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THE IMPACT OF INFORMATION DISCLOSURE ON CONSUMER BEHAVIOR: EVIDENCE FROM A RANDOMIZED FIELD EXPERIMENT OF CALORIE LABELS ON RESTAURANT MENUS

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The Impact of Information Disclosure on Consumer Behavior: Evidence from a Randomized Field Experiment of Calorie Labels on Restaurant Menus
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ABSTRACT

The impact of information on consumer behavior is a classic topic in economics, and there has recently been particular interest in whether providing nutritional information leads consumers to choose healthier diets. For example, a nationwide requirement of calorie counts on the menus of chain restaurants took effect in the U.S. in May, 2018, and the results of such information disclosure are not well known.

To estimate the impact of menu labeling, we conducted a randomized controlled field experiment in two full-service restaurants, in which the control group received the usual menus and the treatment group received the same menus but with calorie counts. We estimate that the labels resulted in a 3.0% reduction in calories ordered, with the reduction occurring in appetizers and entrees but not drinks or desserts. Exposure to the information also increases consumers' support for requiring calorie labels by 9.6%. These results are informative about the impact of the new nationwide menu label requirement, and more generally contribute to the literature on the impact of information disclosure on consumer behavior.

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Introduction

Economics has long been concerned with how consumers respond to information. Classic studies on the economics of information include, e.g. how imperfect information about prices is addressed through consumer search and producer advertising (Stigler, 1961); how imperfect information in health care markets can lead to adverse selection and moral hazard (Arrow, 1963; Pauly, 1968); how imperfect information about product quality can result in bad-quality items driving good-quality ones out of the market (Akerlof, 1970), and how imperfect information about workers can be addressed through signaling by workers and screening by employers (Spence, 1973). The topic of how information affects consumer choice remains an important and active research area; more recent studies have examined consumer responses to report cards for cardiac surgeons (Dranove et al., 2003), rankings of "America's Best Hospitals" (Pope, 2009), report cards of school quality (Figlio and Lucas, 2004), information about HIV risk (Dupas, 2011), restaurant hygiene reports (Jin and Leslie, 2004) and the Nutrition Facts panel on packaged foods (Variyam, 2008; Mathios, 2000). We contribute to this literature by testing how consumers' dietary choices respond to calorie information on restaurant menus.

Calls for restaurants to disclose the calorie content of menu items are motivated in part by a desire to improve Americans' diets. The U.S. has high rates of diet-related chronic disease; for example, among U.S. adults, 35% have cardiovascular disease, 29% have hypertension, 16% have high cholesterol, and 12% have diabetes (USDA, 2015). In addition, the prevalence of adult obesity in the U.S. has nearly tripled in the past fifty years, rising from 13.4% in 1960-62 to 39.6% in 2015-16 (Fryar et al., 2016; Hales et al., 2017).

There are many likely contributors to obesity (Cawley, 2015), but one possible factor is increased consumption of "food away from home," which includes restaurant food; Americans now spend 43.1% of their food dollars and consume a third of their total calories away from home (Guthrie et al., 2013; USDA, 2017a). This is of potential concern because consumers are less well informed about the content of restaurant food than of food that they prepare at home; they tend to underestimate the number of calories in restaurant food (e.g. Block et al., 2013; Elbel, 2011) and meals consumed away from home are associated with higher intake of calories (An, 2016).

Requiring restaurants to disclose the calorie content of their food is seen as a way of allowing consumers to make more informed choices about their diet (IOM 2005, 2012). Menu label laws have been passed by cities such as New York City and Philadelphia, by counties such as King County, Washington (home to Seattle); and by states such as California, Massachusetts, and Oregon. The Patient Protection and Affordable Care Act of 2010 (ACA) included a nationwide law requiring calorie labels on restaurant menus, which took effect in May, 2018.[3]

Past studies have examined the impact of local menu label laws on consumer behavior. Elbel et al. (2009) studied the impact of the New York City (NYC) menu label law using street intercept surveys. They collected receipts from patrons of fast food outlets in low-income neighborhoods of NYC (the treatment city) and Newark, NJ (the control city), both before and after the implementation of the NYC menu label law. Estimates of their difference-in-difference models indicate no detectable change in calories purchased, both shortly after passage of the law (Elbel et al., 2009) and five years later (Cantor et al., 2015).

[3] The law covers a broad range of food retailers, which includes not just restaurants but also supermarkets, convenience stores, bakeries, coffee shops, ice cream stores, movie theaters, bowling alleys, and sports arenas. Food retailers that are exempt are schools, hospitals, trains, airplanes, food trucks, and mobile (as opposed to fixed-location) stadium vendors. The law applies only to chains of 20 or more locations doing business under the same name with substantially the same menu items at each location. For covered retailers, a subset of foods are exempt: daily specials, items only temporarily on the menu (less than 60 days per year), items being market-tested, custom orders, and condiments. For the final regulations, see US DHHS (2014).

Bollinger et al. (2011) study the NYC menu label law using the Starbucks database of transactions. Comparing NYC to the control cities of Boston and Philadelphia, both before and after implementation of the NYC menu label law, their difference-in-differences models indicate that the average number of calories ordered fell by 14.4 (5.8%) due to the law. All of that change was concentrated in food orders; there was no detectable change in calories from beverages.

