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Exploring the Effects of Calorie Labeling Laws

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by

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Abstract

This study explores the effects of Calorie labeling laws implemented in some counties in the United States on several health related variables. The findings show a small significant decreasing effect of the law on Limited activity and Poor health of 0.083 and 0.047 at 95% significant level respectively.

Keywords: Health, nutrition, obesity, calorie labeling, entropy balance weights

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1 Introduction

The state of obesity in the United States, September 2015, reports that adult obesity exceeds 35 percent in Arkansas, West Virginia and Mississippi; 22 states have rates above 30 percent, 45 states are above 25 percent and every state is above 20 percent (Levi et al, 2015).

Obesity is related to medical conditions such as stroke; vascular disease, several types of cancer, cardiovascular disease, and diabetes, which imposes externalities such as lower probability of employment, lower wages, and higher medical care costs (Sturm, 2002). Cawley and Meyerhoefer, 2012, finds that estimates of the obesity impact are underestimated, which negatively impacts the government intervention to reduce obesity externalities.

Economic research on obesity is extensive and covers topics such as economic causes, measurements, medical consequences and costs among others. Overall, the evidence suggests that there is no single economic cause of obesity, but instead there are a variety of contributors to the problem and the current interventions have only modest effects thus a range of policies may be required to achieve a substantial positive effect on the prevalence of obesity (Cawley, 2015).

Deb and Vargas, 2016 studied the effect of calorie labeling laws on BMI in the United States using a Behavioral Risk Factor Surveillance System (BRFSS) dataset comprised by the 2003 to 2012 survey waves. States that implemented the law were identified as treated and neighboring states and counties were used as controls in the study. The analysis was carried out at a county level using a difference in difference regression model. Deb and Vargas found statistically significant decreasing estimated effects of the law on BMI on overweight women as well as significant decreasing estimated effects on normal, overweight and obese males, with the largest effects on overweight and obese males. The importance of the study lies in that by acknowledging the heterogeneity of effects Deb and Vargas were able to identify effects that several studies have failed to identify and opened new possibilities at a policy level calling for stratified interventions that will fulfill subpopulation needs for information on food caloric and nutritional contents. In this study, I am examining the effects of the calorie labeling law on Health status, Exercise, Limited activity, Days of illness and Poor health trying to understand the mechanisms through which the law has an effect on the overweight and obese population (Deb and Vargas, 2016) and also to understand whether there are broader impacts of the law on health.

2 Previous literature

Several studies have been made on the effect of calorie labeling laws on menus and menu boards. Bassett et al, 2008 studied the purchasing behavior and calorie information at 11 fast-food chains in New York and found that consumers purchase lower amount of calories in the presence of caloric information.

Harnack et al, 2008 conducted a randomized experiment were participants ordered a food meal from one of four menus that vary in regards to whether calorie information was provided and value price sizing was used. The study included adolescents and adults habitual fast food patrons. Researchers recorded foods ordered and consumption of participants. No significant differences in energy consumption were found among meals ordered or eaten.

Chu et al, 2009 examined changes in meal selection by patrons in presence of nutrition labels and concluded that the presence of labels reduced the average energy content of purchases without reducing the overall sales.

Kuo et al, 2009 in Los Angeles, California conducted a sensitivity analysis to account for uncertainty in consumer response and in total annual revenue, market share, and average meal price of large chain restaurants. Researchers estimated that 10% of consumers would lower caloric consumption due to the law postings, and as a result, they estimated an average annual reduction of 40.6% of the 6.75 million pound average gain in the county population aged 5 or more. Their findings suggest that the mandate could have a large impact on the state of obesity.

Elbel et al, 2009 examined the effect of the law in New York City. The study collected receipts and surveyed consumers before and after the law was implemented at food chains located in low-income areas. Calories purchased were matched to the nutritional value of items purchased. A difference in difference model indicated that the NYC menu labeling law had no effect on consumers. Newark fast food restaurants were used as controls. Elbel et al, 2011 studied the effect of the law on purchases on children and adolescents in New York City's fast food restaurants located at low income areas and found that they observed calorie information at similar rates as adults, but they were less responsive to the information. Vadiveloo et al, 2011 used the same dataset and a difference in difference design to survey adults in chain restaurants before and after the implementation of the law and found no difference in purchasing as a result of labeling.

Roberto et al, 2010 studied the effect of the law on food choices and intake. The researchers randomly assigned three different menus to study subjects. First menu had no calorie information; second menu informed calorie contents; and third menu informed of calorie contents and daily caloric requirement. Researchers found that additional information is beneficial as individuals consumed 14% less calories when given more information.

