Do Menu Labeling Laws Translate into Results? Impacts on Population Obesity and Diabetes

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Abstract: We separately use the difference-in-differences technique and the synthetic control method on county-level data to test the impact of mandatory menu labeling laws on obesity and diabetes rates. Results show a decline in the growth of obesity rates following passage of the law at the state level in California and for six counties on the East Coast. We identify no significant impact to diabetes rates.

Keywords: Obesity, health, calories, menus
JEL: I12, I18

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Do Menu Labeling Laws Translate into Results? Impacts on Population Obesity and Diabetes

Obesity has ballooned into the US’s largest preventable medical condition and driver of medical expenditures,¹ prompting much legislative and regulatory activity. One such policy is mandatory menu labeling laws for chain restaurants, with the oft-stated goal of providing consumers with more information on calories counts and nutritional content. Given the relative recentness of such laws, the literature on their effectiveness is still young. Most previous economic studies have examined how the provision of such information directly affects consumer choices on calorie intake, calories per transaction, and frequency of fast food meal consumption (see respectively Wisdom et al. 2010, Bollinger et al. 2011, Vadiveloo et al. 2011). Such micro studies shed important light on the mechanisms by which such nutritional information can work, but they cannot address the arguably more important cumulative impact on obesity itself.

Deb and Vargas (2016) address this ultimate outcome by examining longitudinal data from 2003 to 2012 to consider the impact of menu labeling legislation on body mass index (BMI), the continuous measure on which obesity is based.² They find a significant reduction of BMI that follows the implementation of the various laws, most substantially in overweight and obese individuals. Besides our methodological differences with that paper, our work complements theirs in two ways. First, we employ annual county-level data rather than individual data. Confirmation of their results with coarser data provides further assurance of the finding’s robustness. Second, we also explore the impact of such laws on the important and

¹ www.cdc.gov/chronicdisease/overview/
² BMI is calculated as weight in kilograms divided by square of height in meters: \[ \text{BMI} = \frac{\text{Mass}}{	ext{Height}^2}. \]
growing problem of diabetes to consider if there are differential impacts across the two often-related conditions.

**Data and Results**

We study the impact of mandatory menu labeling laws using age-adjusted county-level estimates for obesity and diabetes rates from the Centers for Disease Control and Prevention (CDC) between 2004 and 2012. To construct county-level estimates, the CDC uses Bayesian multilevel modeling techniques. Models predict the probability of an individual being obese or diabetic based on age, sex, and race characteristics from three-year samples (over 1.2 million individuals) of the Behavior Risk Factor Surveillance System (BRFSS) survey. Estimates are calculated using annual county population data from the census and are validated using direct estimates from 298 large counties. A BMI greater than 30 classifies an individual as obese, and a medical diagnosis of diabetes classifies an individual as diabetic.

Under the Patient Protection and Affordable Care Act passed in March 2010, national mandatory menu labeling became the law, taking effect in December 2016. Before this 2010 passage, five states and nine smaller jurisdictions had already passed and implemented menu labeling laws. Given this setting, we first study the impact of California’s state-level legislation using a piecewise linear model and then consider the impact of various county-level laws using the synthetic control method.

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3 Deb and Vargas (2016) use the BRFSS directly.
4 The CDC’s county-level estimation calculation method is online at http://www.cdc.gov/diabetes/pdfs/data/calculating-methods-references-county-level-estimates-ranks.pdf
5 States: California (September 2008), Massachusetts (May 2009), Maine (June 2009), Oregon (June 2009), and New Jersey (January 2010), Counties: New York, NY (January 2008), King, WA (April 2008), Philadelphia, PA (November 2008), Westchester, NY (November 2008), Suffolk, NY (February 2009), Ulster, NY (April 2009), Albany, NY (September 2009), Montgomery, MD (November 2009) and Davidson, TN (February 2010).
California became the first state to pass menu labeling legislation in September 2008, following New York, NY, and King County, WA. Under the requirements of this law, restaurants in California with at least 19 other franchised facilities under the same name must post calorie count information directly next to items on menus or menu boards.6 The law became effective and enforced with fines up to $500 in January 2011. We focus on identifying changes following the passage date of the California law in 2008 instead of the effective date in 2011. After passage, restaurateurs know they will eventually need to comply, so, barring uncertainty about the law’s permanence, we expect to see menu board changes and consumer responses shortly after passage.7 We employ counties from Arizona, Colorado, Idaho, Nevada, New Mexico, Texas, Utah, and Washington (without King County) as our control group.8

Table 1 displays calculated statewide obesity and diabetes rates across our treatment and control groups. California’s mean pre-passage obesity rate of 20.94% rose roughly two percentage points to 22.89% post-passage. A lower pre-passage average in California may be due to low early-sample obesity rates outweighing the early post-passage averages, as the effect is presumably not seen immediately following passage. In contrast, the mean obesity rate for non-California counties rose three percentage points. Mean diabetes rates rose comparably for California and non-California counties.

