Received: 18 July 2024 | Revised: 1 October 2024 | Accepted: 6 October 2024

DOI: 10.1002/oby.24198

Obesity A Research Journal | THE OBESITY SOCIETY | WILEY

ORIGINAL ARTICLE

Epidemiology/Genetics

Relationship between community characteristics and impact of calorie labeling on fast-food purchases

Roxanne Dupuis[1] | Marie A. Bragg[1,2] | Lloyd Heng[1] | Emil Hafeez[1] | Erilia Wu[1] | Tod Mijanovich[3] | Beth C. Weitzman[4] | Pasquale E. Rummo[1] | Brian Elbel[1,5]

[1]Department of Population Health, New York University Grossman School of Medicine, New York, New York, USA

[2]Marketing Department, Stern School of Business, New York University, New York, New York, USA

[3]Department of Applied Statistics, Social Science, and Humanities, Steinhardt School of Culture, Education, and Human Development, New York University, New York, New York, USA

[4]Department of Nutrition and Food Studies, Steinhardt School of Culture, Education, and Human Development, New York University, New York, New York, USA

[5]Wagner Graduate School of Public Service, New York University, New York, New York, USA

Correspondence
Roxanne Dupuis, Department of Population Health, New York University Grossman School of Medicine, 180 Madison Ave., New York, NY 10016, USA.
Email: roxanne.dupuis@nyulangone.org

Funding information
National Heart, Lung, and Blood Institute, Grant/Award Number: 5R01HL147474

Abstract

Objective: The objective of this study was to evaluate potential sources of heterogeneity in the effect of calorie labeling on fast-food purchases among restaurants located in areas with different neighborhood characteristics.

Methods: In a quasi-experimental design, using transaction data from 2329 Taco Bell restaurants across the United States between 2008 and 2014, we estimated the relationships of census tract-level income, racial and ethnic composition, and urbanicity with the impacts of calorie labeling on calories purchased per transaction.

Results: Calorie labeling led to small, absolute reductions in calories purchased across all population subgroups, ranging between −9.3 calories (95% CI: −18.7 to 0.0) and −37.6 calories (95% CI: −41.6 to −33.7) 2 years after labeling implementation. We observed the largest difference in the effect of calorie labeling between restaurants located in rural compared with those located in high-density urban census tracts 2 years after implementation, with the effect of calorie labeling being three times larger in urban areas.

Conclusions: Fast-food calorie labeling led to small reductions in calories purchased across all population subgroups except for rural census tracts, with some subgroups experiencing a greater benefit.

INTRODUCTION

The proportion of household food dollars spent outside the home has been increasing for many years, surpassing food-at-home expenditures in 2010 [1]. Among food-away-from-home expenditures, the most dramatic increase has been for limited-service or fast-food restaurants [1], which, as of 2022, make up the largest proportion of food-away-from-home spending [2]. Fast foods are often ultraprocessed (i.e., "formulations made mostly or entirely from substances derived from foods and additives"; examples include sugar-sweetened beverages and French fries) [3] and are associated with increased consumption of calories, sugar, saturated fat, and sodium among both children and adults [3–5]. In order to promote healthy choices and nutrition literacy while eating out, the 2010 Patient Protection and Affordable Care Act (ACA) mandated calorie labeling for chain restaurants with 20 or more locations across the country [6]. Prior to national implementation in 2018, several local and state governments mandated calorie labeling in their jurisdictions [7].

To date, multiple studies have evaluated the effect of calorie labeling on customer knowledge, food purchasing behaviors, and

See Commentary, pg. 223.

Obesity A Research Journal THE OBESITY SOCIETY — WILEY

menu item reformulation, with mixed results [8]. Many of the early studies were conducted in laboratory settings, which do not capture the real-life experience of eating out or ordering takeout from a restaurant. Of those conducted in real-world settings, most lacked comparison sites or were limited to a single jurisdiction [8]. Recently, two quasi-experimental studies of calorie labeling in fast-food restaurants have been published. The first, using pre- and post-national implementation of calorie labeling transaction data and an interrupted time-series approach, found that calorie labeling led to a decrease of 73 calories per transaction [9]. The second, using pre- and post-local implementation of calorie labeling transaction data with comparison restaurants, found that calorie labeling led to a decrease of 25 calories per transaction, with some variation by location [10]. Although these more robust studies have indicated that calorie labeling, at least in the fast-food setting, does have some small impact on consumer behavior, it remains unclear whether all segments of the population benefit equally from this type of intervention. This has implications for how this policy and others like it are implemented, for understanding the mechanisms by which they impact health, and, ultimately, for health equity.

Much of the work in this area measures whether different sociodemographic groups report noticing and using calorie labels and consistently finds that people with higher income or more education notice and use labels more than those with lower income or less education in both full-service and fast-food restaurants [11–16]. Among studies that have examined differences in calories purchased, multiple systematic reviews and meta-analyses have found limited evidence for heterogeneity in the effect of calorie labeling by socioeconomic position or status [17–19]. However, more recent work has found that, when comparing purchases from the same fast-food franchises before and after national implementation of calorie labeling, there were greater reductions in calories purchased per transaction at restaurants located in higher- versus lower-income census tracts [9]. Similarly, a study of calorie labeling at Starbucks coffee shops found larger decreases in calories per transaction at restaurants located in higher- versus lower-income zip codes [20]. On the other hand, a study in King County, Washington, found no differences in calories purchased among respondents in low-income, diverse areas compared with other areas [21]. In terms of heterogeneity by race and ethnicity, one study found that Black and White, but not Hispanic, adolescents purchased fewer calories from McDonald's after the implementation of calorie labeling [22]. Another study found that the effect of calorie labeling on calories purchased per transaction at a large fast-food franchise in the southern United States was similar in areas differing by racial composition [23].