Finkelstein et al. (2011) studied the menu label law of King County, Washington and used adjacent counties as controls. Using data from a single fast food chain, they compare sales before and after the menu label requirement. Based on results of a difference-in-differences model, they are unable to reject the null hypothesis of no effect of the menu labels on calories ordered. Other research, examining the effect of providing calorie information through means other than menu label laws, has found mixed results, with some finding evidence of reductions in calories ordered but others finding no detectable impact (Bleich et al., 2017; Crockett et al., 2018; Bedard and Kuhn, 2015; Wisdom et al., 2010).[4]

Our contributions to the literature are the following. First, we conduct a randomized controlled field experiment in two restaurants. Second, we have unusually rich data, with information on individual-level food orders, notes from the server that indicate when items were shared between patrons, detailed information on the restaurant experience that allow us to control for fixed effects for server, table, and even seat, plus survey data of the patrons. Third, we

[4] Bedard and Kuhn (2015) conduct an experiment in which 1 out of 39 locations of a single hamburger chain provided calorie and nutrient information on the receipt, as well as recommendations for healthy substitutions, *after* the patron had already ordered (thus it could not affect the order on that visit but could on future visits). They could not reject the null hypothesis of no impact on calories ordered, but found that the treatment store experienced reductions in cholesterol ordered and changes in item orders consistent with the substitution recommendations. Wisdom et al. (2010) intercepted subjects outside of a fast food restaurant and offered them a free lunch, which they chose from a menu that either had calorie information or did not. Receiving the menu with calorie information was associated with a 60-calorie reduction in the lunch ordered.

estimate the impact of menu labeling in full-service, sit-down restaurants, a type of establishment for which we have relatively little information about the effects of menu labels. Fourth, we have a relatively large sample size (N=5,551) which gives us the statistical power to detect plausible effect sizes.

Our estimates indicate that the calorie information results in a reduction in calories ordered of 44.9 or 3.0%. This reduction is concentrated in appetizers and entrees, with no detectable impact on calories ordered in drinks or desserts. Moreover, we find that the treatment raises patrons' support of calorie labels by 9.6%.

Methods and Data

We conducted a randomized field experiment of calorie labels on menus at two sit-down, full-service restaurants. The advantage of having data from more than one restaurant is that it is less likely that results will reflect idiosyncratic features of that restaurant or its clientele; we did not collect data from more than two restaurants because of the fixed costs of securing cooperation and working with additional sets of management and servers. Both restaurants at which we conducted the experiment are located on a university campus. Restaurant A is located in a hotel, has 38 tables, serves all meals (although we conducted the experiment only during dinner), and is open 7 days a week. Restaurant B is operated by the university's School of Hotel Administration to train students, but it is open to the public and students who choose to eat there must pay cash (i.e. cannot use their meal plan). It has 16 tables and serves dinner only, and is open Monday through Friday in the Fall semester and Monday through Thursday in the Spring semester.[5]

[5] The dates of the experiment were May 12, 2016 to September 30, 2017 in Restaurant A and November 9, 2015 to April 28, 2016 in Restaurant B.

Randomization occurred at the level of party (i.e., the table); it was undesirable to randomize at the level of individual guest because parties may discuss the menu while at the table. Upon checking in with the maître d', the entire party was randomized to either the treatment or control group using a smartphone app. The control group received the usual set of menus, and the treatment group received identical menus with the addition of calorie labels.

The calorie counts were calculated using the software MenuCalc, which uses the USDA's nutritional database of 18,000 ingredients and takes into account the loss of nutrients due to cooking methods. One enters the recipe into MenuCalc, indicates the number of servings produced, and MenuCalc calculates the calories and nutrients per serving. MenuCalc was also the source for the calories in the cocktails; the calories for other beverages (e.g. wine, beer, and soda) were taken from manufacturer labels or websites.

Consumers' responses to calorie information may well depend upon the range of options on the menu. If by chance all of the items had the same number of calories, there may not be much consumer response to the treatment (assuming that consumers equally underestimated the calories in each item). The menu items during the time of this study were chosen solely by the restaurants; the researchers played no role in selecting what would be offered. Thus, the menus were not artificially generated by the study but are the real-world set of options from the field. Both restaurants periodically changed their menus; the treatment menu was always updated with accurate calorie information.

As it turned out, there was a wide range of calories on the menu. For example, on the first menu at Restaurant B the number of calories in the appetizers ranged from 200 to 910; the entrees ranged from 580 to 1,840 calories; and the desserts ranged from 420 to 1,150 calories. Even among drinks, calories in beer ranged from 140 to 194, in wine ranged from 100 to 150, and in cocktails ranged from 200 to 370. The wide range of calories suggests that there was an opportunity for consumers to use this information to guide their dietary choices.

Data on orders placed by each individual guest were recorded by the server on the "ticket". The servers also noted which food and beverages were ordered to be split by certain guests or shared by the entire table (the calories for these items were assumed to be divided equally between all indicated patrons who shared). At the conclusion of the meal, a researcher or research assistant approached the table and asked each individual to complete a survey. Afterwards, each ticket was stapled to the relevant survey, and later the data was entered electronically. These data on orders and survey responses were then merged with data on item calories and nutrients and other variables. The experiment was approved by the Cornell IRB, protocol ID # 1509005830.

Our regression model is as follows:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i$$

where Y is an outcome of interest concerning individual i. T is an indicator variable for random assignment to the treatment group. X is a vector of controls and includes age, sex, race, and education.[6] We also control for indicator variables for day of the week because people may behave differently on certain nights (e.g. dates may be more common on Fridays than Mondays). We also control for indicator variables for month-by-year to address any seasonality in decision-making. Because the experiment was conducted in the two restaurants in different, non-overlapping months, the month-by-year indicators also pick up any restaurant fixed effects. We also control for indicator variables for table of the restaurant and seat number to control for any

[6] Even though we conduct a randomized experiment, and cannot reject the null of balance between the treatment and control groups in their observed characteristics, controlling for such observables is still useful because they explain variance in the outcomes; thus, including them as regressors reduces residual variance and the standard error of the regression estimates (Angrist and Pischke, 2009).

possible differences in environment (e.g. amount of light, proximity to the kitchen, or visibility to other patrons). We also control for indicator variables for server because people may order differently based on the appearance or demeanor of their server. The variable ε is an error term. We cluster standard errors at the level of party because that is the level of randomization, and errors may be correlated within party. We estimate the equation using ordinary least squares for continuous outcomes, and linear probability models for binary outcomes.

The primary outcome of interest is the number of calories ordered (overall, and separately by course). Other outcomes examined include the extensive and intensive margin of calories by course; i.e. whether the guest ordered each course (appetizer, entrée, dessert) and how many calories they ordered in that course conditional on ordering any.

The hypothesized effect of providing information depends on individuals' prior beliefs. Evidence suggests that consumers tend to underestimate the number of calories in away-from-home food (e.g. Block et al., 2013; Elbel, 2011), which implies that providing accurate information on calories should lead to consumers ordering fewer calories overall. However, it is possible that, while consumers underestimate calories on average, they may overestimate the calories in some items; if so, providing calorie counts may increase the probability they order those items. We do not observe consumers' prior beliefs regarding calories in each item, so we hypothesize that the treatment will result in consumers reducing their overall number of calories ordered.