Dumanovsky et al, 2010 studied the effect of the law in New York City collecting information before and after the implementation of the law. Consumers were surveyed at 45 randomly selected fast food restaurants. Researchers found no evidence of lower caloric purchase. Increase in customer awareness of the law was found.

Bollinger et al, 2011 estimated the impact of the law in New York City using data from Starbucks purchases in three cities. Researchers used a difference in difference strategy and found that menu labels reduced average calories per transaction by 6%. The law reduced average calories from food consumed and had no impact on beverage purchases. Loyal Starbuck cardholder customers reduced their consumption per transaction by 26%. The cities of Boston and Philadelphia were used as controls.

Dumanovsky et al, 2011 assessed the impact of calorie labeling on fast food restaurants on individual purchases based on consumer register receipts and found no decline on purchasing of calories on the full sample.

Finkelstein et al, 2011 studied the impact of calorie labeling law on transactions and purchasing behavior at one Mexican fast food chain located within and adjacent to King county, Washington. They found no impact of the law on healthier food purchasing.

Swartz et al, 2011 reviewed 7 studies on the effect of calorie labeling from 2006 to 2011 and found that all of them compared calorie ordering and purchasing in two conditions: calorie label versus no calorie label. Only two of the seven studies reported statistically significant reduction in calories purchased. Two of the seven studies were judged to be of good quality and five of fair quality. The evidence suggests that calorie labeling does not have the intended effect on consumer purchasing.

On food label determinants, Stran and Knol, 2013 used a multiple linear regression design to analyze a sample of adults from the 2005-2006 National Health and Nutrition Examination Survey (NHANES) and targeted food label use determinants. The findings indicated that determinants of food label are differential by sex, race, and age.

On searching for most effective ways of presenting menu labels to the general public, Platkin et al, 2014 studied the effect of menu labeling with calories and exercise equivalents on food selection and consumption. They found no significant difference between the information and control groups and suggested that finding more effective ways of presenting the menu labels is needed to improve the effects of the law.

A working paper by Restrepo, 2014 examined the effects of calorie labeling in a number of New York counties between 2008 and 2010. Restrepo used a difference-in-difference design and data from the 2004 to 2012 waves of BRFSS to examine the effects of calorie labeling on body mass index (BMI). He found robust evidence of significant decreases in BMI due to calorie labeling. He estimated quantile regressions to show that there is heterogeneity in the effects of calorie labeling and the effects are generally larger in the upper quantiles of the BMI distribution.

Deb and Vargas, 2016 studied the effects of the calorie labeling law in the United States using a difference in difference design and data from the 2003 to 2012 waves of BRFSS. Deb and Vargas used finite mixture models to identify the heterogeneity of effects and characterize the heterogeneity along the dimensions of the outcome distribution. They identified three latent classes which matched the normal, overweight and obese groups and found significant estimated effects on the overweight classes of men and women. The effects were males significant for the three classes and larger for overweight and obese.

3 Data

The dataset includes the Behavioral Risk Factor Surveillance System (BRFSS) waves of 2003-2012. BRFSS is a yearly telephone survey that collects health related data from every state in the United States (U.S.), including risk behaviors, chronic health conditions and use of preventive services. BRFSS collects data from adults in all 50 states, the district of Columbia and three U.S. territories and it is mainly sponsored by most divisions in the National for Chronic Disease Prevention and Health Promotion (CDC) and other federal agencies. The survey contains self-reported information on demographic and health related information, which is used in the analysis. Preliminary exploration of the data suggested substantial gender heterogeneity, so the analysis was carried out by gender throughout. The dataset is restricted to individuals whose BMI is larger than 24.9 (overweight and obese), and age is within 21 to 75 years old. Because BRFSS has some extremely small and large weights, individuals with the smallest and largest quarter percent of sampling weights were also dropped to avoid complications after the entropy balance reweighing.

The BRFSS dataset is merged with Information from the Area Resource File (ARF) to classify each county by population, income and year. Counties with more than 20,000 individuals are considered urban; small metropolitan areas (population less than 250,000); metropolitan areas (population between 250,000 and 1,000,000) and large metropolitan areas with population larger than a million individuals. Median household income in each county is also included in the dataset. From the County Business Patterns (CBP), data about the number of employees in limited service restaurants (LSR) is obtained to use as a proxy for the size of the LSR sector. This data reports the number of employees in limited service restaurants per 1,000 population in each county.

County-specific information on legislation and implementation of calorie labeling laws was cross-referenced from the National Conference of State Legislature, the Center for Science in the Public Interest and MenuCalc, an online nutrition analysis platform for the food industry endorsed by the National Restaurant Association.

