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CONSUMER RESPONSES TO FIRMS' VOLUNTARY DISCLOSURE OF INFORMATION: EVIDENCE FROM CALORIE LABELING BY STARBUCKS

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ABSTRACT

This paper estimates the impact on consumer behavior of a firm's voluntary disclosure of information. Specifically, we study the impact of Starbucks' disclosure of calorie information on its menu boards in June 2013. Using data on over 250,000 consumers' visits to specific restaurant chains, we estimate difference-in-difference models that compare the change in the probability that consumers recently visited Starbucks to the change in the probability that they recently visited a similar chain that did not voluntarily disclose: Dunkin Donuts. Estimates from difference-in-differences models indicate that we cannot reject the null hypothesis that Starbucks' disclosure of calorie information had no impact on the probability that consumers patronized Starbucks in the past month. However, we find evidence of a transitory negative impact on the probability of visits the first year after disclosure, and evidence that disclosure reduced the probability of visits by men. These results are useful for understanding how consumers respond to the voluntary disclosure of information, a decision faced by many firms.

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Introduction

Economists have long studied how the disclosure of information affects consumer choices (e.g., Stigler, 1961; Arrow, 1963; Pauly, 1968; Akerlof, 1970; Spence, 1973). There is particular interest in how consumers respond to new information concerning health (e.g., Cawley, Susskind, and Willage, 2020; Kim et al., 2019; Bedard and Kuhn, 2015; Handel and Kolstad, 2015; Prina and Royer, 2014; Kolstad, 2013; Bollinger et al., 2011; Dupas, 2011; Wisdom et al., 2010; Pope, 2009; Jin and Leslie, 2009; Variyam, 2008; Dranove et al., 2003; Mathios, 2000).

One area of particular interest is how consumers respond when restaurants disclose calorie and other nutrition information. This is due in part to the tripling in the prevalence of obesity in the U.S., from 13.4% in 1960-62 to 42.4% in 2017-18 (Fryar, Carroll, and Ogden, 2016; Hales et al., 2020). There are many proposed explanations for the rise in obesity (Cawley, 2015), and one possible contributor is increased consumption of restaurant food. The percentage of calories that Americans consume as food away from home has nearly doubled, from 17.8% in 1977-78 to 33.7% in 2013-14 (Guthrie et al., 2018). This is relevant because consumers tend to substantially underestimate the calorie content of restaurant food (see, e.g., Cawley, Willage, and Susskind, 2021; Block et al., 2013; Backstrand et al, 1997) and thus may end up consuming more than they would if they had perfect information. To address this information gap, organizations including the American Heart Association (2009) and the Institute of Medicine (2005, 2012) have recommended listing calorie counts on restaurant menus.

Between 2008 and 2018, calorie labels on restaurant menus in the U.S. went from virtually nonexistent to ubiquitous, due to three factors. First, certain cities and counties passed laws requiring chain restaurants in their jurisdiction to disclose calorie information; this occurred in, e.g., New York City (2008), King County, Washington, which includes Seattle (2009), and Philadelphia (2010); see Courtemanche et al. (2020). Second, some restaurant chains decided to voluntarily post calorie labels, including: Panera (2010); Yum Brands (2011), which includes Pizza Hut, KFC, and Taco Bell; McDonalds (2012); Chik-fil-A (2013); and Starbucks (2013). Third, a national menu label law that was included in the Affordable Care Act took effect on May 7, 2018. After that date, all chain restaurants (20 or more locations operating under the same name) in the U.S. were required to post calorie counts on their menus and/or menu boards.