Our objective in this study was to evaluate potential sources of heterogeneity in the effect of calorie labeling on fast-food purchases among different sociodemographic groups using a quasi-experimental design and transaction data from 2329 Taco Bell restaurants between 2008 and 2014. We build upon previous work on variation in the effects of calorie labeling by community characteristics through our use of the largest dataset of fast-food transactions across six jurisdictions that enacted local calorie labeling ordinances prior to national implementation.

Study Importance

What is already known?

- Calorie labeling at large chain restaurants was mandated by the Patient Protection and Affordable Care Act in May 2018.
- Recent large-scale evaluations at fast-food chains have found that calorie labeling led to a small but significant decrease in calories purchased; it remains unclear whether all segments of the population benefit equally from this type of intervention.

What does this study add?

- Calorie labeling led to reductions in calories purchased across all segments of the population, ranging between −9 and −38 calories 2 years after labeling implementation.
- The largest differences in the effect of calorie labeling were found between restaurants located in rural compared with those located in urban areas 2 years after implementation, with the effect of calorie labeling being three times larger in urban areas.

How might these results change the direction of research?

- Calorie labeling at a large fast-food chain led to small, absolute reductions in calories purchased across all population subgroups.
- In order to have the highest impact on eating behaviors and health equity, calorie labeling should be combined with other policies.

METHODS

Data sources

We used restaurant-level transaction (i.e., receipt) data provided by Taco Bell for purchases made nationwide between 2008 and 2014. We identified 474 Taco Bell restaurants with complete transaction data that implemented calorie labeling prior to 2018 across six jurisdictions (i.e., "treated" restaurants). Additionally, we used data from 1855 restaurants with complete data and matched on multiple restaurant- and community-level characteristics (Table 1) in areas where calorie labeling was never implemented during

TABLE 1 Restaurant- and community-level characteristics of calorie labeling and comparison restaurants.

	Calorie labeling (treated) restaurants	Comparison restaurants
Restaurant-level characteristics: unique restaurants included in analyses, *n* (%)		
California (January 1, 2011, implementation, in-store only)	450 (94.9)	1512 (81.5)[a]
Suffolk County, New York (October 28, 2010, implementation)	16 (3.4)	519 (34.2)[a]
Schenectady County, New York (September 12, 2012, implementation)	1 (0.2)	100 (6.8)[a]
Montgomery County, Maryland (January 1, 2011, implementation)	3 (0.6)	216 (14.6)[a]
Vermont (May 18, 2008, implementation)	1 (0.2)	100 (7.6)[a]
King County, Washington (August 1, 2008, in-store implementation, December 31, 2008, drive-thru implementation)	3 (0.6)	410 (23.5)[a]
Community-level characteristics (weighted)		
Population count, *n* (SD)	5491 (2306)	5339 (1339)[b]
Asian population, % (SD)[c]	12 (12.7)	6.2 (5.9)[b]
Black population, % (SD)[c]	6.5 (9.3)	10.5 (8.2)[b]
Hispanic population, % (SD)[c]	36.4 (23.1)	22.4 (13.3)[b]
White population, % (SD)[c]	63.6 (19.1)	73.2 (11.6)[b]
Median household income, mean (SD)	63,006 (26149)	55,722 (15341)[b]

[a]Percent of eligible comparison restaurants that were used to create synthetic control units; comparison restaurant units can be used more than once (i.e., replacement).
[b]We used synthetic control methods to construct a comparison unit for each restaurant in the calorie labeling group.
[c]Categories of race and ethnicity are not mutually exclusive (e.g., the White population includes both individuals who identified as Hispanic and as non-Hispanic).

the period of 2008 to 2014. Using synthetic control methods [24, 25], from the pool of 1855 eligible control restaurants, we created a synthetic control for each "treated" restaurant, comprising a weighted average of data from multiple restaurants. Using a matched sample for the comparison group helps equalize potential observable differences among locations that implemented menu labeling and those that did not.

For a full description of data sources, how treated and comparison restaurants were selected, and how synthetic control units were created, see Rummo et al. [10]. This study did not involve any human participants.

Primary outcome

Using both automated and manual matching methods to match menu items with the MenuStat nutritional database [26], we assigned caloric information to over 95% of all food and beverage purchases each quarter ($n = 3517$ unique menu items) [10]. We excluded in-store fountain beverages given that these are self-serve, and we could not assign calorie content to specific drink types. The primary outcome for this study is the change in mean calories per transaction in the first and second years after calorie labeling implementation. We used both time periods because we hypothesized, based on results from prior work [9, 22, 27], that the initial effect of calorie labeling would wane over time. We excluded data from the 2 months before and after calorie labeling implementation to account for variation in labeling implementation and customer awareness of the change.