Table 1 shows a chronological list of states and counties that implemented the menu labeling laws and the states included in the control group of the study. Neighboring counties and states were selected for the control group throughout the period of study. Figures 1 and 2 depict the geography of the counties and states included in the study and shades of blue indicate the year of implementation with lighter shades for 2008 and increasing shades of blue for later years of implementation. Control states and counties are simply outlined in black. The figures show a concentration of the laws in the Eastern and Western regions of the United States.

The key variable of the analysis is an indicator variable labeled "County has law enforced" that takes a value of "one" if the county has implemented the menu calorie labeling law in the month and year of the interview and "zero" otherwise. The variable "County has law" takes the value of "one" if the county ever has the law and "zero" otherwise. In addition, there are dummy variables for every state, and every year included in the study, as well as a county indicator variable.

Five dependent (outcome) variables are selected from the dataset and used in the analysis with the aim of exploring the effect of the menu calorie labeling laws on each one of them. The analysis is carried out by gender, clustered by individual county and using the balanced weights. The dependent variables are labeled as follows: 1. Health status corresponds to the question: Would you say that in general your health is: Excellent, very good, good, fair, and poor. Each category takes a numerical value from 1 to 5 respectively. 2. A variable labeled Exercise corresponds to the question: During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise? The variable takes a value of "one" if the participant answers "yes" and "zero" otherwise. 3. A variable labeled Limited activity corresponds to the question: Are you limited in any way in any activities because of physical, mental, or emotional problems? The variable takes a value of "one" if the individual gives an affirmative answer and "zero" otherwise. 4. A variable labeled Days of illness corresponds to the question: Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good? This variable takes a value from "one" to "thirty". 5. Lastly, a variable labeled Poor health corresponds to the question: During the past 30 days, for about how many days did poor physical or mental health keep you from doing your usual activities such as self-care, work, or recreation? This variable takes a value from “one” to “thirty”.

4 Methods

4.1 Entropy balance weights

Entropy balance has been proposed as a preprocessing technique to achieve covariate balance in observational studies with a binary treatment. Weighting / reweighing the sample such that the covariate distribution of the control group becomes more similar to the covariate distribution in the treatment group to achieve balance between treated and control observations, (Abadie and Imbens, 2011). In this study, I include the mean value of the outcome for each pre-treatment year of data by county and gender in the set of covariates used in the entropy balancing algorithm. Thus, following the principles of synthetic control groups proposed by Abadie and Gardeazabal, 2003 and Abadie et al, 2010, not only are the treated and control samples balanced on covariates, they are also balanced on the values of the county-level average outcome in each year of the pre-treatment period.

I use a method for generating weights to create balance: Entropy balancing. The method, developed by Hainmueller, 2011, produces a set of observation-level weights that directly balances covariate distributions across treated and control groups. Inverse propensity score weighting is the popular method for this purpose (Ho et al, 2007) but the entropy balance method has a number of practical advantages. First, it eliminates the need to back and forth between propensity score specification, estimation and balance checking. Second, propensity score weights can lead to worse balance on some covariate dimensions while improving balance on others (Iacus et al, 2011). Third, while the weights are adjusted as far as is needed to accommodate the balance constraints, at the same time they are kept as close as possible to the base weights to retain information in the reweighed data, so extreme weights are much less likely.

In the propensity score weighting method, every treated unit gets a weight $d_i = 1$ and every control unit gets a weight equal to $d_i = \frac{\widehat{p}(x_i)}{1-\widehat{p}(x_i)}$ where $\widehat{p}(x_i)$ is the estimated propensity score. In the entropy balancing method, each treated unit gets either a weight $w_i = 1$ or $w_i = s_i$, where s_i is the sampling weight associated with the treated observations, and every control unit gets a weight that satisfies a set of a priori specified balance constraints. Specifically, w_i for the control units are chosen by the solution to

$$\min_{w_i} H(w) = \sum_{i|D=0} w_i \log(w_i/s_i) \tag{1}$$

subject to

$$\begin{aligned}
&\sum_{i|D=0} w_i c_{ri}(x_i) = k_r \text{ with } r \in 1, ..., R \\
&\sum_{i|D=0} w_i = 1 \\
&w_i \geq 0 \text{ for all } i \text{ such that } D = 0
\end{aligned}$$

where $c_{ri}(Xi) = m_r$ describes a set of R balance constraints imposed on the covariate moments of the reweighed control group. Each balance constraint equates the weighted mean of the covariate in the treated sample to the weighted mean of the covariate in the control sample. In the case of indicator variables, which comprise most of the covariates in the study, equality of means is equivalent to equality of distributions. I conduct entropy balance for each gender and year of data separately, so covariate balance is obtained within each gender-year subsample.