In this paper, we study the consequences of *voluntary* disclosure of information by a firm. In such a case, the disclosing firm continues to compete with local rivals which have not disclosed, which makes it a notably different situation than a firm disclosing in response to a legal requirement that also applies to its competitors. For a firm to voluntarily disclose, it would have to perceive that disclosure is in its interest. Firms selling high-quality goods might choose to disclose because they expect that it would lead to higher sales. Under certain conditions such as costless disclosure, complete unraveling may occur, in which the firms with the highest-quality goods disclose their information, putting pressure on firms with the next-best quality goods to also disclose, lest consumers assume that they have the worst-quality goods, until all firms have disclosed except those of the very lowest quality (Viscusi, 1978; Grossman and Hart, 1980; Grossman, 1981). In practice, however, unraveling tends to be incomplete, meaning that a substantial fraction of firms, which are selling goods of varying quality, do not voluntarily disclose (Jin et al., 2021; Bederson et al., 2018; Luca and Smith, 2015; Mathios, 2000).

A firm might choose to voluntarily disclose because it lowers their costs; e.g. a restaurant chain facing some local disclosure laws might decide to disclose everywhere so it can use a single set of menus and menu boards nationwide. In the case of menus labels, firms knew from

2010 to 2018 that the U.S. had passed, but not yet implemented, a nationwide menu label law, so they may have opted to simply begin the process of compliance early. In this paper, we do not study the decision of a firm to disclose, but rather how consumers respond when a firm voluntarily discloses.

Our research question is: does voluntary provision of information by a firm make consumers more or less likely to patronize the firm? More specifically, does a restaurant chain's decision to voluntarily implement calorie labeling make consumers more or less likely to visit the chain?

It is unclear whether voluntary information disclosure would affect the probability that consumers patronize a firm, and if so, in which direction. Disclosure could attract patrons if consumers assume that disclosing firms must have better quality products than those that refuse to disclose. It could also attract consumers if the items turned out to be lower-calorie than consumers believed, raising consumers' expected marginal utility from the items. Alternatively, information disclosure could deter patrons if they are surprised by how high the calorie counts are; for example, if they have optimism bias (Sharot, 2011; Miles and Scaife, 2003) then they may believe that rival chains that did not disclose have lower-calorie items than those that did disclose. Consumers might also be put off by disclosure if they enjoy their meal more if they do not know its calorie content, a phenomenon known as information aversion (Andries and Haddad, 2020) or strategic self-ignorance (Thunstrom et al., 2016). Sunstein (2021) argues that, for those who do not want to change their behavior, disclosure of calorie information can serve as an unpleasant reminder and thus a hedonic tax. Consumers may seek to avoid that by patronizing competing chains that do not disclose. Finally, disclosure could have no impact at all on consumer visits. This might be the case for several reasons: if consumer choice of chain is not meaningfully affected by calorie counts; if they didn't notice the disclosed information because it wasn't salient (e.g., Bordalo et al., 2013); if consumers were unable, due to bounded rationality, to effectively comprehend or use the disclosed information (e.g., Rice, 2013; Simon, 1955); or if they already had accurate information about the calorie content of menu items.

Previous research provides some information regarding the plausibility of those scenarios. There is some evidence that a firm's reputation can be enhanced by voluntary disclosure. Berry, Burton and Howlett (2018) find that voluntary, as opposed to mandatory, calorie labeling can increase perceived concern for customer well-being which in turn increases patronage intentions. As previously mentioned, numerous studies have found that, in the absence of calorie disclosure, consumers do not have accurate information about the calories in restaurant food, and that specifically they tend to greatly underestimate them. Previous studies have not found evidence of information aversion or strategic self-ignorance concerning calorie labels. In a randomized experiment of restaurant menu calorie labels, Cawley, Susskind and Willage (2020) found that over 70% of both the treatment and control groups reported that they support having calorie labels on menus, and that exposure to the randomized treatment of calorie labels increased by 9.6% the probability that the respondent supported having them on menus. However, a national poll of U.S. adults in 2017 found that the public was equally split (49% to 49%) in whether they favored or opposed the government *requiring* chain restaurants to post calorie counts (Politico/Harvard Public Health Poll, 2017); the lower support found in the national poll may be due to it asking about a government requirement as opposed to a voluntary decision by restaurants.[2]

[2] In an Amazon Turk survey of 400 Americans by Sunstein (2021), less than half (43%) wanted calorie labels in restaurants.