Community characteristics

We investigated three different sources of heterogeneity, all measured at the census tract level of the restaurant locations. Although individuals may purchase fast food outside of their census tract, given that our data are only available at the restaurant level (i.e., Taco Bell did not provide patron demographic information), we were limited to this level of analysis. The three hypothesized sources of heterogeneity were as follows: 1) census tract-level median household income, operationalized as quartiles of income; 2) census tract-level population race and ethnicity, operationalized as quartiles of percent race and ethnicity for each of four race and ethnicity groups separately (i.e., Asian, Black, Hispanic, and White; the percentage of individuals identifying as each race and ethnicity group increases from Quartile 1 to Quartile 4); and 3) census tract-level urbanicity, operationalized into four categories of population density along the rural–urban continuum (i.e., rural, suburban/small town, lower-density urban, and higher-density urban) [28]. We used these categories instead of rural–urban community area codes because they offered more granularity.

Statistical analyses

In order to assess how different sources of heterogeneity at the community level moderated the effect of calorie labeling on calories purchased per transaction, we developed a matched comparison group using synthetic control methods and estimated ordinary least-squares models with both restaurant-level and 12 calendar month fixed effects to control for time-invariant confounding and seasonality, as well as a count of months relative to implementation at each location [10]. We included a triple difference term to parameterize the difference in the effect of calorie labeling at different quartiles of each of the three hypothesized sources of heterogeneity. The coefficient on the triple difference (DDD) is interpreted as the difference between difference-in-difference estimates of the effect of calorie labeling on calories purchased per transaction for pairs of quartiles representing community subgroups as described earlier (see online Supporting Information for regression equation). For reference, the original difference-in-difference estimates published by Rummo et al. were 21.9 (95% confidence interval [CI]: 20.9–22.9) fewer calories per transaction in the first year after implementation and 25.0 (95% CI: 24.0–26.1) fewer calories per transaction in the second year after implementation [10].

Each source of heterogeneity was modeled separately. We assigned the treated restaurant's community characteristic quartile to its synthetic control (Figures S1–S3). Standard errors were estimated using the delta method with the marginaleffects package in R [29]. All analyses were conducted using R version 4.1.2.

RESULTS

We included 474 Taco Bell restaurants that implemented calorie labeling prior to 2018 across six jurisdictions, the majority of which (94.3%) were in California (Table 1). Census tracts where these restaurants were located had a predominantly White population and a median annual household income of $63,006. Comparison restaurants had similar characteristics. Calorie labeling led to decreases in calories purchased per transaction across all quartiles of census tract-level median household income, population race and ethnicity, and community urbanicity, with the smallest absolute effect observed in rural census tracts (−9.3 calories [95% CI: −18.7 to 0.0], the only absolute effect with a confidence interval overlapping 0) and the largest absolute effect observed in census tracts in the first quartile of percent White individuals (−37.6 calories [95% CI: −41.6 to −33.7]) 2 years after implementation.

One year after implementation, the impact of calorie labeling among restaurants in the highest-income quartile (−12.6 calories per transaction [95% CI: −16.6 to −8.7]) was 9.5 calories less (95% CI: 3.9 to 15.1, i.e., a smaller reduction) than the impact observed in the lowest-income quartile (−22.1 calories [95% CI: −26.1 to −18.2]). This difference, however, was attenuated 2 years after calorie labeling implementation (5.4 calories [95% CI: −0.2 to 10.9]) (Table 2).

We observed small differences in the effect of calorie labeling by quartile of percent race and ethnicity 1 and 2 years after implementation (Table 3). For White individuals, the largest racial group, the impact of calorie labeling among restaurants in Quartile 4 (−22.9 calories [95% CI: −26.8 to −19.0]) was 7.8 calories greater (95% CI: −13.4 to −2.2, i.e., a larger reduction) than the impact observed in Quartile 1 (−15.1 calories [95% CI: −19.1 to −11.2]) of percent White individuals 1 year after implementation. Two years after implementation, the difference between these quartiles was 11.8 calories (95% CI: 6.3 to 17.4), reflecting a larger absolute effect of calorie labeling among restaurants in census tracts with the smallest proportion of White individuals (−37.6 calories [95% CI: −41.6 to −33.7]).

One year after implementation, the impact of calorie labeling among restaurants in higher-density urban census tracts (−18.2 calories [95% CI: −21.5 to −14.8]) was not significantly different (−3.5 calories [95% CI: −13.8 to 6.8]) than the impact observed in rural census tracts (−14.7 calories [95% CI: −24.4 to −4.9]) (Table 4). Two years after implementation, however, we observed the largest differences in the effect of calorie labeling between restaurants in both lower- and higher-density urban census tracts (−21.7 calories [95% CI: −31.5 to −11.9] and −24.7 calories [95% CI: −34.7 to −14.8], respectively) compared with those in rural census tracts.

DISCUSSION

In this quasi-experimental study, we found mixed results for the impact of census tract-level sources of heterogeneity on the effect of calorie labeling on calories purchased at Taco Bell restaurants in the United States in the period of 2008 to 2014. We found the largest differences in the effect of calorie labeling between restaurants

TABLE 2 Effect of calorie labeling by census tract-level median household income quartile on calories purchased per transaction.[a]

