 lbs. A coefficient of 0.002 in the height model corresponds to much less than a 1% increase from the sample mean (1.69 m), and this estimate is statistically insignificant. A 1.2 kg reduction in weight is about a 1.5% reduction from the sample mean of weight (77.7 kg), which is similar in magnitude to the estimated reduction in BMI from the sample mean.

As a final robustness check, I conduct placebo regressions. Implementation of mandatory calorie labeling is expected to have an impact on health-related behaviors that are related to diet and exercise, but it should have a much smaller (if any) impact on other health-related behaviors. I analyze the impact of calorie labeling on smoking, preventive health practices such as obtaining flu and pneumonia vaccinations, and getting an HIV test. Rows 8a and 8b reveal that the estimated impacts of calorie labeling are generally small in magnitude, they follow no clear pattern, and I fail to reject the null that the estimated impact of calorie labeling on each of these behaviors is zero.[7]

D. Investigating the Importance of other Mechanisms

Most studies have focused on purchasing behavior in chain restaurants in response to calorie labels, but there are many other potential margins of adjustment. In this section, I explore various other mechanisms that might explain the effects of calorie labeling on body weight. In its battery of questions to survey respondents, the BRFSS includes information on exercise, and a limited set of food and beverage items. In particular, the BRFSS contains self-reported information on exercise at the intensive and extensive margins, as well as alcohol, fruit, and vegetable consumption. However, all of this information is not available for the full sample period in the BRFSS.[8] Also, the food consumption data do not allow me to identify foods consumed at home versus away from home, so I am unable to test whether mechanisms related to substitution behaviors over (a) foods consumed away from versus at home or (b)

[7] Sample means for the flu shot, pneumonia shot, current smoker, and HIV test dummies are 0.43, 0.32, 0.17, and 0.43 respectively.

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

foods consumed *within* food-away-from-home establishments are important for understanding the body weight impacts estimated here.

Nonetheless, in Appendix Table 10, I examine whether there is evidence that calorie labeling induces individuals to adopt healthier lifestyles by following a healthier diet and getting more exercise. I find no evidence that physical activity responded to calorie labeling. The estimated effect of calorie labeling on the extensive margin is negative, and the estimated effect on the intensive margin is positive. Both estimates are small in magnitude and are statistically insignificant (columns 1-2). I find a statistically insignificant reduction in fruit and vegetable consumption, and a statistically significant increase in alcohol consumption (columns 2-4). Relative to sample means, these estimated effects are very small in magnitude: they indicate a reduction of 0.12 units of fruit and vegetable servings a day, and an increase of 0.01 units of alcohol per day.

The BRFSS does not contain a comprehensive list of foods that individuals eat on a daily basis. Nonetheless, the total number of fruit and vegetable servings and alcohol units that a respondent reports having per day may be viewed as a very rough proxy for total daily calorie consumption. In column 5 of Appendix Table 10, I find that calorie labeling reduces the sum of fruit, vegetable, and alcohol intake by less than 1%, but this estimate is not statistically significant at conventional levels.[9]

To get a better sense of the magnitude of these estimated effects, I calculated the average calories in a serving of fruit, vegetables and a unit of alcohol.[10] The estimated impact of calorie labeling is equivalent to a reduction of about 6.1 calories in fruit and vegetable

[9] This exercise is similar to taking the sum of coefficients across the two specifications in columns 3 and 4 of Appendix Table 10. However, in column 5 I show results from a regression on a subsample that has information both on fruit/vegetable and alcohol consumption because the samples for fruit/vegetable and alcohol consumption vary due to availability of information across years in the BRFSS.
[10] I obtained calorie information for the 20 most frequently consumed raw fruits and vegetables from the 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). Using this list, I calculate that 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).

consumption, and an increase of 3.7 calories from alcohol. The analysis in Appendix Table 10reveals no evidence that calorie labeling promoted changes toward healthier behaviors *per se*, as measured by greater physical activity and fruit and vegetable consumption. The estimates do imply a net reduction of about 2.4 calories per day, but this daily reduction in calories is very small relative to the average daily recommended caloric intake of 2000 calories. For an individual to lose 1 lb or 0.5 kg, 3,500 more calories have to be expended than consumed. Holding all else constant, it would take almost 4 years to lose 1 lb if calorie expenditure were outstripping calorie intake at a rate of 2.4 calories per day. This analysis indicates that changes in diet related to the consumption of alcohol, fruits, and vegetables are not the main driver in explaining the body weight effects I estimate in the analysis.[11]

[11] Separately analyzing physical activity, food, and beverage consumption as dependent variables using models similar to those employed in Tables 3 and 4 also did not reveal patterns that explain the pattern in impacts on body weight found here.