Regarding the salience of the information, evidence indicates that not all patrons see calorie labels. Four weeks after the New York City menu labeling law took effect, Elbel et al. (2009) found that 46% of New York City respondents (all of whom had just exited a fast food restaurant) reported that they had not noticed calorie information in the establishment. In a randomized experiment, Cawley, Susskind, and Willage (2020) found that 21.1% of patrons in the treatment group reported that they had not seen the calorie labels that were on their menus. One explanation for the difference in the estimates of the two studies is that the former concerned menu boards while the latter concerned hand-held menus, and it may be harder to see information on a menu board.

There is also evidence that consumers have bounded rationality; even with disclosure, patrons continue to significantly underestimate the number of calories they have ordered. Cawley, Susskind, and Willage (2021) find that the probability of underestimating the number of calories in one's dinner by 25% or more, on a post-meal survey, is 44.6% in the control group not given calorie labels and 36.8% in the treatment group whose menus had calorie labels. Thus, calorie labels improved knowledge of the number of calories in foods but considerable error remains. In summary, there are many reasons that information disclosure may attract or deter patrons, and the overall effect is difficult to predict.

In this paper we examine the voluntary disclosure of calorie information by Starbucks, which voluntarily posted calorie counts on its menu boards on June 25, 2013, nearly five years before the U.S. law required chains to disclose this information.[3] The comparison firm is Dunkin Donuts, which did not voluntarily disclose calorie counts prior to the nationwide

[3] Prior to Starbucks posting calorie counts on its menu boards, the calorie information was available online or in printed brochures. However, the information is presumably much more salient when posted on the menu board. Several studies have found that salience increases consumer response to information, taxes, and prices (e.g. Bordalo, 2013; Chetty, Looney, & Kroft, 2009; Blake et al., 2018).

requirement in 2018. We estimate difference-in-difference models that compare the change in the probability that consumers visit Starbucks after it disclosed calorie information to the change in the probability that consumers visit Dunkin Donuts over the same period. We exclude the handful of areas where local laws required all restaurant chains – including both Starbucks and Dunkin Donuts – to disclose their calorie counts, and thus examine the vast majority of the country where Starbucks began voluntarily disclosing calorie information and Dunkin Donuts did not.

Dunkin Donuts is a suitable comparison firm for Starbucks because Starbucks and Dunkin Donuts are the #1 and #2 coffee chains in the U.S. Although some might think of Dunkin Donuts as primarily a donut store (which is understandable given its name), Dunkin Donuts has positioned itself as a national coffee chain. Delventhal (2020) writes: "Dunkin' Donuts markets itself primarily as a coffee seller that also offers donuts and food, a fact made apparent by a coffee cup prominently featured on the company's logo and executive management's explicit assertion that Dunkin' Donuts is a beverage company." As an example of the latter, David Hoffman, the CEO of Dunkin' Brands, has said: "Brands that stay narrow in their lane do their best…On the Dunkin' side, that is great coffee, fast. It's our sweet spot." (Anderson, 2018). Further evidence of this is that, in 2019, the word 'Donuts' was removed from the chain's name and it is now simply named 'Dunkin" to reflect the that the company is "beverage-led" (Dunkin', 2018).[4] Dunkin Donuts has previously been used as a comparison firm for Starbucks in an economic study of calorie labels (Bollinger et al., 2011).

[4] Although Dunkin Donuts changed its name to Dunkin in 2019, for the sake of consistency and clarity we will refer to it as Dunkin Donuts throughout this paper.

To our knowledge, this is the first study to examine the impact of voluntary calorie labeling by a chain on the probability that consumers patronize the chain.[5] Most of the related previous research has examined the impact of city and county laws that required calorie labels on restaurant menus (e.g., Todd et al., 2021; Courtemanche et al., 2020; Restrepo, 2017; Cantor et al., 2015; Auchincloss et al., 2013; Bollinger et al., 2011; Finkelstein et al., 2011; Elbel et al., 2009). Notably, Bollinger et al. (2011) use data from Starbucks to estimate the effect of a 2008 New York City law mandating calorie counts be posted on restaurant menus. They find that the average number of calories ordered fell by 6%.