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6 http://www.leginfo.ca.gov/pub/07-08/bill/sen/sb_1401-1450/sb_1420_bill_20080903_enrolled.html. Brochures accessible upon request are required to show carbohydrates, saturated fat, and sodium.
7 As a check of this, we estimated our model using the effective date as the relevant threshold. Those estimates (unreported) indicated that a significant instantaneous impact as well as a further gradual impact, results that are consistent with misspecification.
8 While Oregon passed similar legislation in 2009, we choose to consider California as our focal state for two reasons. First, the later passage of the Oregon legislation leaves one less year to observe an impact before the national standard likely started to have an effect. Second, Multnomah County (home of Portland, OR, and comprising about 20% of the state’s population) passed legislation in July 2008, creating an overlapping legislation conflict.
While we estimate the unrestricted model and then impose various restrictions, the following continuous piecewise linear function model is our preferred specification and facilitates discussion:

\[
y_{c,t} = \beta_0(t \leq t_0) + \beta_1(t > t_0) + \beta_2(t > t_0) \cdot CA_c + x_{c,t}\gamma + \epsilon_{c,t},
\]

in which \(y_{c,t}\) is the obesity or diabetes rate in county \(c\) at year \(t\), \(t_0\) is the labeling law’s passage year of 2008, \(CA\) is an indicator for California counties, and \(x_{c,t}\) includes county fixed effects and other variables. The primary coefficient of interest is the interaction of the post-passage time trend with the California indicator, capturing the differential trend in the post-passage dependent variables between California and the control group.

Results from the piecewise linear regression and its various restrictions can be found in Table 2. We begin with obesity. After identifying no immediate impact from Post and Post*CA estimates and no significant difference between pre-passage trend for California and non-California counties, we ultimately narrow the model down to simply include the pre-passage trend, the post-passage trend, and an interaction between post-passage trend and the California dummy as shown in equation (1). We find that California’s obesity trend following legislation significantly differs from that of non-California states, with California’s trend 0.55 percentage points per year lower (t-stat of 6.8). In fact, California’s post-passage trend decreased by 0.17 percentage points, while non-California states experienced a continued, though slower, increase of 0.37 percentage points (respective t-stats of 2.6 and 6.5). In contrast, the diabetes results suggest no such impact, in that we observe comparably less rapid growth of diabetes rates in both California and non-California states following passage of the law. Therefore, we do not find any significant impacts on diabetes rates in response to California’s menu labeling legislation.

Qualitatively similar results are observed after county-level legislation. Following the methods of Abadie et al. (2010), we develop a synthetic control group to compare to counties
with legislation. Counties nationwide that had not passed menu labeling legislation and have
similar demographic characteristics to the treatment county are included in the synthetic control
donor pool. Pre-passage median income, race, education, poverty, population density, and
diabetes or obesity rates of the treatment county are used as predictors in developing the
synthetic control. The synthetic control aims to represent the counterfactual obesity and diabetes
rates in the absence of legislation.

Of the nine counties with menu labeling legislation, six showed consistently lower
obesity rates than the synthetic control following passage of the law. Figure 1 displays two cases,
both of which passed legislation in 2008. Philadelphia, PA, showed the most dramatic results of
the legislation, with its obesity rate falling 1.3 percentage points lower than the synthetic control
one year following passage and progressing to 1.8 percentage points in 2012. New York, NY,
reached a maximum of 1.5 percentage points lower than the synthetic control one year following
passage and maintained lower obesity rates than the synthetic control through 2012. Other
counties also show their largest impacts one to two years following legislation. We expect that a
lack of enforcement through fines (King County, WA) or a passage date close to the national
preemption in 2010 (Albany, NY and Davidson, TN) prevented results from being seen in the
remaining three counties.

Similar to the state-level piecewise linear regression results, the synthetic controls did not
identify any comparable impacts on diabetes. Using the same method as obesity rates, none of
the nine counties tested show diabetes rates consistently lower than the synthetic control.
Discussion

Our results show that menu labeling can have significant impacts on obesity rates through at least four years following passage. Actions taken at restaurants to improve transparency of nutrition information apparently not only resulted in changes in consumer behavior but also affected the ultimate measures of interest. In a society that is attentive to calorie counts when dieting and losing weight, calorie information posted on restaurant boards could transform consumption decisions inside and outside of the restaurant environment.