	Year 1		Year 2	
Income category	**β (95% CI)[b]**	**DDD (95% CI)[c]**	**β (95% CI)[b]**	**DDD (95% CI)[c]**
Quartile 1	−22.1 (−26.1 to −18.2)	Ref.	−29.5 (−33.4 to −25.5)	Ref.
Quartile 2	−22.2 (−26.2 to −18.2)	−0.1 (−5.7 to 5.5)	−29.8 (−33.8 to −25.9)	−0.4 (−6.0 to 5.2)
Quartile 3	−19.8 (−23.7 to −15.9)	2.3 (−3.2 to 7.8)	−33.1 (−36.9 to −29.2)	−**3.6** (−9.1, 1.9)
Quartile 4	−12.6 (−16.6 to −8.7)	**9.5 (3.9 to 15.1)**	−24.1 (−28.0 to −20.2)	**5.4** (−0.2, 10.9)

Note: Bold values indicate a statistically significant difference ($p < 0.05$) between the category and the reference group.
[a]Using the primary analytic approach of synthetic control matching and weighting.
[b]Values can be interpreted as the absolute effect of calorie labeling on calories purchased per transaction associated with each census tract-level median household income quartile.
[c]Values can be interpreted as the triple difference estimate, representing the difference in the effect of calorie labeling on calories purchased per transaction between each census tract-level median household income quartile and the reference category.

TABLE 3 Effect of calorie labeling by census tract-level percent race and ethnicity quartile on calories purchased per transaction.[a]

	Year 1		Year 2	
Race and ethnicity category	β (95% CI)[b]	DDD (95% CI)[c]	β (95% CI)[b]	DDD (95% CI)[c]
Asian				
Quartile 1	−21.8 (−25.8 to −17.8)	Ref.	−21.1 (−25.1 to −17.2)	Ref.
Quartile 2	−23.0 (−27.0 to −19.1)	−1.2 (−6.8 to 4.4)	−34.0 (−37.9 to −30.1)	**−12.9 (−18.5 to −7.3)**
Quartile 3	−16.4 (−20.3 to −12.4)	**5.4** (−0.2 to 11.0)	−33.9 (−37.8 to −29.9)	**−12.7 (−18.3 to −7.1)**
Quartile 4	−15.8 (−19.7 to −11.8)	**6.1 (0.5 to 11.7)**	−27.7 (−31.6 to −23.8)	**−6.6 (−12.1 to −1.0)**
Black				
Quartile 1	−24.8 (−28.8 to −20.8)	Ref.	−29.2 (−33.1 to −25.2)	Ref.
Quartile 2	−22.5 (−26.4 to −18.6)	2.3 (−3.3 to 7.9)	−28.5 (−32.4 to −24.5)	0.7 (−4.8 to 6.3)
Quartile 3	−18.8 (−22.7 to −14.9)	**6.0 (0.4 to 11.6)**	−29.0 (−33.0 to −25.1)	0.2 (−5.4 to 5.7)
Quartile 4	−10.6 (−14.5 to −6.6)	**14.3 (8.6 to 19.9)**	−29.9 (−33.8 to −26.0)	−0.7 (−6.3 to 4.9)
Hispanic				
Quartile 1	−17.7 (−21.6 to −13.8)	Ref.	−24.3 (−28.2 to −20.5)	Ref.
Quartile 2	−16.7 (−20.7 to −12.8)	1.0 (−4.6 to 6.5)	−29.1 (−33.1 to −25.2)	**−4.8** (−10.3 to 0.7)
Quartile 3	−19.1 (−23.0 to −15.1)	−1.4 (−6.9 to 4.2)	−31.5 (−35.4 to −27.7)	**−7.2 (−12.7 to −1.7)**
Quartile 4	−23.3 (−27.2 to −19.3)	**−5.6** (−11.1 to 0.0)	−31.7 (−35.7 to −27.7)	**−7.3 (−12.9 to −1.8)**
White				
Quartile 1	−15.1 (−19.1 to −11.2)	Ref.	−37.6 (−41.6 to −33.7)	Ref.
Quartile 2	−18.5 (−22.4 to −14.5)	**−3.3** (−8.9 to 2.3)	−30.5 (−34.4 to −26.6)	**7.1 (1.5 to 12.7)**
Quartile 3	−19.9 (−23.8 to −15.9)	**−4.7** (−10.3 to 0.9)	−22.6 (−26.6 to −18.7)	**15.0 (9.4 to 20.6)**
Quartile 4	−22.9 (−26.8 to −19.0)	**−7.8 (−13.4 to −2.2)**	−25.8 (−29.7 to −21.9)	**11.8 (6.3 to 17.4)**

Note: Bold values indicate a statistically significant difference ($p < 0.05$) between the category and the reference group.
[a]Using the primary analytic approach of synthetic control matching and weighting.
[b]Values can be interpreted as the absolute effect of calorie labeling on calories purchased per transaction associated with each census tract-level percent race and ethnicity quartile. Percent race and ethnicity quartiles for each race and ethnicity category are not mutually exclusive.
[c]Values can be interpreted as the triple difference estimate, representing the difference in the effect of calorie labeling on calories purchased per transaction between each census tract-level percent race and ethnicity quartile and the reference category.