Appendix Table 1: Additional Summary Statistics

	(1) CL Implemented Over Sample Period (No. Counties = 11)		(2) CL Not Implemented Over Sample Period: Metro Counties[a] (No. Counties = 25)		(3) CL Not Implemented Over Sample Period: Neighbor Counties[b] (No. Counties = 13)	
2004-2012 BRFSS	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Body Mass Index (BMI)	26.790	5.396	27.214	5.522	27.470	5.670
1 if Obese (BMI≥30)	0.225		0.250		0.267	
Age	46.364	16.929	47.071	16.643	47.706	17.191
1 if Male	0.498		0.516		0.500	
1 if Black	0.224		0.072		0.089	
1 if Other Race	0.158		0.068		0.054	
1 if Hispanic	0.193		0.087		0.056	
1 if HGC is High School Deg	0.234		0.275		0.286	
1 if HGC is Some College	0.238		0.271		0.282	
1 if HGC is >= 4 Year College Deg	0.427		0.367		0.352	
Log(Family Income in $2012)	10.715	0.661	10.801	0.606	10.730	0.616
Number of Children	0.754	1.101	0.806	1.169	0.755	1.133
1 if Married	0.513		0.612		0.583	
County-Level Information						
County Unemployment Rate	6.715	2.284	6.078	1.997	6.263	1.833
Fast Food Restaurants[c]	10.192	3.939	8.666	1.026	8.720	1.189
Full Service Restaurants[c]	9.722	6.718	9.131	1.695	8.347	1.777
Fitness and Recreation Centers[c]	1.211	0.772	1.215	0.475	1.196	0.322
Supermarkets and Grocery Stores[c]	5.543	1.792	2.704	0.820	2.381	0.620
Convenience Stores[c]	0.994	0.385	0.976	0.384	1.028	0.364
Specialty Stores[c]	2.157	0.726	0.967	0.430	0.976	0.335
Sample Size	25,067		4,984		16,242	

Note: These weighted summary statistics are for the Table 2 regression sample. Individual-level information was drawn from the 2004-2012 Behavioral Risk Factor Surveillance System (BRFSS). 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 & recreation centers, fast food and full-service restaurants, supermarkets and grocery stores, and specialty food stores was drawn from the 2004-2011 County Business Patterns; information for 2012 was extrapolated.

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

[b]Neighboring counties are counties that have never adopted calorie labeling, but are adjacent to a county that did.

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

Appendix Table 2: Summary Statistics for the 2007-2008 NHANES

	(1) Mean	(2) S.D.	(3) Sample Size
# Fast Food Meals in Past Wk	2.178	2.903	4,801
Had 2 Fast Food Meals in Past Wk	0.447		4,801
Would Often Use Nutrition Info if Readily Available in:			
Fast Food Restaurants	0.260		3,925
Restaurants with Waiter	0.272		3,777
Age	45.760	17.224	6,228
1 if Male	0.483		6,228
1 if Black	0.114		6,228
1 if Other Race	0.060		6,228
1 if Hispanic	0.134		6,228
1 if HGC is High School Deg	0.259		6,221
1 if HGC is Some College	0.286		6,221
1 if HGC is >= 4 Year College Deg	0.244		6,221
Log(Family Income in $2012)	10.713	0.864	5,636
1 if Married	0.545		6,224

Note: These are weighted summary statistics for the variables that are used to estimate the propensity to be a "regular fast food customer", a "likely user of nutrition information in fast food restaurants", and a "likely user of nutrition information in sit-down restaurants" in the BRFSS sample.