I apply the entropy balance algorithm iteratively. In the first application of the algorithm, I set the weights for the treated group to their sampling weights and have one balance constraint for each covariate used in the regression analysis. The second application of the entropy balance algorithm adds county-mean of Health Status (in addition to the regression covariates) into the set of balance constraints. This generates a new set of balance-weights, which I use to recalculate county-level mean Health Status for the pre-treatment years. The third application of the entropy balance algorithm uses, once again, balances constraints for covariates and county-level mean. The balance algorithm is applied again adding county-means of Exercise, Limited activity, Days of illness, Poor health consecutively. The revised balance weights have a correlation of 0.99 with the weights from the prior iteration, so I consider the process to have converged to a stable set of balance weights.

4.2 Logistic regression

The case when the outcome is a discrete variable or a binary variable that has a value of 1 if the event is true and zero otherwise, such as whether a person was cured after receiving a treatment, or whether the person is employed or unemployed, and some independent variables that may or may not be continuous. The outcome could also be an ordered outcome which has more than two categories and they are assumed to have a logical order. For instance, a customer satisfaction survey may ask how satisfied you are with your purchase. The options for answering the question might be "great satisfaction", "average satisfaction", "poor satisfaction". This options may be represented by an integer that conveys the ordered value of the answers. Finally, the outcome could be a count variable that counts the number of times something has happened, such as the number of times in a month the patient went to the emergency room. In all these cases, I am going to use a model that fits the individual characteristics to the dependent variable of interest (Long et al, 2014). The linear regression model does not fit this set of data, and therefore I need to find a different solution. I have a binary dependent variable Y, and I want to model the conditional probability $Pr(Y = 1|X = x)$ as a function of x; and any unknown parameters in the function are to be estimated by maximum likelihood. In a binary response model, interest lies primarily in the response probability

$$P(y = 1|x) = P(y = 1|x_1, x_2, ..., x_i), \tag{2}$$

where x denotes the full set of explanatory variables, for example in this study one of the dependent variables is *exercise* and some of the independent variables are education, race, income, and marital status.

Consider a class of binary response models of the form

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + ... + \beta_k x_k) = G(\beta_0 + x\beta), \tag{3}$$

where G is a function taking values strictly between zero and one: $0 < G(z) < 1$, for all real numbers z. This assures that the estimated response probabilities are strictly between zero and one.

$$x\beta = \beta_1 x_1 + ... + \beta_k x_k \tag{4}$$

In the logit model, G is the logistic function:

$$G(z) = \exp(z)/[1 + \exp(z)] = A(z), \tag{5}$$

which is between zero and one for all real numbers z. This is the cumulative distribution function for a standard logistic random variable.

The logit model can be derived from an underlying latent variable model. Let $y*$ be an unobserved, or latent variable determined by

$$y* = \beta_0 + x\beta + e, y = 1[y* > 0], \tag{6}$$

where the notation 1[.] defines a binary outcome. The function 1[.] is called the indicator function, which takes the value of one if the event in brackets is true, and zero otherwise. Therefore, y is one if $y* > 0$, and y is zero if $y* \leq 0$. I assume that e is independent from x and that e has the standard logistic distribution. In addition, e is symmetrically distributed about zero, which means that $1 - G(-z) = G(z)$ for all real numbers z.

Assume that I have a random sample of size n. To obtain the maximum likelihood estimator, conditional on the explanatory variables, I need the density of y_i, given x_i.

$$f(y|x_i;\beta) = [G(x_i\beta)^y[1 - G(x_i\beta)]^{1-y}, y = 0, 1, \tag{7}$$

The log-likelihood for an observation i is a function of the parameters and the data (x_i, y_i) and is obtained by taking :

$$l_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i)log[1 - G(x_i\beta)]. \tag{8}$$

The log-likelihood for a sample size of n is obtained by summing equation 11 across all observations :

$$L_i(\beta) = \sum_{i=1}^{n} l_i(\beta). \tag{9}$$

The MLE of β denoted by $\hat{\beta}$ maximizes this log-likelihood. If $G[.]$ is the standard logit cdf, then $\hat{\beta}$ is the logit estimator.

The general theory of MLE for random samples implies that, under general conditions the MLE is consistent, asymptotically normal, and asymptotically efficient. Each $\hat{\beta}_j$ comes with an (asymptotic) standard error, which are reported along with the estimated coefficients by any statistical package(Wooldridge, 2009), (Archer and Lemeshow, 2006).