TABLE 4 Effect of calorie labeling by census tract-level community type on calories purchased per transaction.[a]

	Year 1		Year 2	
Community type	β (95% CI)[b]	DDD (95% CI)[c]	β (95% CI)[b]	DDD (95% CI)[c]
Rural	−14.7 (−24.4 to −4.9)	Ref.	−9.3 (−18.7 to 0.0)	Ref.
Suburban/small town	−16.1 (−21.8 to −10.4)	−1.5 (−12.8 to 9.8)	−15.8 (−21.5 to −10.1)	**−6.5** (−17.4 to 4.5)
Lower-density urban	−21.1 (−23.9 to −18.3)	**−6.5** (−16.6 to 3.7)	−31.0 (−33.8 to −28.2)	**−21.7 (−31.5 to −11.9)**
Higher-density urban	−18.2 (−21.5 to −14.8)	−3.5 (−13.8 to 6.8)	−34.0 (−37.4 to −30.7)	**−24.7 (−34.7 to −14.8)**

Note: Bold values indicate a statistically significant difference ($p < 0.05$) between the category and the reference group.
[a]Using the primary analytic approach of synthetic control matching and weighting.
[b]Values can be interpreted as the absolute effect of calorie labeling on calories purchased per transaction associated with each census tract-level community type.
[c]Values can be interpreted as the triple difference estimate, representing the difference in the effect of calorie labeling on calories purchased per transaction between each census tract-level community type quartile and the reference category.

located in rural compared with urban census tracts. The overall effect of calorie labeling on calories purchased 2 years after implementation found by Rummo et al. was 25 fewer calories per transaction [10]. We found that the absolute effect of calorie labeling 2 years after implementation was 9.3 fewer calories in rural census tracts compared with 31.0 and 34.0 fewer calories in low-density urban and high-density urban areas, respectively; the effect of calorie labeling was three times larger in urban compared with rural census tracts. We found smaller differences in the effect of calorie labeling by census tract-level median household income quartiles and percent race and ethnicity quartiles, with differences in both the directionality and timing of the effects. Overall, except for differences by census tract income level and by percent race and ethnicity quartiles for Black individuals, differences among groups were stronger 2 years versus 1 year after implementation.

Our study adds to the literature on the impact of calorie labeling on calorie purchases prior to national implementation. A systematic review and meta-analysis by Long et al. of controlled studies evaluating the effect of calorie labeling on calories purchased, including five studies in fast-food restaurants or coffee shops and one study in a full-service restaurant, found a 7.63-calorie reduction (95% CI: −21.02 to 5.76) [30]. Another systematic review and meta-analysis of seven studies conducted in real-world settings, including worksite cafeterias and fast-food and full-service restaurants, during this time period found a 77.8-calorie reduction (95% CI: −121.6 to −34.1), with no strong evidence of heterogeneity in the effect by ethnicity or socioeconomic status [31]. A third systematic review and meta-analysis of studies conducted prior to national implementation of calorie labeling found that, across five quasi-experimental studies in fast-food restaurants, only one found a statistically significant reduction in calories purchased, with greater reductions in higher-education and higher-income areas [32]. Finally, a randomized field experiment of calorie labeling in two full-service restaurants conducted between 2015 and 2017 found that, when controlling for patron demographics and server, calorie labeling led to a 44.9-calorie reduction ($p < 0.10$), with no strong evidence of heterogeneity by race or education level [33]. By comparison, we found that the effect of calorie labeling at a large fast-food chain led to reductions in calories purchased that ranged between −9.3 and −37.6 calories, with some evidence of heterogeneity by income, race and ethnicity, and urbanicity.

Although the magnitude of differences in the effect of calorie labeling by each potential source of heterogeneity varied, even some relatively small differences, both overall and among groups, can have a large impact on health outcomes and health equity at the population level [34]. A study using 2003 to 2014 National Health and Nutrition Examination Survey (NHANES) data of the effect of calorie labeling on calorie consumption prior to national implementation found a 21-calorie reduction on daily intake in adults and a 34-calorie reduction in children living in an area where calorie labeling was implemented compared with those living in areas without mandatory calorie labeling [35]. Another study using 2004 to 2012 Behavioral Risk Factor Surveillance System data found a 1.5% reduction in body mass index among individuals living in New York counties where calorie labeling was implemented compared with those living in the New York/New Jersey/Pennsylvania metropolitan-area counties without calorie labeling, with a stronger effect among individuals with lower compared with higher income [36]. A cost-effectiveness analysis of calorie labeling in fast-food and full-service restaurants over the period of 2015 to 2025, using the estimate for the effectiveness of calorie labeling on calories purchased from the systematic review and meta-analysis by Long et al. that was mentioned earlier (−7.63 calories) [30], found that the policy was projected to prevent 41,015 cases of childhood obesity in 2025 (95% uncertainty interval: −41,324 to 122,396) [37].

There are several potential explanations for our findings. First, the literature is already mixed as to whether the effect of calorie labeling differs by income, measured at either the individual or restaurant levels. However, results from more recent quasi-experimental calorie labeling studies have found a stronger effect of calorie labeling among restaurants located in higher-income census tracts [9, 23]. Although we found small differences 1 year after implementation between restaurants located in the highest-income quartile compared with those located in the lowest-income quartile, the effect of calorie labeling was strongest among restaurants in the lowest-income quartile. Potential explanations for these conflicting results include differences in the types of restaurants studied, study timelines, and restaurant customer bases. In the long term, however, potential income-based differences in the effect of calorie labeling on health outcomes may be augmented or mitigated by differences in baseline weight; evidence has suggested that individuals with lower income have a higher prevalence of obesity [38] and that dietary changes have a larger impact on individuals with higher weight [39], which is something that we could not explore in the current study.