We test for heterogeneous effects; specifically, whether the treatment effect is greater among (e.g.) those who report using nutrition information, or those who have recently dieted. Our main models estimate the effect of intention to treat (i.e. the impact of being randomly assigned to the treatment group), but we also estimate the impact of treatment on the treated (i.e. being randomized to the treatment group and reporting afterward having seen the labels).

Figure 1 lists the sample sizes and exclusion criteria. We have data from tickets (receipts) for 8,317 unique observations. We exclude all patrons for whom we lack information on assignment to treatment or control group (N=95).[7] The remaining patrons were assigned either to the treatment group (T=4,129) or the control group (C=4,093). We drop the few who ordered zero calories (N=85; T=44; C=41). We drop from the analysis all patrons who are on return visits to the restaurant since the study began (N=1,987; T=972; C=1,015); the concern is that people on their return visit may remember the treatment from their first visit. Thus, the analysis sample consists entirely of people on their first visit to the restaurant since the study began. Finally, 599 (T=307, C=292) were dropped for being minors or non-English speakers. We are left with data on orders for 5,551 individuals (T=2,806; C=2,745). With this sample size, we have almost 100% power to detect a 5.8% difference in total calories ordered. (We chose a 5.8% effect size because that is the estimated effect of the NYC menu labeling law according to Bollinger et al., 2011).

Our other main source of data is the post-meal surveys. Of the 5,551 patrons with valid ticket data, 850 refused to participate in the survey (T=439: C=411). Of the remaining 4,701 individuals (T=2,367; C=2,334), 778 (T=360; C=418) either did not return or did not answer any part of the survey. Thus, we have survey data for 3,923 individuals (T=2,007; C=1,916). The model includes indicator variables for missing data for the regressors taken from the survey: sex, age, race, ethnicity, and education.

[7] In a very small percentage of cases (28 of 2,700 parties, or 1.04%) the RA failed to record whether the party had been randomized to the treatment or control group.

Empirical Results

Summary Statistics and Balance between Treatment and Control Groups

We first present summary statistics for the sample and test for balance between the treatment and control groups.[8] Table 1 provides summary statistics for the pooled sample as well as for the treatment and control group separately. The sample is 43.3% male, average age is 34.2, and 65.9% of the sample is white. Given the location of the restaurants on a college campus, it is not surprising that college students are over-represented; they comprise 37.8% of the sample. Consistent with the assumption of balance, there are no significant differences between the treatment and control groups in these characteristics.

Number of Calories Ordered, Overall and By Course

Figure 2 illustrates the unconditional average number of calories ordered by the treatment and control group, both overall and by course. Overall, the number of total calories ordered is slightly lower for the treatment group than the control group (1,461.5 versus 1,487.5) but the difference is not statistically significant. The only significant difference is in calories ordered from appetizers; the treatment group ordered 366.8, which is significantly less than the number ordered by the control group (386.6). The number of calories ordered by the treatment and control group was very similar for other courses such as drinks (105.9 versus 102.5), entrees (805.8 versus 817.7) and dessert (162.3 versus 167.0). These are all unconditional means, however.

In Table 2 we present results of our regression models that control for characteristics of the individual (e.g. age, race, sex, education), and the restaurant experience (e.g. server, table,

[8] Appendix Table 1 provides summary statistics for the pooled sample as well as for each restaurant separately. The patrons drawn from Restaurant A, relative to those from Restaurant B, are more likely to be male, older, and white. The sample drawn from Restaurant B has a much higher percentage of college students than that drawn from Restaurant A (62.2% versus 17.0%).

seat, day of week). We present results for total calories as well as separately by course. The treatment is associated with patrons ordering 44.9 fewer calories overall; based on a mean of 1474.4 calories ordered, that is a reduction of 3.0%. This reduction is statistically significant at the 10% level. Looking separately by course, one can see that this is due to a reduction of 22.5 calories (6.0%) in the appetizer course and a reduction of 26.6 calories (3.3%) in the entrée course; both are statistically significant at the 10% level. The modest reduction in dessert calories and small increase in drink calories are not statistically significant.

We next examine the extensive and intensive margins by course; the extensive margin is the probability of ordering any item in that course (drink, appetizer, entrée, dessert) and the intensive margin is the number of calories ordered conditional on ordering any. Table 3 lists results from regressions of the extensive margin. The treatment of calorie labels on menus is associated with a 1.5 percentage point (1.6%) decrease in the probability of ordering an entrée, and a 3.5 percentage point (7.6%) *increase* in the probability of ordering a drink. (We define "drink" as a caloric beverage; i.e. we exclude water and diet soda.) Both of those effects are statistically significant at the 10% level. The estimated effects on ordering an appetizer and ordering a dessert were not statistically significant.

Table 4 lists the results of regressions of the intensive margin of calories. Conditional on ordering a dessert, the treatment effect of calorie labels is to reduce the number of dessert calories ordered by 33.6 or 6.7%, which is statistically significant at the 10% level.

Impact on Calories per Dollar

In past research, some researchers have found unanticipated and potentially welfare-reducing responses to the provision of information. For example, Dranove et al. (2003) found evidence that, after the release of report cards tracking outcomes of cardiac surgeons, the surgeons began selecting only the healthiest patients who were most likely to have positive outcomes, and sicker patients became worse off.

A concern about calorie labels is that they could lead consumers to order *more* calories if they seek to maximize value, defined as the number of calories ordered per dollar spent (akin to bang for the buck). We test this by estimating models in which the dependent variable is the number of calories per dollar. The results, shown in Table 5, column 1, indicate that calorie labels had no significant impact on calories per dollar, and the point estimate is very small (less than 1). Reasoning that college students may be more likely to seek to maximize the number of calories for their dollar, we re-estimated this model for the sample of college students and again found a small, statistically insignificant change as a result of the treatment (Table 5, column 2).