Appendix Table 3: Factors Affecting Helpfulness of Calorie Info in Chains (BRFSS 2012)

Dep Var: Frequency that Calorie Info in Chain Restaurants Helps Chain Restaurant Menu Item Choice (Conditional on Seeing Calorie Info in Restaurants)	Without County Fixed Effects	With County Fixed Effects
1 if Aged 25 to 34	-0.011	-0.016
	(0.112)	(0.116)
1 if Aged 35 to 44	-0.130	-0.153
	(0.142)	(0.146)
1 if Aged 45 to 54	-0.074	-0.089
	(0.114)	(0.113)
1 if Aged 55 to 59	-0.032	-0.042
	(0.148)	(0.152)
1 if Aged 60 to 64	0.048	0.038
	(0.142)	(0.147)
1 if Aged 65 and Over	-0.223	-0.250*
	(0.144)	(0.150)
1 if Male	-0.568***	-0.577***
	(0.057)	(0.057)
1 if Black	-0.023	-0.038
	(0.057)	(0.063)
1 if Other Race	0.063	0.008
	(0.093)	(0.098)
1 if Hispanic	0.143**	0.090
	(0.059)	(0.061)
Number of Children	-0.039	-0.037
	(0.025)	(0.025)
1 if Married	0.123**	0.132**
	(0.062)	(0.063)
1 if High School Graduate	-0.033	-0.027
	(0.111)	(0.116)
1 if Some College	0.239**	0.241**
	(0.107)	(0.115)
1 if Four Years of College or More	0.338***	0.338***
	(0.107)	(0.107)
Log(Family Income)	0.131***	0.105**
	(0.041)	(0.047)
1 if County Has Implemented Calorie Labeling Law	0.274***	
	(0.057)	
Psuedo R-squared	0.044	0.054
Month FE	x	x

Note: The exact wording of question used to create the dependent variable is the following: "The next question is about eating out at fast food and chain restaurants. When calorie information is available in the restaurant, how often does this information help you decide what to order?" These are coefficient estimates from ordered probit regressions, where the dep variable takes the following values: 1=Never, 2=Sometimes, 3=About Half the Time, 4=Most of the Time, 5=Always. Standard errors are clustered at the county level, and are in parentheses below coefficient estimates. All regressions used sample weights. *, **, *** denote statistical signifiance at the 10%, 5%, and 1% level, respectively. Sample size is 3,597.

Appendix Table 4: The Timing of Bans on the Use of Artificial Trans Fat in Restaurants

NYS County	Effective Dates of Trans Fat Bans	Notes
Albany	Phase I 1/1/2009; Phase II 7/1/2009	
Bronx	Phase I 7/1/2007; Phase II 7/1/2008	
Broome	12/2011	No cooking oils, shortenings or margarines can be used for frying that contain ≥ 0.5g of artificial trans fat
Kings	Phase I 7/1/2007; Phase II 7/1/2008	
Nassau	Phase I 4/1/2008; Phase II 4/1/2011	Original Phase II date was 4/1/2009
New York	Phase I 7/1/2007; Phase II 7/1/2008	
Queens	Phase I 7/1/2007; Phase II 7/1/2008	
Richmond	Phase I 7/1/2007; Phase II 7/1/2008	
Rockland	1/1/2011	No food item with ≥ 0.5g of artificial trans fat can be stored, used, or served
Suffolk	Phase I 10/28/2010; Phase II 10/28/2011	
Westchester	4/9/2008	No cooking oils, shortenings or margarines can be used for frying that contain ≥ 0.5g of artificial trans fat

Note: Phase I bans the use of partially hydrogenated vegetable oils (PHVO), shortenings, and margarines for frying, grilling or as spread unless the manufacturer's label shows that it contains < 0.5g of artificial trans fat per serving. The use of trans fat-containing oils and shortenings for deep frying cake batter and yeast dough was allowed until Phase II. Phase II prohibits storing, using, or serving any food item containing PHVO oils, shortenings, or margarines if it contains more than or equal to 0.5g of artifical trans fat per serving.