We observed small differences in both the directionality and timing by census tract-level percent race and ethnicity quartiles. The underlying cause of these differences, however, is less clear. One possible explanation has less to do with who eats fast food and more to do with where restaurants are located within communities. For example, a geospatial analysis of the continental United States found greater fast-food access among census block groups with a higher percentage of Black residents [40]. This suggests that individuals residing in predominantly minority census tracts may have greater exposure to calorie labels if they eat at multiple chain restaurants in those tracts, which may lead to bigger changes in purchases. Similarly, a study of the predicted impact of the national calorie labeling mandate in New Jersey found that, compared with restaurants in predominantly non-Hispanic White census tracts, those in predominantly non-Hispanic Black and mixed race and ethnicity census tracts had higher odds of being required to post calorie labels, meaning that more chain restaurants with 20 or more establishments are located in predominantly minority census tracts [41]. This could help explain, for example, why we observed a smaller reduction in calories purchased per transaction 2 years after implementation in census tracts with a higher percentage of White individuals (Quartiles 2 and 4) compared with census tracts with a lower percentage of White individuals (Quartile 1).

Finally, similar to the findings by race and ethnicity, the differences that we observed in the effect of calorie labeling 2 years after implementation by census tract-level urbanicity may be explained by where fast-food restaurant chains are located and are consistent with the literature on fast-food access by population density. For example, a study looking at fast-food access by neighborhood type found that rural zip codes had 0.14 times the number of fast-food restaurants compared with urban zip codes [42], whereas another study found that the distance to the nearest fast-food restaurant was shorter in townships with higher population density compared with lower population density [43]. Relatedly, a study using 2013 to 2018 NHANES data found that, as urbanization level increases, the share of energy intake from quickservice (including fast-food) restaurants increases [44], suggesting that individuals residing in more densely populated areas may have greater exposure to calorie labels if the share of calories that they obtain from fast food is greater, potentially leading to bigger changes in purchases. Taken together, these findings may indicate the need for a more comprehensive approach to calorie labeling in rural areas, such as by pairing labeling with educational campaigns.

Despite our strong study design using data from restaurants that implemented calorie labeling and comparison restaurants, a few limitations should be noted. All data are at the restaurant level, both for the primary outcome (calories per transaction) and for community characteristics associated with a differential effect of calorie labeling (measured at the restaurant census tract level). Given that we do not have data on who made individual purchases, including sociodemographic characteristics, caution should be used in making inferences regarding individual behavior from restaurant-level data, which could lead to an ecological fallacy. There is evidence, for example, suggesting that individuals make most of their food purchases at establishments outside of their census tract [45]. Matching was performed using continuous measures of each community characteristic and resulted in some covariate imbalance (Figures S1–S3). The matching approach may also be biased if there are large, unobserved differences between treated and control restaurants [10, 25]. For estimates by race and ethnicity, we did not simultaneously control for changes in other racial and ethnic groups; therefore, it is possible that effect heterogeneity associated with a given racial category could, in fact, be due to changes in other racial categories. Additionally, race and ethnicity categories are not mutually exclusive (e.g., the percent of White individuals in a census tract includes both Hispanic and non-Hispanic White individuals). We used data from Taco Bell restaurants, and most of the results are driven by changes seen in California; findings may not be generalizable to other regions or restaurants [10]. The results by urbanicity should be interpreted with caution given the small number of restaurants located in rural census tracts in our sample. Relatedly, we were only able to measure changes in what was ordered, but not changes in food consumption.

CONCLUSION

Overall, our findings suggest that calorie labeling at large fast-food chains leads to reductions in calories purchased across all segments of the population except for rural census tracts, but that some sociodemographic groups or areas may more greatly benefit from this policy than others. Our results provide support for the implementation of calorie labeling across chain restaurants. However, this policy should be combined with other multilevel and multisectoral interventions to eliminate disparities in diet and diet-related conditions.O

AUTHOR CONTRIBUTIONS

Brian Elbel had full access to the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. Concept and design: Pasquale E. Rummo, Marie A. Bragg, and Brian Elbel. Acquisition, analysis, or interpretation of data: All authors. Drafting of the manuscript: Roxanne Dupuis. Critical review of the manuscript for important intellectual content: All authors. Statistical analysis: Tod Mijanovich, Erilia Wu, Lloyd Heng, Emil Hafeez, and Brian Elbel. Obtained funding: Marie A. Bragg and Brian Elbel. Administrative, technical, or material support: Erilia Wu, Lloyd Heng, Emil Hafeez, Beth C. Weitzman, and Brian Elbel. Supervision: Marie A. Bragg and Brian Elbel.

FUNDING INFORMATION

This work was supported by the National Heart, Lung, and Blood Institute of the National Institutes of Health (grant 5R01HL147474). The National Heart, Lung, and Blood Institute had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication. Taco Bell did not sponsor the study or have any role in the design or conduct of the study or in the conclusions drawn.

CONFLICT OF INTEREST STATEMENT

The authors declared no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data are not available because they are proprietary.