Support for Calorie Labels

It is unclear whether calorie labels are welfare-enhancing. Consumers may prefer not to know the number of calories in their meal (a phenomenon referred to as strategic self-ignorance; see Thunstrom et al., 2016) or be annoyed by the disconfirmed expectancy when they discover that they underestimated the number of calories in restaurant food (Burton et al., 2006). On the other hand, consumers may be happy to have the information because it allows them to better manage their diet and optimize their ordering.

We investigated consumer support for this policy by asking on the post-meal survey, "Are you in favor of having calorie information on restaurant menus?" To test whether the treatment, exposure to the labels, increases or decreases support for the policy, we estimated models of supporting calorie labels on menus as a function of being randomly assigned to the treatment group and the other control variables. The estimates indicate that the treatment raised expressed support for the labels policy by 7.3 percentage points or 9.6%, which is statistically significant at the 1% level.[9] Thus, exposure to the treatment of calorie labels on menus increases consumer support for the policy, which is inconsistent with strategic self-ignorance and expectancy disconfirmation.

Impact of Treatment on the Treated

So far we have estimated the effect of intention to treat (ITT) – i.e. the effect of randomization to the treatment group that received calorie labels. However, not everyone assigned to that group may actually have been exposed to the treatment; some people may have ordered without looking at the menu or may have looked at the menu but not noticed the calorie labels. To investigate this, we asked on the post-meal survey: "Do you recall seeing any calorie information in this restaurant on the menus TONIGHT during your meal?" The vast majority of the treatment group (79.9%) reported seeing calorie information, but so did 12.1% of the control group. We estimate a model of reporting seeing calorie information as a function of random assignment to the treatment group and the other controls, and found that random assignment to the treatment group was associated with a 68.2 percentage point increase in the probability of reporting seeing the calorie information.

We next estimate the impact of treatment on the treated (TOT). For the purposes of this regression, we classify someone as in the treatment group if they were both randomly assigned to the treatment group and reported after the meal that they saw the calorie information; anyone for whom either or both of those things is false is classified as in the control group. In Table 6, we estimate the effect of treatment on the treated of calorie labels on the number of calories ordered, overall and by course. The estimated impact of calorie labels on appetizer calories is similar for TOT as for ITT: a reduction of 23.8 versus a reduction of 22.5. However, the impact on entrée

[9] Unconditionally, support for calorie information on menus was expressed by 79.9% of the treatment group and 72.5% of the control group.

calories is actually smaller for TOT than for ITT: -3.5 (not statistically significant) versus a significant -26.6. As a result, the impact on total number of calories for TOT is smaller (-32.1) and not statistically significant. In contrast, the ITT estimate was larger (-44.9) and statistically significant.

Heterogeneous Effects on Calories by Subgroup

We next test for heterogeneous effects by subgroup. To do this, we estimate new regression models that add to the previous equation an interaction term between the treatment indicator and the possible mediating variable.

$$Y_i=\alpha+\beta T_i+\delta T_i*Z_i+\gamma X_i+\varepsilon_i$$

Where T_i*Z_i is the interaction of the treatment indicator T and a possible mediating variable Z for which the main effect is also included in the vector X. Note that the equation also controls for the main treatment effect T. Our parameter of interest is the interaction term δ, which is informative about whether the impact of the treatment on Y differs by the value of Z.

Tables 7A, 7B, and 7C report the coefficients on the interaction terms δ for a variety of possible mediators (the main treatment effects β are not shown). We hypothesized that individuals who report reading calorie information (always, often, or sometimes as opposed to rarely or never), or using calorie information (always, often, or sometimes), or who say they typically order fewer calories based on calorie information, may have a greater response to the treatment. However, for each of those variables, we cannot reject the null of no interaction for overall calories or by course (Table 7A, columns 1-3).

Although we exclude repeat customers from the sample, it is possible that having a repeat customer at the table influences outcomes because the repeat customer advises his or her tablemates about the food items. We do find that having a repeat customer at the table leads patrons to order 61.5 fewer calories as appetizers if they were exposed to the menu labels, which is statistically significant; however, there is no significant impact on overall calories ordered (Table 7A, column 4).

We hypothesized that people who had dieted in the past year, and those who had a good quality of diet, might be more responsive to the information. In most cases, we cannot reject the null of no interaction for either variable (Table 7B, columns 1-2). The exception is that those who had dieted in the past year ordered an additional 44.7 fewer calories as appetizers if they were exposed to the menu labels.

We also tested whether obesity mediated the treatment effect. In the post-meal survey, respondents self-reported their weight and height. These were used to compute body mass index (BMI) and those with a BMI≥30 were classified as obese.[10] We find that the interaction of the obesity indicator with the treatment indicator was not statistically significant, either overall or by course (Table 7B, column 3).

We also test for heterogeneous effects by sex, race, and whether currently in college. When we include an interaction between the treatment and an indicator for being female, the results indicate that women order 42.6 (11.3%) more calories than men during the appetizer course in response to the treatment (Table 7C, column 1). When we include an interaction of the treatment with an indicator variable for white, we find that whites respond to the treatment by ordering 58.8 (7.2%) more calories in entrees than non-whites (Table 7C, column 2). A substantial percentage (37.5%) of our sample is currently in college, so for the purposes of generalizability it is important to test whether college students responded differently to the

[10] It is well-established that people tend to underreport their weight, and the underreporting is greater the higher the actual weight (Cawley et al., 2015). This implies that there is error in our classification into obesity status that may bias the estimated coefficient on the interaction term.

treatment than others. We find no significant interactions between the treatment and being a current college student (Table 7C, column 3).

Overall, we do not find strong consistent evidence of heterogeneity in treatment effects. In addition, if we make a Bonferroni correction to account for the fact that we tested for heterogeneous effects for ten groups, there are no statistically significant differences at all.