Appendix Table 5: Estimated Effects of Other Control Variables in Table 2

Dep Var	BMI	1 if Obese
1 if County Has Implemented Trans Fat Ban	-0.095	-0.002
	(0.104)	(0.011)
1 if County Has Implemented Calorie Labeling Law	-0.408**	-0.027**
	(0.177)	(0.013)
1 if Aged 25 to 34	2.324***	0.120***
	(0.203)	(0.014)
1 if Aged 35 to 44	2.806***	0.137***
	(0.237)	(0.016)
1 if Aged 45 to 54	3.426***	0.171***
	(0.178)	(0.013)
1 if Aged 55 to 59	3.613***	0.185***
	(0.150)	(0.012)
1 if Aged 60 to 64	3.628***	0.180***
	(0.173)	(0.012)
1 if Aged 65 and Over	2.460***	0.106***
	(0.152)	(0.010)
1 if Male	0.909***	0.016
	(0.166)	(0.011)
1 if Black	1.506***	0.087***
	(0.183)	(0.012)
1 if Other Race	-0.800***	-0.053***
	(0.160)	(0.014)
1 if Hispanic	0.770***	0.042***
	(0.161)	(0.012)
Number of Children	0.04	0.001
	(0.056)	(0.003)
1 if Married	0.059	0.006
	(0.092)	(0.008)
1 if High School Graduate	-0.368	-0.024*
	(0.236)	(0.015)
1 if Some College	-0.358	-0.020
	(0.236)	(0.015)
1 if Four Years of College or More	-1.431***	-0.100***
	(0.257)	(0.014)
Log(Family Income)	-0.340***	-0.024***
	(0.072)	(0.005)
County Unemployment Rate	0.054	0.004
	(0.059)	(0.004)
Fast Food Restaurants Per 10,000 Persons	-0.085	-0.01
	(0.134)	(0.010)
Full Service Restaurants Per 10,000 Persons	0.171	-0.002
	(0.105)	(0.009)
Fitness and Recreation Centers Per 10,000 Persons	0.149	-0.01
	(0.476)	(0.031)
Supermarkets and Grocery Stores Per 10,000 Persons	0.167	0.01
	(0.231)	(0.013)
Convenience Stores Per 10,000 Persons	-0.148	0.016
	(0.314)	(0.025)
Specialty Stores Per 10,000 Persons	-0.957**	-0.088***
	(0.370)	(0.029)
Constant	27.377***	0.574***
	(2.143)	(0.171)

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 sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Sample Size is 45, 939.

Appendix Table 6: Additional Robustness Checks

	(1)	(2)
(1) Using Adoption Date Instead of Effective Date (N = 45,939)	BMI	1 if Obese
1 if County Has Adopted Calorie Labeling Law	-0.307**	-0.029**
	(0.144)	(0.012)
(2) Dropping 2012 BRFSS to Avoid Extrapolated Data (N = 41,661	BMI	1 if Obese
1 if County Has Implemented Calorie Labeling Law	-0.431**	-0.025*
	(0.163)	(0.013)
(3) Omitting Neighbor Counties from Control Group (N = 40,955)	BMI	1 if Obese
1 if County Has Implemented Calorie Labeling Law	-0.373**	-0.024*
	(0.172)	(0.013)
(4) Using Metro Counties as Alt Control Group (N = 41,309)	BMI	1 if Obese
1 if County Has Implemented Calorie Labeling Law	-0.492***	-0.035**
	(0.170)	-(0.013)
(5) Allowing County-Specific Effects of Unemp Rates (N = 45,939)	BMI	1 if Obese
1 if County Has Implemented Calorie Labeling Law	-0.406**	-0.024*
	(0.169)	(0.014)
(6) Correcting BMI for Self-Reporting Error (N = 45,939)	BMI	1 if Obese
1 if County Has Implemented Calorie Labeling Law	-0.407**	-0.038**
	(0.180)	(0.014)
(7) Impacts on Components of BMI (N = 45,939)	Height (m)	Weight (kg)
1 if County Has Implemented Calorie Labeling Law	0.002	-1.242**
	(0.003)	(0.567)
(8a) Placebo Tests 1 (N = 45,044; 40,997)	1 if Flu Shot	1 if Pnemonia Shot
1 if County Has Implemented Calorie Labeling Law	0.017	-0.017
	(0.022)	(0.015)
(8b) Placebo Tests 2 (N = 45,681; 33,838)	1 if Smoker	1 if HIV Test
1 if County Has Implemented Calorie Labeling Law	-0.010	0.042
	(0.012)	(0.034)
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 has a trans fat ban. 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, and # of specialty stores. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Apendix Table 7: Who is Most Likely to be Affected by the Calorie Labeling Law? (NHANES 2007-2008)