ORCID

Roxanne Dupuis https://orcid.org/0000-0003-3161-6310
Pasquale E. Rummo https://orcid.org/0000-0002-9285-5430

REFERENCES

1. Saksena MJ, Okrent AM, Anekwe TD, et al. America's eating habits: food away from home. Economic Information Bulletin, no. 196. Economic Research Service; 2018.
2. USDA Economic Research Service. Food expenditures by outlet. Updated October 3, 2024. Accessed November 16, 2023. https://www.ers.usda.gov/data-products/food-expenditure-series/interactive-charts-food-expenditures/#outlet
3. Monteiro CA, Cannon G, Moubarac JC, Levy RB, Louzada MLC, Jaime PC. The UN decade of nutrition, the NOVA food classification and the trouble with ultra-processing. *Public Health Nutr*. 2018;21(1): 5-17. doi:10.1017/S1368980017000234
4. Nguyen BT, Powell LM. The impact of restaurant consumption among US adults: effects on energy and nutrient intakes. *Public Health Nutr*. 2014;17(11):2445-2452. doi:10.1017/s1368980014001153
5. Powell LM, Nguyen BT. Fast-food and full-service restaurant consumption among children and adolescents: effect on energy, beverage, and nutrient intake. *JAMA Pediatr*. 2013;167(1):14-20. doi:10.1001/jamapediatrics.2013.417
6. Food and Drug Administration. Food labeling; nutrition labeling of standard menu items in restaurants and similar retail food establishments. Final rule. *Fed Regist*. 2014;79(230):71155-71259.
7. Center for Science in the Public Interest. Menu labeling timeline: an infographic. Accessed November 16, 2023. https://www.cspinet.org/resource/menu-labeling-timeline
8. Bleich SN, Economos CD, Spiker ML, et al. A systematic review of calorie labeling and modified calorie labeling interventions: impact on consumer and restaurant behavior. *Obesity (Silver Spring)*. 2017; 25(12):2018-2044. doi:10.1002/oby.21940
9. Petimar J, Zhang F, Rimm EB, et al. Changes in the calorie and nutrient content of purchased fast food meals after calorie menu labeling: a natural experiment. *PLoS Med*. 2021;18(7):e1003714. doi:10.1371/journal.pmed.1003714