A smaller number of studies have examined the impact of voluntary disclosure of calorie information in individual restaurants on what consumers ordered during their visit (e.g., Cawley, Willage, and Susskind, 2020, 2021; Bedard and Kuhn, 2015; Pulos and Leng, 2010), but these studies were not, given their data, able to estimate the impact on the probability that consumers visit in the first place.

There are relatively few studies of the effects of chain-wide voluntary adoption of calorie labels prior to the nationwide law. This is of particular interest because problems of asymmetric information are ubiquitous, and many firms may be considering voluntarily disclosing information to consumers. Two previous studies examined restaurant chains' decisions to voluntarily post calorie labels, although they examined a different outcome: the food items on the menus. Specifically, Bleich et al. (2015) and Theis and Adams (2019) found that the average calorie content of menu items was lower in chains which had voluntarily posted menu labels than in chains which did not; these were cross-sectional comparisons after the information had been

[5] For reviews of the research on calorie labeling in restaurants, see Bleich et al., (2017), VanEpps et al. (2016), and Swartz et al. (2011).

disclosed - neither study was able to examine the change in calorie content from before to after the labels were posted.

Another contribution of our study is that it examines an outcome important for firms – the probability that consumers patronize the chain. Virtually all previous research on menu labels has focused on consumer outcomes such as the number of calories ordered and BMI. One previous study that did examine firm outcomes found, in a randomized experiment of calorie labels, that the disclosed information had no detectable impact on revenue per patron or profit per patron (Cawley, Susskind, and Willage, 2021). However, this study was not able to examine the impact of menu labeling on the probability that a consumer visits in the first place. The present study contributes to the literature by examining an outcome that was missing in previous studies: the probability that patrons visit the chain.

More generally, this study sheds light on whether firms are likely to find voluntary disclosure of information to be advantageous. This is an important contribution, as there are many cases in which firms face decisions about whether to disclose (see, e.g., Dranove and Jin, 2010; Loewenstein, Sunstein, and Golman, 2014). This study contributes to the economic literature on the voluntary disclosure of the following types of information: restaurants posting hygiene report cards (Bederson et al., 2018), manufacturers' labeling of the fat content in salad dressing (Mathios, 2000), business schools posting their rankings (Luca and Smith, 2015), colleges releasing the SAT scores of admitted students (Conlin et al., 2013), HMOs voluntarily seeking external accreditation to signal quality (Jin, 2005), publicly traded companies releasing financial information to investors (Suijs, 2007), sellers of used cars disclosing private quality information (Lewis, 2011; Akerlof, 1970), and job applicants signaling their abilities (Spence, 1973). Given the wide range of contexts in which firms decide whether to disclose information to consumers, the findings of this paper are widely useful and applicable.

Data: Simmons National Consumer Survey (NCS)

We examine data from the Simmons National Consumer Survey (NCS), which is uniquely well-suited for our purpose because it is a nationwide survey that includes information from a large number of adult respondents (over 250,000), contains information on their visits to specific branded chain restaurants (including Starbucks and Dunkin Donuts), and was conducted in several years both before and after Starbucks voluntarily disclosed calorie information in 2013.

The Simmons NCS is a proprietary nationally representative repeated cross-sectional survey. For each survey wave (of which there are 2 to 4 per year), the survey is administered to an independently-drawn multi-stage stratified probability sample of individuals. The response rate for the NCS during these years of data averaged 19%. The NCS data include an intentional over-representation of higher-income households because the survey is intended to be useful for informing marketing decisions. Overall, the weighted NCS sample is comparable to U.S. Census data in terms of as age, gender, race, ethnicity, marital status, income, and health care insurance coverage (See Appendix Table 1).