4.3 Poisson regression model

Another kind of nonnegative dependent variable is a count variable, which can take on integer non-negative values. I am interested in the case where y takes on relatively few values including *zero*. In my study, I consider a variable that takes values from one to thirty responding to the question how many days of illness the participant had in a month. A linear model can not provide the best fit for this type of explanatory variables because the distribution of this data can be very different from normal. Instead, the nominal distribution for count data is Poisson distribution.

Because I am interested in the effect of explanatory variables on y, then I look at the Poisson distribution conditional on x. This distribution is entirely determined by the mean, so I only need to specify $E(y|x)$. I assume that this has the form

$$E(y|(x_1, x_2, ... + x_k) = \exp(\beta_0 + \beta_1 x_1 + ... + \beta_k x_k) \tag{10}$$

which is also $exp(x\beta)$. So, the probability that y equals the value h, conditional on x, is

$$P(y = h|x) = \exp[-\exp(x\beta)][\exp(x\beta)]^h / h!, h = 0, 1, ... \tag{11}$$

where $h!$ denotes factorial. This distribution allows us to find conditional probabilities for any values of the explanatory variables. Once I have estimates of of the β_j, I can plug them into the probabilities for various values of x.

Given a random sample $[(x_i, y_i) : i = 1, 2, ..., n]$, I can construct the log-likelihood function:

$$L(\beta) = \sum_{i=1}^{n} l_i(\beta) = \sum_{i=1}^{n} [y_i x_i \beta - \exp(x_i \beta)], \tag{12}$$

Then, I maximize the likelihood function and obtain the $\hat{\beta}_j$ estimates and the standard errors. These are reported by any statistical package.

Poisson is a natural step for a count data but it is often too restrictive because all the probabilities and higher moments are determined entirely by the mean. In particular, the variance is equal to the mean:

$$Var(y|x) = E(y|x) \tag{13}$$

Fortunately, the Poisson distribution has a very nice robustness property: whether or not the Poisson distribution holds, I still get consistent, asymptotically normal estimators of the β_j. (Wooldridge, 2009). This is analogous to the OLS estimator, which is consistent and asymptotically normal whether or not the normality assumption holds; yet OLS is the MLE under normality.

5 Results

Summary statistics are displayed in tables 2 and 3 and are stratified by gender and law status. Means are calculated using survey weights, and balanced weights obtained after using the entropy balancing algorithm by year, by gender, and by each one of the dependent variables. The total sample has 627,346 individuals and is composed by 332,857 females and 294,489 males. Females in counties with the law are 111,383 and the remaining 221,857 are located in counties without the law. There are 97,283 males in counties with the law and 197,206 in counties without the law. The sample summary statistics, calculated using survey weights, show that individuals in counties with the law are more likely to be of other minority, Hispanic race, unmarried, less than high school educated, and low income. After using the entropy balance weights then the covariate distribution is adjusted to minimize the difference between the treated and untreated covariate groups, allowing me to interpret the regression estimates as being “doubly robust”.

Tables 4 and 5 depict the dependent variables that are used in the regressions. The means are stratified by gender and law status. Means are calculated using survey weights and entropy balanced weights respectively.

I carried out an ordered logit regression on variable Health Status stratified by gender and clustered by county. The output shows no significant effect of the menu calorie labeling law. Likewise, a logit regression on variable Exercise by gender and clustered by county shows no significant effect of the calorie labeling law. Table 6 shows the estimated coefficients.

A logit regression on variable Limited Activity stratified by gender and clustered by county shows a significant decreasing effect of the law in the amount of 0.083 at 95% significance level on women. Other coefficients are significant and have the expected sign, such as age, black race, Hispanic ethnicity, married, some college, and income. There is no effect of the law on men. See the estimated coefficients on table 7.

A Poisson regression on Poor Health depicts a significant small decreasing effect of the law in the amount of 0.047 at 95% significant level on women. No effect of the law is found on men. Other coefficients such as age, other minority, education and income are significant and show the expected signs. See the estimated coefficients on table 7.

Lastly, a Poisson regression stratified by gender and clustered by county on Days of Illness also finds no signifficant effect of the law for neither men nor women.

6 Conclusion

Physical activity and inactivity rates vary across states and regions of the US, as reported by the CDC [1]. Americans in the Southern states are less likely to be physically active as compared to Americans in the West, Northeast and Midwest regions of the country. Some groups are also more physically active than others. For example, Men (54%) are more likely than women (46%) to meet the 2008 Physical Activity Guideline for aerobic activity.

Research evidence also indicates that adults with more education are more likely to meet the required levels of physical activity recommended for healthy living, as well as, adults whose income is above the poverty level are more likely to meet healthier levels of physical activity and consequently, improve their health self-perception.