	(1)	(2)	(3)
Dep Var	1 if Regularly Eat Fast Food	1 if Would Often Use Nutrition Info (Fast Food)	1 if Would Often Use Nutrition Info (Sit Down)
1 if Aged 25 to 34	-0.092***	0.073*	-0.005
	(0.034)	(0.038)	(0.037)
1 if Aged 35 to 44	-0.085**	0.070*	0.044
	(0.035)	(0.039)	(0.040)
1 if Aged 45 to 54	-0.158***	0.103***	0.058
	(0.034)	(0.040)	(0.039)
1 if Aged 55 to 59	-0.227***	0.059	0.061
	(0.039)	(0.050)	(0.052)
1 if Aged 60 to 64	-0.195***	0.132***	0.102**
	(0.038)	(0.050)	(0.049)
1 if Aged 65 and Over	-0.354***	0.061	0.021
	(0.024)	(0.039)	(0.038)
1 if Male	0.115***	-0.113***	-0.134***
	(0.019)	(0.018)	(0.019)
1 if Black	0.119***	0.02	0.032
	(0.023)	(0.022)	(0.023)
1 if Other Race	-0.011	-0.005	-0.039
	(0.048)	(0.052)	(0.051)
1 if Hispanic	-0.004	0.036*	0.049**
	(0.022)	(0.022)	(0.023)
1 if Married	-0.036	-0.026	-0.008
	(0.023)	(0.021)	(0.022)
1 if High School Graduate	0.022	0.034	-0.005
	(0.028)	(0.029)	(0.029)
1 if Some College	0.012	0.042	0.011
	(0.028)	(0.028)	(0.029)
1 if Four Years of College or More	-0.069**	0.113***	0.080**
	(0.031)	(0.033)	(0.033)
Log(Family Income)	0.009	0.004	0.009
	(0.012)	(0.012)	(0.012)
Sample Size	4,359	3,605	3,642

Note: These are marginal effects (evaluated at sample means) from a probit regresson. Robust standard errors are in parantheses below marginal effects. These regressions used NHANES sample weights. *, **, *** denote statistical signifiance at the 10%, 5%, and 1% level, respectively.

Appendix Table 8: The Impact of Calorie Labeling on the Pr(Obese) by Likelihood of Treatment

	Predicted Value from NHANES	
	< Median	> Median
Panel A: Predicted Likelihood of Being Regular Fast Food Customer		
1 if County Has Implemented Calorie Labeling Law	-0.012	-0.035*
	(0.019)	(0.019)
R-squared	0.040	0.049
Sample Size	23,029	22,910
Panel B: Predicted Likelihood of Being Likely User of Fast Food Nutrition Info		
1 if County Has Implemented Calorie Labeling Law	-0.029	-0.030**
	(0.022)	(0.012)
R-squared	0.045	0.064
Sample Size	22,976	22,963
Panel C: Predicted Likelihood of Being Likely User of Sit Down Nutrition Info		
1 if County Has Implemented Calorie Labeling Law	-0.014	-0.052**
	(0.014)	(0.025)
R-squared	0.047	0.065
Sample Size	22,964	22,975
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 has a trans fat ban. 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, and # of specialty stores. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix Table 9: The Timing of the Impact of Calorie Labeling on Pr(Obese)