From the NCS, we obtain information on each individual's demographic characteristics, such as age, race, ethnicity, gender, education, household income, location of residence (designated marketing area (DMA), marital status, employment characteristics, household income number of members in the household, hours worked, and health insurance status.

We have data from Fall 2003 through Fall 2016, with wave 39 from Fall 2004 dropped due to data corruption. We combine waves into calendar years. We drop the small number of observations (N=11) which are missing demographic information. Our final sample consists of 257,493 adults.[6] Each of those individuals appears twice in the data – once regarding their visits to Starbucks and once regarding their visits to Dunkin Donuts – so our total sample size is 514,986. A strength of using the NCS is that it provides a large sample size and thus substantial statistical power to detect even modest effects.

The NCS questionnaires ask consumers the number of times they visited specific restaurant chains in the past 30 days, with the possible answers recorded in bins, such as 0, 1-2, and 3-5.[7] Our primary outcome is the extensive margin of visits: whether the consumer reported visiting that chain in the past 30 days. There is some difficulty in examining changes on the intensive margin of visits when the number of visits is reported categorically and those categories change over time[8], but we are able to consistently classify the intensive margin of visits in the last 30 days as low (1-5 visits) or high (6 or more visits). We estimate secondary models examining the intensive margin of visits using this binary (high vs low) dependent variable.

The NCS contains information about the respondent's Designated Marketing Area (DMA), which is the media market in which they live. Identification of location is important

[6] The NCS surveys each person in the household. We study adults (aged 18 years and older), but not youths because they were not consistently asked about visits to Starbucks and Dunkin Donuts. Specifically, kids (aged 6-11) were not asked about Starbucks in any wave, and teens (aged 12-17) ceased to be asked about Starbucks in only one survey wave after Starbucks began posting calorie counts.
[7] Specifically, respondents are first asked whether they go to fast food and drive-in restaurants. If they respond yes, then they are asked to mark the number of times, in the last 30 days, they visited each of a list of chain restaurants, which includes Starbucks and Dunkin Donuts.
[8] The categories concerning number of times visited in the last 30 days are not consistent across wave; for example, in some waves the categories include 3-5 and 6-9, in other waves it is 6-13, in still other waves it is 6 or more. However, across all waves we are able to consistently categorize people as having 0, 1-5, or 6 or more visits.

because in some years there were local menu labeling laws that required both Starbucks and Dunkin Donuts to disclose their calorie counts. The boundaries of DMAs are much larger than those of cities or counties; for example, while we know that someone lives in the Seattle-Tacoma DMA we do not know whether they live in King County, WA, which had a menu label law, or Pierce County, WA, which did not have a menu label law. Lacking more specific residential information than DMA, we drop all observations in DMAs in which any subset of the DMA has a menu label law.[9]

Methods

We estimate differences-in-differences (DiD) models, in which we compare the change over time in the probability that consumers patronize the chain that began voluntarily disclosing calorie information (Starbucks), relative to the change over time in the probability that consumers patronize the chain that did not disclose calorie information (Dunkin Donuts). The data are at the level of individual-chain-year; thus, each individual appears as two observations in the sample, once regarding their visits to Starbucks and once regarding their visits to Dunkin Donuts. The Simmons NCS is a repeated cross-section, so each individual appears in one year of data. Specifically, we estimate the following difference-in-differences (DiD) models:

$$Y_{icdy} = \beta_0 + \beta_1 TREAT_c + \beta_2 YEAR_y + \beta_3 POST_y * TREAT_c + \beta_4 DMA_d + \beta_5 X_i + \varepsilon_{icdy}$$

Where Y_{icdy} is our outcome of interest, for example a binary indicator of whether individual i living in designated marketing area (DMA) d and observed in year y visited restaurant chain c in the previous 30 days. *TREAT* is an indicator variable that equals one if the

[9] Specifically, the DMAs that were dropped are: Albany, NY; Burlington, VT; New York, NY; Philadelphia, PA; and Seattle, WA. In total we drop 88,268 individuals (14.6% of the sample) who live in one of those DMAs. Two-thirds of those individuals live in the New York, NY DMA.