Because diabetes can be caused by excessive sugar consumption, additional nutritional information might reasonably be expected to have similar impacts on that disease. Our study of diabetes rates, though, found no comparable results for either state or county interventions. Carbohydrate information was mandated only for brochures, and this may drive our finding of such laws having no impact on diabetes. As menu labeling becomes enforced at the national level in December 2016, it will be instructive to look for patterns already observed in California and these various counties throughout the rest of the nation.

Works cited


**Data sources (all retrieved on May 24, 2016)**


Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>California</th>
<th></th>
<th>Non-California</th>
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<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>N</td>
<td>Mean</td>
</tr>
<tr>
<td>Pre-Passage</td>
<td>20.94</td>
<td>2.83</td>
<td>232</td>
<td>23.35</td>
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<tr>
<td>Post-Passage</td>
<td>22.89</td>
<td>3.54</td>
<td>290</td>
<td>26.35</td>
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<tr>
<td>Post – Pre</td>
<td>1.95</td>
<td>3.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-Passage</td>
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<td>0.68</td>
<td>232</td>
<td>7.49</td>
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<tr>
<td>Post-Passage</td>
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<td>0.82</td>
<td>290</td>
<td>8.34</td>
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<tr>
<td>Post – Pre</td>
<td>0.92</td>
<td>0.86</td>
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</tbody>
</table>

Note: For California and non-California samples, population-weighted sample means and standard deviations are calculated for each year. Pre-Passage and Post-Passage are averages of the mean and standard deviations from 2004-2007 and 2008-2012 respectively.

Table 2: California Obesity and Diabetes Impacts after Passage Date (n = 4968)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
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<th>(6)</th>
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<td>Obesity</td>
<td>0.974***</td>
<td>0.937***</td>
<td>0.934***</td>
<td>0.395***</td>
<td>0.329***</td>
<td>0.325***</td>
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<tr>
<td></td>
<td>(0.058)</td>
<td>(0.043)</td>
<td>(0.045)</td>
<td>(0.065)</td>
<td>(0.033)</td>
<td>(0.035)</td>
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<tr>
<td>PreTrend</td>
<td>-0.154</td>
<td>-0.092*</td>
<td>----</td>
<td>-0.072</td>
<td>-0.085**</td>
<td>----</td>
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<tr>
<td></td>
<td>(0.091)</td>
<td>(0.048)</td>
<td>(0.070)</td>
<td>(0.030)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post*CA</td>
<td>0.237</td>
<td>----</td>
<td>----</td>
<td>-0.117</td>
<td>----</td>
<td>----</td>
</tr>
<tr>
<td></td>
<td>(0.348)</td>
<td></td>
<td>(0.164)</td>
<td></td>
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<tr>
<td>PostTrend</td>
<td>0.368***</td>
<td>0.359***</td>
<td>0.372***</td>
<td>0.127**</td>
<td>0.115**</td>
<td>0.128**</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.069)</td>
<td>(0.058)</td>
<td>(0.041)</td>
<td>(0.049)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>PostTrend*CA</td>
<td>-0.530***</td>
<td>-0.505***</td>
<td>-0.547***</td>
<td>-0.007</td>
<td>-0.010</td>
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<tr>
<td></td>
<td>(0.062)</td>
<td>(0.082)</td>
<td>(0.080)</td>
<td>(0.031)</td>
<td>(0.048)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>R²</td>
<td>0.9204</td>
<td>0.9203</td>
<td>0.9203</td>
<td>0.9206</td>
<td>0.9190</td>
<td>0.9186</td>
</tr>
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</table>

Clustered standard errors at the state level in parentheses.

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

Note: All regressions include county fixed effects. Other regressors are race, age, and population density (2000 and 2010 Census, interpolated/extrapolated as needed); income and education (American Community Survey 5-Year Estimates); poverty rate (SAIPE); and unemployment rate (BLS). Years of observation are 2004-2012. County level obesity and diabetes rates are taken from CDC. The control group includes counties in Arizona, Colorado, Idaho, Nevada, New Mexico, Texas, Utah, and Washington (without King County). Oregon is omitted due to overlapping legislation.
Figure 1: Obesity Impacts by Synthetic Control after County Passage Date

Notes: Estimates constructed using method of Abadie et al. (2010). Counties nationwide without menu labeling legislation but with similar demographic characteristics to the treatment county are included in the synthetic control donor pool. Obesity rates come from the CDC county estimates. Median income and poverty rates (SAIPE), population density, bachelor’s degree %, and black % (2000 and 2010 Census, interpolated/extrapolated as needed), and pre-passage obesity rates from the treatment county are used as predictors. All variables except the lagged obesity rates are averaged over pre-passage period of 2004-2007.