Panel A: Using the Full Sample		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.021*	
	(0.012)	
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.037	
	(0.028)	
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	-0.020	
	(0.030)	
	Predicted Value from NHANES	
	< Median	> Median
Panel B: Predicted Likelihood of Being Regular Fast Food Customer		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.002	-0.032
	(0.020)	(0.019)
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.019	-0.046
	(0.026)	(0.040)
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	0.011	-0.036
	(0.041)	(0.045)
Panel C: Predicted Likelihood of Being Likely User of Fast Food Nutrition Info		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.019	-0.031**
	(0.019)	(0.014)
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.033	-0.049*
	(0.035)	(0.028)
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	0.003	-0.058
	(0.033)	(0.035)
Panel D: Predicted Likelihood of Being Likely User of Sit Down Nutrition Info		
1 if Calorie Labeling Law Has Been Effective > 0 & ≤ 12 Months	-0.004	-0.052*
	(0.014)	(0.029)
1 if Calorie Labeling Law Has Been Effective > 12 & ≤ 24 Months	-0.010	-0.082**
	(0.030)	(0.037)
1 if Calorie Labeling Law Has Been Effective > 24 & ≤ 53 Months	0.033	-0.096**
	(0.028)	(0.044)
County, Month, and Year FE	x	x
Control Variables	x	x
County Dummies × Year	x	x

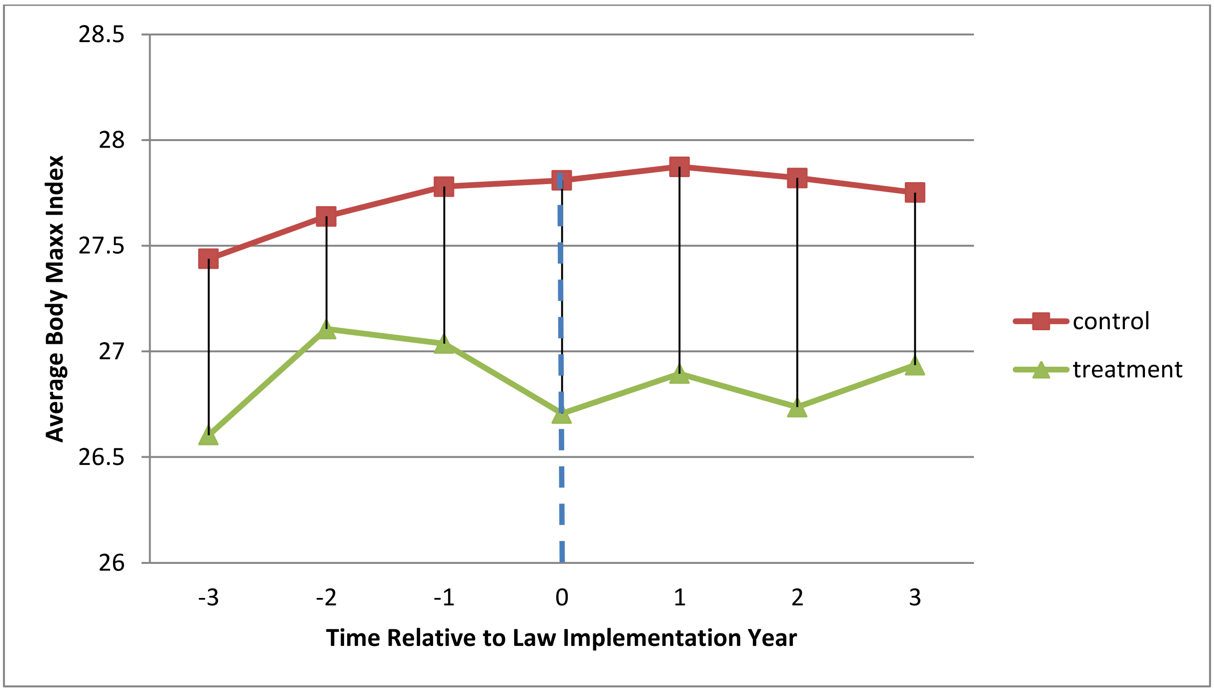
Note: Controls included but not shown: age group dummies (25-34, 35-44, 45-54, 55-59, 60-64, 65+), gender, race, and ethnicity dummies (black, other race, hispanic), education dummies (HS graduate, some college, 4-year college graduate or more), # of children, indicator for married, log of family income, and a dummy for whether a county has a trans fat ban. 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, and # of specialty stores. Standard errors are clustered at the county level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix Table 10: The Effect of Calorie Labeling on Physical Activity and Diet (2004-2012 BRFSS)