observation concerns Starbucks and equals zero if it concerns Dunkin Donuts. *YEAR* is a vector of indicator variables for year. $POST_y$ is an indicator set equal to one if Starbucks had implemented menu labels by year y, and zero otherwise; thus it equals zero for 2003 to 2012, and equals one for 2013 to 2016. We drop one partially treated wave of the Simmons NCS that spans the period during which Starbucks implemented its policy in June 2013. *DMA* is a vector of indicator variables for DMA of residence *d*, and it also includes an indicator variable for those living outside a DMA or if their DMA of residence is missing; indicator variables for region are included as well because this information is known even for those outside of DMAs or when DMA is missing. The vector X_i includes a vector of characteristics of individual *i* that may be associated with the dependent variable: gender, age, race, educational attainment, employment status, marital status, household income, household size, and season of interview.

As previously mentioned, we drop observations for those living in DMAs which implemented local laws requiring calorie labels on menus during the years covered by our analysis. Our model also controls for an indicator variable for whether any part of the DMA had passed but not yet implemented a menu label law. Dates of the passage and implementation of local menu label laws are taken from Courtemanche et al. (2020).

Standard errors ε were clustered at the DMA level *d* in recognition of the fact that errors may be correlated within DMAs due to, e.g., the number of locations each chain has in that DMA, local advertising by chains in each DMA, weather, and other correlates of demand that vary with local characteristics. This is more conservative (i.e. results in larger standard errors) than clustering at the household level.

Our parameter of interest is β_3, which is the difference-in-differences estimate – how the probability of people visiting Starbucks changed after it adopted menu labels, relative to the change in the probability that people visited Dunkin Donuts, which did not adopt menu labels. In contrast to other situations in which researchers wish to measure the change in outcomes for a treatment group relative to a control group which is completely unaffected, in this case we wish to measure how the firm that voluntarily discloses information fares relative to a competitor that does not disclose. The identifying assumption is the standard one in difference-in-differences models – that the treatment and comparison chains would have experienced the same time trends in the absence of the treatment, something which we investigate by conducting an event study in order to test for parallel trends prior to the treatment.

The outcomes *Y* examined in the model above include both the extensive margin of visits in the last 30 days, and the intensive margin of visits conditional on at least 1 visit (measured by an indicator variable for a high frequency of visits, defined as 6 or more, versus a low frequency of visits, defined as 1 to 5 in the last 30 days).

We also examine whether there may exist heterogeneous treatment effects. One important characteristic that may moderate the influence of calorie information is the consumer's level of education. On the one hand, patrons with higher education may assign greater value to, or be better able to use, health-related information (Grossman, 1972), and thus we might expect to see better educated consumers particularly attracted to chains that voluntarily disclose calorie information. On the other hand, highly-educated consumers may already be well-informed about the calorie content of food and thus calorie labels may provide less new information for them, and thus there could be a smaller response by them. To investigate this, we estimate our models separately for those with and without a college degree.

We also test for heterogeneous treatment effects on two other dimensions. First, those with a high body mass index (BMI) may find disclosure of calorie information more or less appealing than others. Attempts to lose weight are, not surprisingly, more common among those with a higher BMI (see, e.g., Ruhm, 2012), and those with high BMI may be more likely to patronize firms that disclose calorie information if they are interested in using it to manage their weight. On the other hand, those with high BMI may be particularly likely to be information averse in this context, and thus they may avoid places with calorie counts. To investigate heterogeneous effects by BMI we estimate our models separately by whether the respondent's BMI is in the overweight or obese range (i.e. if BMI >=25).[10]

Another potentially relevant characteristic is sex. Women are more likely than men to report dissatisfaction with their weight, and are more likely to attempt to lose weight, controlling for BMI. For example, in the nationally representative National Health and Nutrition Examination Survey (NHANES) data for 1999-2006, 77.7% of women reported that their preferred weight was less than their current weight, compared to 57.6% of men (Ruhm, 2012). Also, a majority of women (56.1%) reported attempting to lose weight in the past year, compared to roughly a third of men (35.9%); see Ruhm (2012). To investigate heterogeneous effects by sex we estimate our models separately for women and men.