10. Rummo PE, Manjovich T, Wu E, et al. Menu labeling and calories purchased in restaurants in a US national fast food chain. *JAMA Netw Open*. 2023;6(12):e2346851. doi:10.1001/jamanetworkopen.2023.46851
11. Green JE, Brown AG, Ohri-Vachaspati P. Sociodemographic disparities among fast-food restaurant customers who notice and use calorie menu labels. *J Acad Nutr Diet*. 2015;115(7):1093-1101. doi:10.1016/j.jand.2014.12.004
12. Breck A, Cantor J, Martinez O, Elbel B. Who reports noticing and using calorie information posted on fast food restaurant menus? *Appetite*. 2014;81:30-36. doi:10.1016/j.appet.2014.05.027
13. Feng W, Fox A. Menu labels, for better, and worse? Exploring socioeconomic and race-ethnic differences in menu label use in a national sample. *Appetite*. 2018;128:223-232. doi:10.1016/j.appet.2018.06.015
14. Restrepo BJ, Minor T, Peckham J. The association between restaurant menu label use and caloric intake. Economic Research Report, no. 259. Economic Research Service; 2018.
15. Lee-Kwan SH, Pan L, Maynard LM, McGuire LC, Park S. Factors associated with self-reported menu-labeling usage among US adults. *J Acad Nutr Diet*. 2016;116(7):1127-1135. doi:10.1016/j.jand.2015.12.015
16. Neff Warner LR, Ruderman SA, Zinsli KA, Jones-Smith JC, Littman AJ. Menu labeling utilization and socioeconomic status in West Virginia and Mississippi. *J Nutr Educ Behav*. 2022;54(2):172-180. doi:10.1016/j.jneb.2021.11.005
17. Sarink D, Peeters A, Freak-Poli R, et al. The impact of menu energy labelling across socioeconomic groups: a systematic review. *Appetite*. 2016;99:59-75. doi:10.1016/j.appet.2015.12.022
18. Shangguan S, Afshin A, Shulkin M, et al. A meta-analysis of food labeling effects on consumer diet behaviors and industry practices. *Am J Prev Med*. 2019;56(2):300-314. doi:10.1016/j.amepre.2018.09.024
19. Robinson E, Polden M, Langfield T, et al. Socioeconomic position and the effect of energy labelling on consumer behaviour: a systematic review and meta-analysis. *Int J Behav Nutr Phys Act*. 2023;20(1):10. doi:10.1186/s12966-023-01418-0
20. Bollinger B, Leslie P, Sorensen A. Calorie posting in chain restaurants. *Am Econ J Econ Policy*. 2011;3(1):91-128. doi:10.1257/pol.3.1.91
21. Krieger JW, Chan NL, Saelens BE, Ta ML, Solet D, Fleming DW. Menu labeling regulations and calories purchased at chain restaurants. *Am J Prev Med*. 2013;44(6):595-604. doi:10.1016/j.amepre.2013.01.031
22. Petimar J, Ramirez M, Rifas-Shiman SL, et al. Evaluation of the impact of calorie labeling on McDonald's restaurant menus: a natural experiment. *Int J Behav Nutr Phys Act*. 2019;16(1):99. doi:10.1186/s12966-019-0865-7
23. Petimar J, Zhang F, Cleveland LP, et al. Estimating the effect of calorie menu labeling on calories purchased in a large restaurant franchise in the southern United States: quasi-experimental study. *BMJ*. 2019;367:l5837. doi:10.1136/bmj.l5837
24. Abadie A, Diamond A, Hainmueller J. Synthetic control methods for comparative case studies: estimating the effect of California's tobacco control program. *J Am Stat Assoc*. 2010;105:493-505.
25. Abadie A. Using synthetic controls: feasibility, data requirements, and methodological aspects. *J Econ Lit*. 2021;59:391-425.
26. MenuStat interactive restaurant nutrition database. https://www.menustat.org/
27. Cantor J, Torres A, Abrams C, Elbel B. Five years later: awareness of New York City's calorie labels declined, with no changes in calories purchased. *Health Aff (Millwood)*. 2015;34(11):1893-1900. doi:10.1377/hlthaff.2015.0623
28. Thorpe LE, Adhikari S, Lopez P, et al. Neighborhood socioeconomic environment and risk of type 2 diabetes: associations and mediation through food environment pathways in three independent study samples. *Diabetes Care*. 2022;45(4):798-810. doi:10.2337/dc21-1693
29. Arel Bundock A, Greifer N, Heiss A. How to interpret statistical models using marginaleffects for R and Python. *J Stat Softw*. 2024;111(9). doi:10.18637/jss.v111.i09
30. Long MW, Tobias DK, Cradock AL, Batchelder H, Gortmaker SL. Systematic review and meta-analysis of the impact of restaurant menu calorie labeling. *Am J Public Health*. 2015;105(5):e11-e24. doi:10.2105/ajph.2015.302570
31. Littlewood JA, Lourenço S, Iversen CL, Hansen GL. Menu labelling is effective in reducing energy ordered and consumed: a systematic review and meta-analysis of recent studies. *Public Health Nutr*. 2016;19(12):2106-2121. doi:10.1017/S1368980015003468
32. Sinclair SE, Cooper M, Mansfield ED. The influence of menu labeling on calories selected or consumed: a systematic review and meta-analysis. *J Acad Nutr Diet*. 2014;114(9):1375-1388. doi:10.1016/j.jand.2014.05.014
33. Cawley J, Susskind A, Willage B. The impact of information disclosure on consumer behavior: evidence from a randomized field experiment of calorie labels on restaurant menus. *J Policy Anal Manage*. 2020;39(4):1020-1042. doi:10.1002/pam.22219
34. Dupuis R, Block JP, Barrett JL, et al. Cost effectiveness of calorie labeling at large fast-food chains across the U.S. *Am J Prev Med*. 2024;66(1):128-137. doi:10.1016/j.amepre.2023.08.012
35. Todd JE, Mancino L, Restrepo BJ, Kavanaugh C, Dicken C, Breneman V. Food away from home and caloric intake: the role of restaurant menu labeling laws. *Econ Inq*. 2021;59(1):53-71. doi:10.1111/ecin.12923
36. Restrepo BJ. Calorie labeling in chain restaurants and body weight: evidence from New York. *Health Econ*. 2017;26(10):1191-1209. doi:10.1002/hec.3389
37. Gortmaker SL, Wang YC, Long MW, et al. Three interventions that reduce childhood obesity are projected to save more than they cost to implement. *Health Aff (Millwood)*. 2015;34(11):1932-1939. doi:10.1377/hlthaff.2015.0631
38. Ogden CL, Fakhouri TH, Carroll MD, et al. Prevalence of obesity among adults, by household income and education — United States, 2011–2014. *MMWR Morb Mortal Wkly Rep*. 2017;66(50):1369-1373. doi:10.15585/mmwr.mm6650a1
39. Katan MB, de Ruyter JC, Kuijper LD, Chow CC, Hall KD, Olthof MR. Impact of masked replacement of sugar-sweetened with sugar-free beverages on body weight increases with initial BMI: secondary analysis of data from an 18 month double-blind trial in children. *PLoS One*. 2016;11(7):e0159771. doi:10.1371/journal.pone.0159771
40. James P, Arcaya MC, Parker DM, Tucker-Seeley RD, Subramanian SV. Do minority and poor neighborhoods have higher access to fast-food restaurants in the United States? *Health Place*. 2014;29:10-17. doi:10.1016/j.healthplace.2014.04.011
41. Gruner J, DeWeese RS, Lorts C, Yedidia MJ, Ohri-Vachaspati P. Predicted impact of the Food and Drug Administration's menu-labeling regulations on restaurants in 4 New Jersey cities. *Am J Public Health*. 2018;108(2):234-240. doi:10.2105/ajph.2017.304162
42. Powell LM, Chaloupka FJ, Bao Y. The availability of fast-food and full-service restaurants in the United States. *Am J Prev Med*. 2007;33(4):S240-S245. doi:10.1016/j.amepre.2007.07.005
43. Liu GC, Wilson JS, Qi R, Ying J. Green neighborhoods, food retail and childhood overweight: differences by population density. *Am J Health Promot*. 2007;21(4 suppl):317-325. doi:10.4278/0890-1171-21.4s.317
44. Ansai N, Wambogo EA, Herrick KA, et al. Dietary contributions of food outlets by urbanization level in the US population aged 2 years and older—NHANES 2013–2018. *Am J Clin Nutr*. 2023;117(5):946-954. doi:10.1016/j.ajcnut.2023.02.014

45. Liu JL, Han B, Cohen DA. Beyond neighborhood food environments: distance traveled to food establishments in 5 US cities, 2009–2011. *Prev Chronic Dis*. 2015;12:150065. doi:10.5888/pcd12.150065

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Dupuis R, Bragg MA, Heng L, et al. Relationship between community characteristics and impact of calorie labeling on fast-food purchases. *Obesity (Silver Spring)*. 2025;33(2):356-364. doi:10.1002/oby.24198