In this study, I wanted to examine the effects of the calorie labeling law on self-reported Health status, Exercise, Limited Activity, Days of Illness, and Poor Health in order to understand the mechanisms through which the law has an effect on the overweight and obese males and females. I find a very small significant decreasing effect of the law on

[1] http://www.cdc.gov/physicalactivity/data/facts.htm

the self-reported Limited physical activity and Poor health variables, which capture a small improvement in the individuals well being that could be attributed to the menu calorie labeling law. The non continuous variables used in the study are not appropriate to quantify the causal effect of the calorie labeling law, and the expectation for the near future is to have the law implemented in a larger number of counties and states as mandated by the Affordable Care Act; and along with it, have surveys introduce variables tailored to capture people's eating habits changes and persistent health improvements.

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Tables

Table 1: Sample geography by calorie-labeling law status and dates

Date	State	County
8/2008	New York	Queens
8/2008	New York	Kings
8/2008	New York	Richmond
8/2008	New York	Bronx
8/2008	New York	New York City
6/2009	New York	Westchester
11/2009	New York	Ulster
7/2009	California	Statewide
1/2009	Washington	King
8/2009	Oregon	Multnomah
4/2010	New York	Albany
10/2010	New York	Schenectady
11/2010	New York	Suffolk
2/2010	Pennsylvania	Philadelphia
5/2010	Maine	Statewide
11/2010	Massachusetts	Statewide
1/2011	Oregon	Statewide

The following states with no calorie-labeling laws through 2012 are included in the control group: Connecticut, Delaware, New Hampshire, Maryland, New Jersey, Rhode Island, Vermont, Arizona, Idaho, Nevada.

Table 2: Covariate means using sampling weights

	Women		Men	
	No law	Law	No law	Law
County has law enforced	0.109	0.385	0.107	0.386
Age / 10	4.795	4.678	4.681	4.611
Age (/10) squared	2.206	2.261	2.161	2.159
Black race	0.049	0.052	0.034	0.031
Other minority	0.022	0.031	0.026	0.036
Hispanic ethnicity	0.042	0.130	0.039	0.097
Married	0.594	0.544	0.683	0.645
Less than High School	0.089	0.175	0.076	0.137
High school graduate	0.305	0.244	0.285	0.229
Some college	0.300	0.284	0.260	0.255
Income $< \$15,000$	0.082	0.166	0.048	0.094
Income \$15,000 - \$25,000	0.143	0.154	0.101	0.121
Income \$25,000 - \$35,000	0.103	0.102	0.085	0.088
Income \$35,000 - \$50,000	0.143	0.124	0.135	0.121
Income \$50,000 - \$75,000	0.163	0.142	0.175	0.150
Income unknown	0.110	0.075	0.085	0.058
Pregnant	0.018	0.019		
Metro county pop. 250K-1M	0.237	0.184	0.240	0.186
Metro county pop. < 250K	0.090	0.046	0.087	0.049
Urban county pop. > 20K	0.072	0.022	0.069	0.023
County median HH income (\$10K)	5.636	5.506	5.705	5.658
County LSR employees per 1000 pop.	9.310	9.630	9.272	9.684
N	221,474	111,383	197,206	97,283

Means calculated using sampling weights
Year and state coefficients are not displayed in the table

Table 3: Covariate balanced means using balanced weights

	Women		Men	
	No law	Law	No law	Law
County has law enforced	0.100	0.385	0.100	0.386
Age / 10	4.678	4.678	4.611	4.611
Age (/10) squared	2.261	2.261	2.159	2.159
Black race	0.052	0.052	0.031	0.031
Other minority	0.031	0.031	0.036	0.036
Hispanic ethnicity	0.130	0.130	0.097	0.097
Married	0.544	0.544	0.645	0.645
Less than High School	0.175	0.175	0.137	0.137
High school graduate	0.244	0.244	0.229	0.229
Some college	0.284	0.284	0.255	0.255
Income $< \$15,000$	0.166	0.166	0.094	0.094
Income \$15,000 - \$25,000	0.154	0.154	0.121	0.121
Income \$25,000 - \$35,000	0.102	0.102	0.088	0.088
Income \$35,000 - \$50,000	0.124	0.124	0.121	0.121
Income \$50,000 - \$75,000	0.142	0.142	0.150	0.150
Income unknown	0.075	0.075	0.058	0.058
Pregnant	0.019	0.019		
Metro county pop. 250K-1M	0.184	0.184	0.186	0.186
Metro county pop. < 250K	0.046	0.046	0.049	0.049
Urban county pop. > 20K	0.022	0.022	0.023	0.023
County median HH income (\$10K)	5.506	5.506	5.658	5.658
County LSR employees per 1000 pop.	9.630	9.630	9.684	9.684
N	221,474	111,383	197,206	97,283