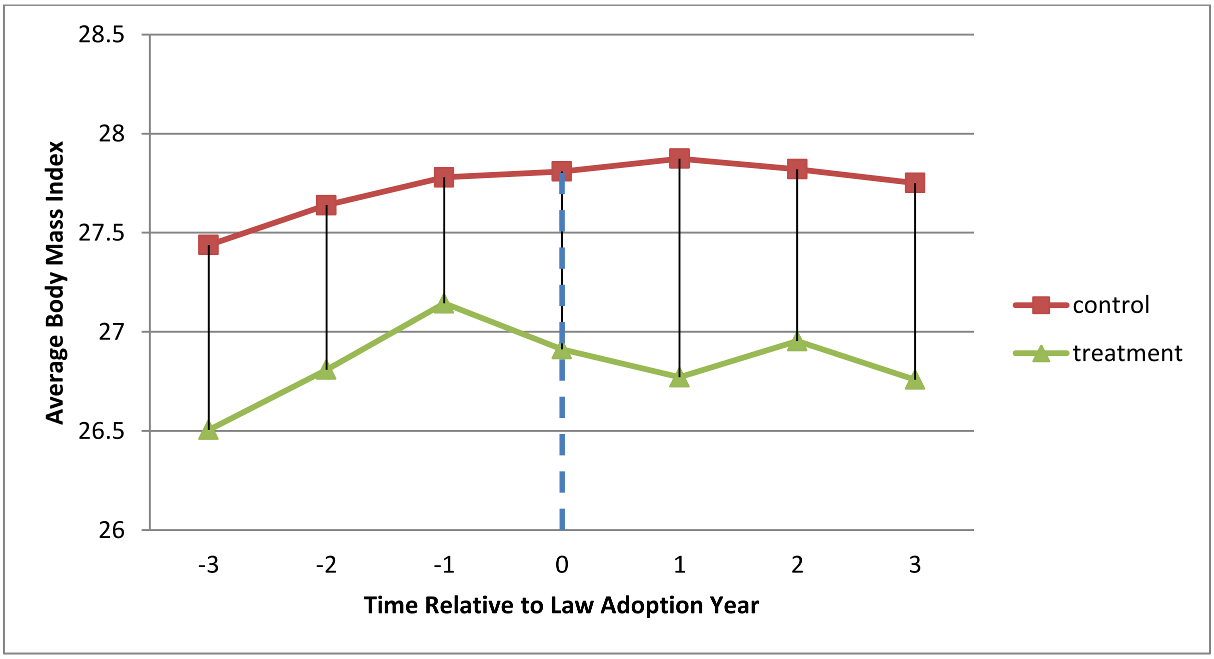
	(1)	(2)	(3)	(4)	(5)
Dep Var	1 if Exer	Ln(Mins of Exer/Wk + 1)	Ln(Fruit & Veg Srv/Day +1)	Ln(Alcohol Units/Day + 1)	Ln (Fruit & Veg Srv + Alc Units/Day + 1)
Sample Mean	0.755	327.332	3.840	0.391	4.256
1 if County Has Implemented CL Law	-0.015	0.029	-0.030	0.027***	-0.001
	(0.020)	(0.079)	(0.029)	(0.010)	(0.033)
R-squared	0.081	0.194	0.107	0.112	0.080
Sample Size	45,608	17,338	20,085	44,620	19,585
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, and log of family income. 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, and # of specialty stores. Standard errors are clustered at the county-level, and are in parentheses below OLS coefficients. All regressions used sample weights. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix Figure 1a: Trends in Body Mass Index (BMI) by Treatment Status (Effective Date)



Appendix Figure 1b: Trends in Body Mass Index (BMI) by Treatment Status (Adoption Date)



Note: For each county, I have normalized the first year calorie labeling is adopted or becomes effective to zero, *i.e.* "0" corresponds to the first year of adoption or implementation for each county. The graph shows weighted means taken by treatment status and time relative to the first year the law is adopted or becomes effective. "Treatment" counties are counties that implemented a calorie labeling law at some point over the sample period. NYC was the first to implement calorie labeling in 2008, and other New York State counties implemented calorie labeling in 2009 and 2010.

Appendix Figure 2: Geographic Distribution of Mandatory Calorie Labeling in NY