Models Estimated at the Level of Party

So far, all of the models in this paper have been estimated at the level of individual consumer. However, it may also be informative to estimate models at the level of party, for several reasons: 1) entire parties are randomized to the treatment and control group; 2) there may be splitting or sharing of items that we are unaware of (we do observe sharing in the server notes and incorporate that into our division of calories amongst the party, but these notes may be incomplete); and 3) there could be idiosyncratic errors on the tickets about which member of the party ordered what. For these reasons we re-estimate the main models with all data collapsed to the level of party. Calories are expressed as per-person averages, and individual-level indicator variables, such as sex, are converted into percentages for the party. The results are presented in Table 8, and indicate that being randomized to the treatment group lowers entrée calories per person by 28.7 (3.6%) and total calories per person by 51.9 (3.5%), both of which are statistically significant at the 5% level. The point estimate of the effect on appetizer calories is very similar but is no longer statistically significant because of the smaller sample size. Overall, the results of the party-level analysis are very consistent with those from the patron-level analysis.

Summary and Conclusion

There is considerable public health concern about the quality of the American diet and about the rise in the prevalence of obesity. In response, numerous cities, counties, and states have passed laws requiring disclosure of calorie information on restaurant menus, and a nationwide law took effect in the U.S. in May, 2018.

In order to estimate the impact of such information disclosure on consumer behavior, we conducted a randomized controlled field trial of restaurant menu calorie labels. The contributions to the literature include: unusually rich data that include not only item orders but also sharing of items, the identity of server, and table and seat in the restaurant; our setting of full-service, sit-down restaurants (which have not before been studied in this context); and a relatively large sample.

The model results indicate that the treatment of calorie labels on menus is associated with a reduction in calories ordered of 44.9 or 3.0%. This is due to reductions in calories ordered for appetizer and entrees but not for desserts or drinks. We find no evidence that calorie labels lead people to order more calories per dollar, even among college students. Finally, we find that exposure to the calorie labels increases support for them by 9.6%; this shows that consumers value the information and do not exhibit either a desire for strategic self-ignorance or expectancy disconfirmation.

To determine the longer-term impact of the estimated effect of menu labels on calories ordered, we undertake a back-of-the-envelope calculation of how the point estimate of the effect (a 44.9 calorie reduction) would affect long-run weight. First, we convert calories ordered to calories consumed. In restaurants, approximately 89% of food is consumed rather than left on plates (Massow and McAdams, 2015; Engstrom and Carlsson-Kanyama, 2004). This implies a reduction in calories consumed of 40 at that one meal. We next convert this to a daily change in calories consumed.[11] 20-25% of Americans consume food at a full-service restaurant on any given day (An, 2016), which implies that labels would reduce daily calorie consumption by 8-10. Next, we convert that daily calorie reduction into a change in weight. It is estimated that a permanent reduction in consumption of 10 calories per day leads to an eventual weight loss of one pound – half of that in one year, and 95% of it in three years (Hall et al., 2011). Thus, a rough estimate of the impact of calorie labels in full-service restaurants is a reduction in weight of one pound after three years. This is based on our estimate of the immediate impact on calories ordered; it is possible that consumers' long-run response could be greater (if there is learning) or less (if people respond more when the labeling is new). It is also the estimate of the mean impact; those who rarely eat in restaurants may not benefit at all, whereas those who eat out frequently might experience a greater effect.

Comparing our results to those of the previous literature, the impact on calories ordered that we find in full-service, sit-down restaurants is less than that previously found for coffee shops but greater than that previously found for fast-food outlets. Specifically, we find that menu labels reduced the number of calories ordered in a sit-down, full-service restaurant by 44.9 calories or 3.0%. Past research based on Starbucks sales data found that the NYC law reduced calories ordered by 14.4 or 5.8% (Bollinger et al., 2011). In contrast, past studies of the NYC and King County, WA laws on orders at fast food restaurants were unable to reject the null hypothesis of no effect on overall calories ordered (Elbel et al., 2009; Cantor et al., 2015; Finkelstein et al., 2011). The difference in findings between previous research and this paper may be due in part to the difference in type of food retailers, difference in methods (this study is experimental whereas the ones cited above were not), or difference in patrons (e.g. the Elbel et

[11] We acknowledge that exposure to calorie labels may affect not just what is ordered but how much of that order is consumed, but we do not observe how much is consumed.

al., 2009, and Cantor et al., 2015, studies specifically focused on low-income minority neighborhoods).

Our results also contribute to the larger literature on behavioral economics and consumer decision making. We find a detectable impact on appetizers, which tend to be one of the first decisions made. It is possible that calorie labels are effective for early decisions, due their initial novelty or salience (Thaler, 2016; Roberto and Kawachi, 2016). Conversely, the last decision made – dessert – exhibits no effect of the calorie labels on number of calories ordered. This could be a result of decision fatigue: it may be costly for people to interpret the information and make decisions, and while the information may affect the initial decision, consumers may become fatigued with decision making and lapse into their usual patterns. Several studies have documented the phenomenon of decision fatigue, in the contexts of doctors prescribing more unnecessary antibiotics (Linder et al., 2014) or being less likely to disinfect their hands before entering a new hospital room (Dai et al., 2015) the further they are into their shift, and parole judges becoming stricter the more cases they have heard without a break (Danziger et al., 2011). Future studies should examine whether restaurant patrons likewise exhibit decision fatigue when using calorie information. Another behavioral economics interpretation is that people use mental accounting (Thaler, 2008) for calories, and think of the dessert course as one in which they will splurge, whereas appetizers and entrees are courses in which they should be more healthy. This paper also contributes to the broader literature on the effects of information disclosure relating to health (Dranove et al., 2003; Dupas, 2011; Jin and Leslie, 2004; Variyam, 2008; Mathios, 2000).

The results have numerous policy implications. They are useful for projecting the impact of the new nationwide menu label law on consumer choices in full-service, sit-down restaurants. We find that providing information about calorie content reduces calories ordered by 3.0%, which, in a back-of-the-envelope calculation, could reduce weight slightly - by a pound over three years. Consumers like the policy – exposure to the labels increases the probability that they support having calorie information on restaurant menus by 9.6%. Furthermore, labels could increase consumer surplus by facilitating better matching. For example, an individual might prefer the taste of entrée A to entrée B, but order entrée B because he mistakenly thinks that entrée B has fewer calories, when in fact they have equal calories. Providing calorie information would lead the individual to switch from entrée B to entrée A; this would have no impact on the number of calories ordered but would increase the individual's utility. Such improvements in matching, which we do not observe, may in part explain why consumers desire the information.