Means calculated using entropy balanced weights
Year and state coefficients are not displayed in the table

Table 4: Dependent variables means using sampling weights

	Women		Men	
	No law	Law	No law	Law
Health status	2.570	2.674	2.425	2.466
Exercise	0.721	0.719	0.788	0.788
Limited activity	0.242	0.235	0.190	0.188
Days of illness	10.482	10.690	9.788	9.912
Poor Health	10.622	10.445	10.590	10.387

Means calculated using sampling weights

Table 5: Dependent variables balanced means using balanced weights

	Women		Men	
	No law	Law	No law	Law
Health status	2.676	2.674	2.491	2.466
Exercise	0.694	0.719	0.771	0.788
Limited activity	0.250	0.235	0.196	0.188
Days of illness	11.191	10.690	10.310	9.912
Poor Health	11.410	10.445	11.224	10.387

Means calculated using entropy balanced weights

Table 6: Regressions on variables Health status and Exercise

	[1]Health Status		[2]Exercise	
	Women	Men	Women	Men
County has law enforced	0.026	0.015	-0.014	0.018
	(0.023)	(0.025)	(0.030)	(0.038)
County has law	0.126***	-0.004	-0.022	-0.038
	(0.031)	(0.023)	(0.049)	(0.045)
Age / 10	0.140***	0.207***	-0.079***	-0.091***
	(0.008)	(0.006)	(0.008)	(0.009)
Age (/10) squared	-0.058***	-0.026***	0.027***	0.052***
	(0.005)	(0.003)	(0.005)	(0.005)
Black race	0.173***	0.077	-0.094*	-0.132**
	(0.027)	(0.051)	(0.055)	(0.055)
Other minority	0.314***	0.147***	-0.285***	-0.246***
	(0.060)	(0.053)	(0.071)	(0.064)
Hispanic ethnicity	0.384***	0.282***	-0.390***	-0.468***
	(0.045)	(0.042)	(0.045)	(0.039)
Married	-0.110***	-0.053***	0.083***	-0.003
	(0.015)	(0.014)	(0.027)	(0.024)
Less than High School	1.088***	1.047***	-0.793***	-0.929***
	(0.031)	(0.033)	(0.036)	(0.046)
High school graduate	0.428***	0.533***	-0.562***	-0.669***
	(0.017)	(0.020)	(0.028)	(0.033)
SomeCollege	0.263***	0.372***	-0.265***	-0.394***
	(0.016)	(0.016)	(0.025)	(0.030)
Income $< 15,000$	1.540***	1.629***	-0.718***	-1.060***
	(0.029)	(0.038)	(0.047)	(0.039)
Income $15,000 - 25,000$	1.073***	1.159***	-0.640***	-0.895***
	(0.026)	(0.028)	(0.035)	(0.028)
Income $25,000 - 35,000$	0.756***	0.765***	-0.459***	-0.699***
	(0.028)	(0.037)	(0.036)	(0.032)
Income $35,000 - 50,000$	0.508***	0.531***	-0.330***	-0.574***
	(0.021)	(0.027)	(0.028)	(0.030)
Income $50,000 - 75,000$	0.286***	0.302***	-0.181***	-0.382***
	(0.021)	(0.019)	(0.030)	(0.029)
Income unknown	0.791***	0.562***	-0.505***	-0.700***
	(0.034)	(0.028)	(0.046)	(0.036)
Pregnant	-0.377***		-0.408***	
	(0.057)		(0.084)	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[1] Ordered logit model; [2] Logit model

Population, year, and state coefficients are not displayed in the table.

Table 7: Regressions on variables Limited activity, Poor health, and Days of illness

	[1]Limited Activity		[2]Poor Health		[2]Days of Illness	
	Women	Men	Women	Men	Women	Men
County has law enforced	-0.083**	-0.013	-0.047**	0.011	-0.012	-0.001
	(0.041)	(0.034)	(0.024)	(0.027)	(0.020)	(0.027)
County has law	-0.129*	-0.091	-0.046	-0.071***	-0.030	-0.066**
	(0.074)	(0.068)	(0.041)	(0.024)	(0.027)	(0.031)
Age / 10	0.249***	0.311***	0.095***	0.122***	0.098***	0.139***
	(0.013)	(0.011)	(0.007)	(0.007)	(0.008)	(0.005)
Age (/10) squared	-0.085***	-0.069***	-0.031***	-0.036***	-0.039***	-0.037***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)
Black race	-0.415***	-0.235***	-0.007	0.002	-0.031	-0.033
	(0.033)	(0.078)	(0.033)	(0.049)	(0.026)	(0.044)
Other minority	0.063	-0.069	0.153***	0.155***	0.067**	0.101**
	(0.061)	(0.067)	(0.042)	(0.041)	(0.030)	(0.040)
Hispanic ethnicity	-0.569***	-0.462***	-0.082*	-0.020	-0.009	-0.003
	(0.050)	(0.073)	(0.042)	(0.044)	(0.029)	(0.029)
Married	-0.295***	-0.274***	-0.024	-0.022	-0.037***	-0.057***
	(0.032)	(0.021)	(0.018)	(0.018)	(0.011)	(0.015)
Less than High School	-0.120**	-0.062	0.298***	0.355***	0.278***	0.290***
	(0.059)	(0.060)	(0.028)	(0.035)	(0.024)	(0.030)
High school graduate	-0.045	0.138***	0.255***	0.332***	0.198***	0.277***
	(0.031)	(0.028)	(0.020)	(0.026)	(0.021)	(0.019)
SomeCollege	0.193***	0.348***	0.227***	0.292***	0.202***	0.231***
	(0.020)	(0.026)	(0.017)	(0.023)	(0.015)	(0.020)
Income $< 15,000$	1.163***	1.475***	0.577***	0.648***	0.553***	0.617***
	(0.082)	(0.049)	(0.029)	(0.033)	(0.032)	(0.031)
Income $15,000 - 25,000$	0.693***	0.883***	0.422***	0.470***	0.409***	0.439***
	(0.051)	(0.052)	(0.023)	(0.030)	(0.023)	(0.023)
Income $25,000 - 35,000$	0.330***	0.464***	0.311***	0.304***	0.292***	0.264***
	(0.048)	(0.045)	(0.025)	(0.033)	(0.022)	(0.030)
Income $35,000 - 50,000$	0.218***	0.341***	0.137***	0.276***	0.168***	0.213***
	(0.041)	(0.032)	(0.035)	(0.035)	(0.026)	(0.025)
Income $50,000 - 75,000$	0.166***	0.218***	0.101***	0.158***	0.092***	0.145***
	(0.034)	(0.028)	(0.029)	(0.035)	(0.022)	(0.031)
Income unknown	0.466***	0.494***	0.456***	0.461***	0.396***	0.389***
	(0.048)	(0.036)	(0.027)	(0.038)	(0.026)	(0.033)
Pregnant	0.126		0.069		0.100*	
	(0.100)		(0.080)		(0.057)	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[1] Logit model; [2] Poisson model

Population, year, and state coefficients are not displayed in the table.

Figures

Figure 1: Eastern US geography of calorie-labeling laws

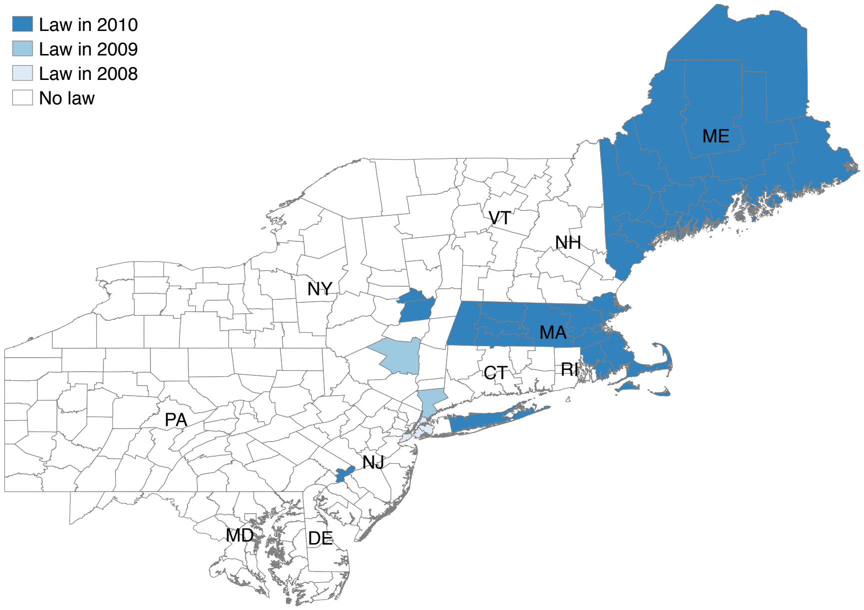

Figure 2: Western US geography of calorie-labeling laws