The study has a number of limitations. First, it is almost always a limitation of randomized experiments that they take place with a select group of subjects, which limits generalizability (Shadish, Cook, and Campbell, 2002; Deaton and Cartwright, 2018). That is true for this study, which took place at two restaurants that are located on a college campus, and 37.8% of the sample are college students. However, it is also important to note that much can be learned from data from one or two firms (e.g. Royer et al., 2015; Charness and Gneezy, 2009; Finkelstein and Poterba, 2004). Still, it would be helpful to conduct this experiment at additional restaurants. The effect of calorie labels likely depends on the exact set of food items offered; disclosing calorie information may change behavior more when there is greater variance in calories among options, or when the calorie counts of the offered items are particularly difficult to estimate.

Another limitation is that we measure the immediate effect of the labels. It is possible that the longer-term effect could be larger (e.g. because of learning by doing) or smaller (e.g. if labels are more noticeable or effective when they are new). However, studies of the NYC menu label law found no detectable effect of the labels on calories ordered from fast food outlets in either the first year (Elbel et al., 2009) or fifth year after implementation (Cantor et al., 2016).

We observe only orders, not consumption. It is possible that people respond to labels not by changing their order, but by changing how much they eat of their order. Studies have found that the vast majority (89%) of calories ordered in restaurants are consumed there (Massow and McAdams, 2015; Engstrom and Carlsson-Kanyama, 2004), but it would be useful if future studies could test for changes in consumption.

There are several important directions for future research. Field experiments should be conducted in additional restaurants, of varying format, customer base, and menu offerings to assess the robustness of these findings. Another priority is to evaluate methods of making the calorie information more salient and easy for patrons to understand; e.g. one option is to list the distance one would have to walk to burn the calories in that item (e.g. Dorway et al., 2013). A bigger-picture question is whether calories should even be the information listed, as opposed to saturated fat, cholesterol, or sodium, which may be of greater interest to patrons with heart disease, high cholesterol, or high blood pressure. Additional such studies would further add to our understanding of how provision of information affects consumer decision-making.

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Table 1: Summary Statistics and Test of Balance

	Full Sample	Control	Treated	Difference
Male	0.433	0.422	0.444	-0.022
	(0.496)	(0.494)	(0.497)	(0.016)
	N=3923	N=1916	N=2007	p-value=0.169
Age	34.185	34.268	34.104	0.164
	(17.765)	(17.887)	(17.652)	(0.571)
	N=3878	N=1897	N=1981	p-value=0.774
White	0.659	0.656	0.662	-0.006
	(0.474)	(0.475)	(0.473)	(0.015)
	N=3908	N=1910	N=1998	p-value=0.689
Asian	0.239	0.240	0.239	0.001
	(0.427)	(0.427)	(0.426)	(0.014)
	N=3908	N=1910	N=1998	p-value=0.943
Other Races	0.102	0.104	0.100	0.005
	(0.302)	(0.306)	(0.300)	(0.010)
	N=3908	N=1910	N=1998	p-value=0.617
Hispanic	0.078	0.075	0.081	-0.006
	(0.268)	(0.263)	(0.272)	(0.009)
	N=3903	N=1906	N=1997	p-value=0.505
Weight	152.894	152.467	153.301	-0.834
	(34.478)	(34.680)	(34.287)	(1.123)
	N=3772	N=1841	N=1931	p-value=0.458
Height	67.159	67.075	67.238	-0.163
	(4.072)	(4.088)	(4.056)	(0.131)
	N=3844	N=1871	N=1973	p-value=0.215
Currently in College	0.378	0.382	0.375	0.008
	(0.485)	(0.486)	(0.484)	(0.015)
	N=3921	N=1917	N=2004	p-value=0.594

Table 2: Effect of Menu Labeling on Calories Ordered

	Estimated Effect
Appetizer Calories	-22.5*
Mean=376.6	(12.7)
	N=5551
Entree Calories	-26.6*
Mean=811.7	(13.8)
	N=5551
Dessert Calories	-6.4
Mean=164.6	(11.3)
	N=5551
Drink Calories	3.2
Mean=104.2	(5.2)
	N=5551
Total Calories	-44.9*
Mean=1474.4	(23.3)
	N=5551

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 3: Effect on Probability of Ordering Each Course

	Estimated Effect
Appetizer	-0.006
Mean=0.735	(0.017)
	N=5551
Entree	-0.015*
Mean=0.926	(0.009)
	N=5551
Dessert	-0.007
Mean=0.329	(0.020)
	N=5551
Drink (Caloric Only)	0.035*
Mean=0.458	(0.018)
	N=5551

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 4: Effect of Menu Labeling on Calories, Conditional on Ordering Course

	Estimated Effect
Appetizer Calories	-22.6
Mean=512.6	(14.7)
	N=4078
Entree Calories	-13.2
Mean=876.8	(12.1)
	N=5139
Dessert Calories	-33.6*
Mean=501.1	(19.7)
	N=1824
Drink Calories	-11.2
Mean=227.7	(8.3)
	N=2540

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 5: Effect of Menu Labeling on Calories Per Dollar

	Full Sample	College Students Only
Calories Per Dollar	-0.90	0.16
Mean=51.20	(0.64)	(1.63)
	N=5551	N=1379

* p<0.10, ** p<0.05, *** p<0.01

Standard errors in parentheses (se); clustered at the party level.

Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 6: Effect of Menu Labeling on Calories Ordered – Treatment on the Treated

	Estimated Effect
Appetizer Calories	-23.8*
Mean=376.6	(13.6)
	N=5551
Entree Calories	-3.5
Mean=811.7	(15.7)
	N=5551
Dessert Calories	-11.1
Mean=164.6	(13.3)
	N=5551
Drink Calories	-0.9
Mean=104.2	(6.1)
	N=5551
Total Calories	-32.1
Mean=1474.4	(25.9)
	N=5551

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 7A: Testing for Heterogeneous Effects

	Read Calorie Info (Always, Often, Sometimes)	Use Calorie Info (Always, Often, Sometimes)	Order Fewer Calories Based on Calorie Info	Repeat Customer at Table
	(1)	(2)	(3)	(4)
%	0.779	0.667	0.502	0.273
Appetizer Calories	6.7	-27.1	-8.7	-61.5*
Mean=376.6	(27.1)	(23.3)	(22.8)	(32.8)
	N=3646	N=3649	N=3580	N=5551
Entree Calories	-21.9	9.3	-20.4	-22.3
Mean=811.7	(36.5)	(30.7)	(27.7)	(31.2)
	N=3646	N=3649	N=3580	N=5551
Dessert Calories	0.9	5.0	9.6	15.9
Mean=164.6	(25.4)	(22.1)	(20.3)	(25.3)
	N=3646	N=3649	N=3580	N=5551
Drink Calories	1.0	-1.5	-10.5	4.8
Mean=104.2	(12.9)	(11.1)	(10.4)	(11.3)
	N=3646	N=3649	N=3580	N=5551
Total Calories	-22.3	-19.0	-31.7	-44.3
Mean=1474.4	(51.3)	(45.6)	(42.0)	(50.0)
	N=3646	N=3649	N=3580	N=5551

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 7B: Testing for Heterogeneous Effects (Cont)

	Dieted (Past Year)	Diet Quality (Excellent, Very Good, Good)	Obese (BMI>30)
	(1)	(2)	(3)
%	0.293	0.854	0.067
Appetizer Calories	-44.7*	-3.4	35.2
Mean=376.6	(23.8)	(37.0)	(48.3)
	N=3650	N=3658	N=3507
Entree Calories	-30.4	-19.8	17.2
Mean=811.7	(29.7)	(40.9)	(53.1)
	N=3650	N=3658	N=3507
Dessert Calories	4.1	15.5	16.8
Mean=164.6	(21.1)	(30.4)	(43.2)
	N=3650	N=3658	N=3507
Drink Calories	8.1	1.6	19.0
Mean=104.2	(11.0)	(15.7)	(25.6)
	N=3650	N=3658	N=3507
Total Calories	-61.0	-4.8	89.0
Mean=1474.4	(44.7)	(61.5)	(85.2)
	N=3650	N=3658	N=3507

* $p<0.10$, ** $p<0.05$, *** $p<0.01$
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Table 7C: Testing for Heterogeneous Effects (Cont)

	Female	White	Currently in College
	(1)	(2)	(3)
%	0.567	0.662	0.375
Appetizer Calories	42.6*	0.9	-29.2
Mean=376.6	(22.5)	(26.7)	(25.9)
	N=3680	N=3664	N=3677
Entree Calories	-30.0	58.8*	-22.1
Mean=811.7	(28.5)	(31.5)	(31.7)
	N=3680	N=3664	N=3677
Dessert Calories	-27.4	16.6	-5.7
Mean=164.6	(18.9)	(24.7)	(23.8)
	N=3680	N=3664	N=3677
Drink Calories	-0.1	8.6	0.1
Mean=104.2	(10.6)	(11.5)	(11.6)
	N=3680	N=3664	N=3677
Total Calories	-8.8	79.6	-58.5
Mean=1474.4	(41.1)	(48.5)	(46.9)
	N=3680	N=3664	N=3677

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se); clustered at the party level.
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE,
server FE, party size, gender, age, Hispanic, race, and education.

Table 8: Effect of Menu Labeling on Calories Ordered – Party Level

	Estimated Effect
Appetizer Calories	-20.9
Mean=372.8	(13.5)
	N=2215
Entree Calories	-28.7**
Mean=799.8	(14.3)
	N=2215
Dessert Calories	-10.6
Mean=162.1	(11.5)
	N=2215
Drink Calories	0.8
Mean=107.2	(5.7)
	N=2215
Total Calories	-51.9**
Mean=1462.8	(23.2)
	N=2215

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses (se).
Covariates: treated, day of week FE, month-by-year FE, table FE, seat FE, server FE, party size, gender, age, Hispanic, race, and education.

Figure 1: Sample Size and Exclusion Criteria

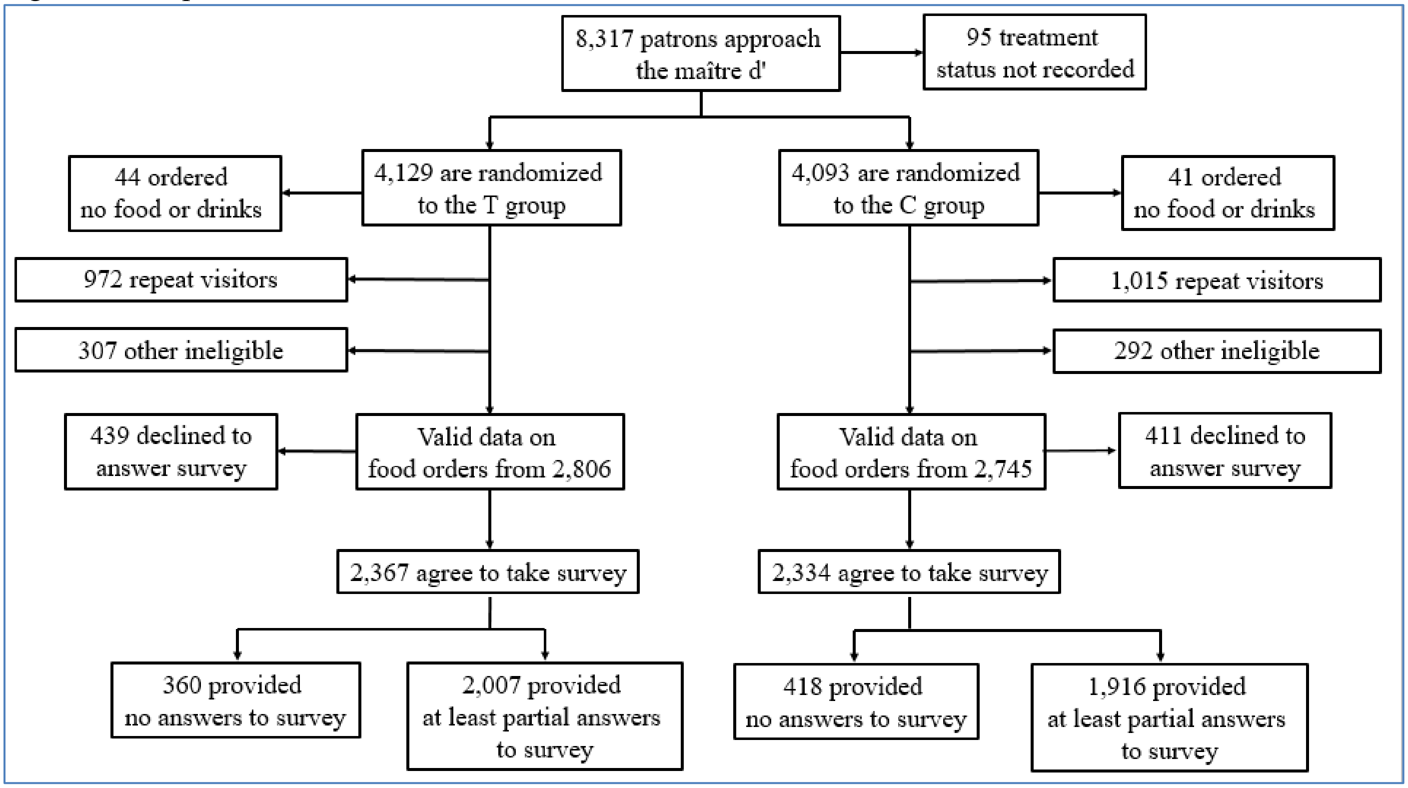
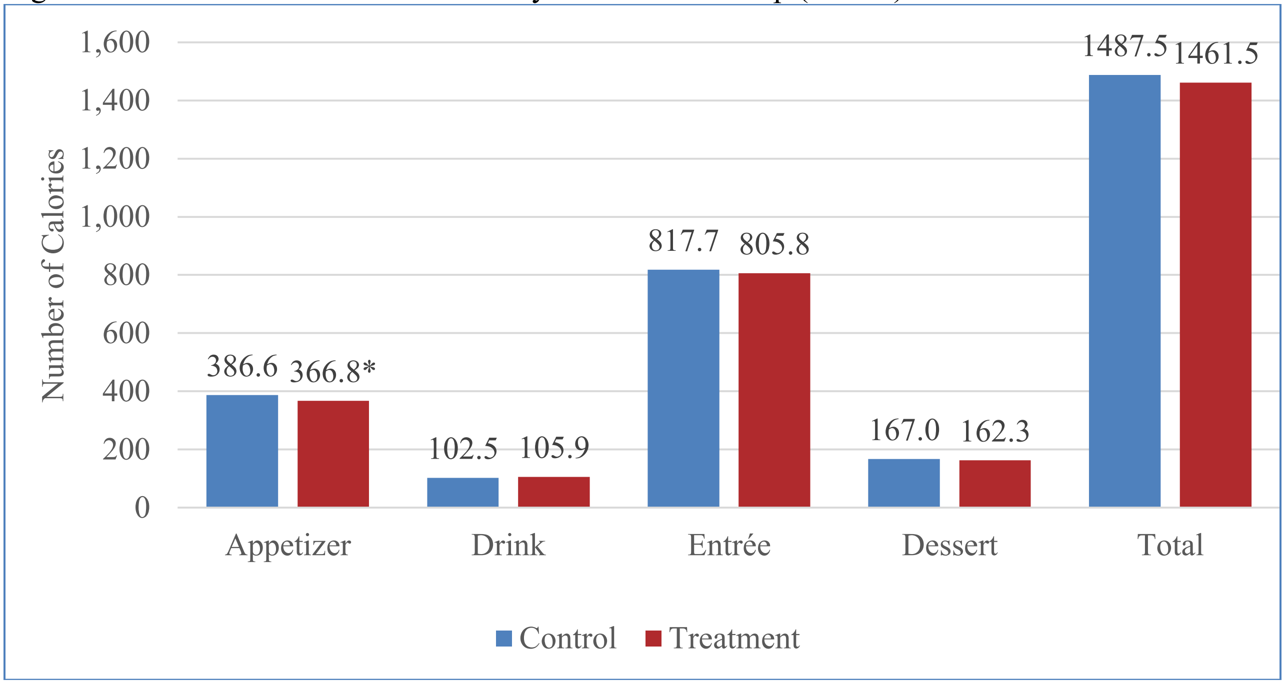


Figure 2: Unconditional Mean Calories by Course and Group (T vs C)



Appendix Table 1: Summary Statistics by Restaurant

	Full Sample	Restaurant A	Restaurant B	Difference
Male	0.433	0.463	0.398	-0.065
	(0.496)	(0.499)	(0.490)	(0.016)
	N=3923	N=2112	N=1811	p-value<0.001
Age	34.185	42.578	24.373	-18.205
	(17.765)	(18.408)	(10.483)	(0.492)
	N=3878	N=2090	N=1788	p-value<0.001
White	0.659	0.726	0.581	-0.146
	(0.474)	(0.446)	(0.494)	(0.015)
	N=3908	N=2101	N=1807	p-value<0.001
Asian	0.239	0.191	0.296	0.105
	(0.427)	(0.393)	(0.456)	(0.014)
	N=3908	N=2101	N=1807	p-value<0.001
Other Races	0.102	0.083	0.124	0.041
	(0.302)	(0.276)	(0.330)	(0.010)
	N=3908	N=2101	N=1807	p-value<0.001
Hispanic	0.078	0.066	0.092	0.026
	(0.268)	(0.248)	(0.288)	(0.009)
	N=3903	N=2100	N=1803	p-value=0.003
Weight	152.894	156.569	148.551	-8.018
	(34.478)	(35.749)	(32.388)	(1.119)
	N=3772	N=2043	N=1729	p-value<0.001
Height	67.159	67.272	67.026	-0.247
	(4.072)	(4.054)	(4.090)	(0.132)
	N=3844	N=2077	N=1767	p-value=0.061
Currently in College	0.378	0.170	0.622	0.453
	(0.485)	(0.375)	(0.485)	(0.014)
	N=3921	N=2112	N=1809	p-value<0.001