Empirical Results

Summary Statistics

Table 1 presents summary statistics for the sample. The percentage of the sample that visited each chain in the past 30 days was 12.3% for Starbucks and 9.3% for Dunkin Donuts. The sample is 56.2% female, 78.4% white, and 29.7% have a college degree or higher education.

Testing the Parallel Trends Assumption

[10] Body mass index is calculated as weight in kilograms divided by height in meters squared. See Burkhauser and Cawley (2008) for a discussion of the strengths and weaknesses of BMI as a measure of fatness.

Figure 1 graphs the unconditional percentage of the sample that reports having patronized Starbucks and Dunkin Donuts in the past 30 days. The unconditional trends prior to Starbucks implementing menu labeling in June 2013 (indicated with a vertical line) seem to track each other quite closely.

We also conduct an event study to better test the identifying assumption of parallel trends. The event study model is similar to the difference-in-differences model, but in place of the POST*TREAT indicator variable, the indicator for Starbucks is interacted with indicator variables for individual years (with 2012, the year immediately prior to treatment, excluded). Table 2 presents the coefficients from the event study. Prior to Starbucks' voluntary disclosure in 2013, there is no significant difference in the time trend in visits to Starbucks relative to Dunkin Donuts. Of the coefficients on eight pre-treatment event time periods, none are statistically significant at the 10% level. A test of joint significance for all such interactions prior to the treatment has an F-statistic of 4.24, which is statistically significant given our large sample size of over half a million observations, but the pattern of individual coefficients is consistent with the identifying assumption of parallel trends prior to the treatment.

The coefficients from the event study, along with their 95% confidence intervals, are graphed in Figure 2. The figure indicates that, prior to Starbucks' disclosure in 2013, there is no individual year in which the trend for Starbucks differed from that from Dunkin Donuts. The individual point estimates are small, and there is no consistent trend in a single direction prior to the event; the point estimates hover closely around either side of zero. This is consistent with the identifying assumption.

Results of Difference-in-Difference Regressions

Table 3 presents results of our difference-in-difference regressions, and the first row presents results for the full sample. Starbucks' voluntarily disclosing calorie information is estimated to have reduced the probability that consumers visit in the past month by 0.5 percentage points (4.3%), which is not statistically significant. The estimate is relatively precise; based on the 95% confidence interval, we can rule out that the impact of calorie disclosure was to increase the probability of visiting Starbucks by 0.7 percentage points or lower it by 1.6 percentage points. The lack of a detectable impact after disclosure is consistent with the unconditional trends in Figure 1, which show little change in the probability of patronizing Starbucks relative to Dunkin Donuts, from before disclosure to after disclosure.

The event study provides more granular results. Table 2 provides evidence of a transitory negative impact. The first year after disclosure (2013), the probability of visits fell by 0.8 percentage points (6.8%), which is statistically significant at the 5% level. However, in subsequent years (2014 and 2015), the point estimates fall in absolute value (to -0.7 and then -0.4 percentage points) and are not statistically significant. In the final year (2016), the point estimate is larger in absolute value than that in 2014 (-0.9 ppts versus -0.7 ppts) but is less precise and so is statistically significant at the 10% but not 5% level. These event study coefficients are plotted in Figure 2. In summary, while we cannot reject the null hypothesis of no effect over the entire post-disclosure period, there is evidence of a transitory negative impact the first year after disclosure.

Testing for Heterogeneous Effects

We test for heterogeneity in effects by estimating DiD models separately by education, sex, and BMI; these results are presented in subsequent rows of Table 3. Among those with a college degree, disclosure of calorie information by Starbucks was followed by a decrease of 0.4

percentage points in the probability of visiting a Starbucks in the last 30 days. Among those without a college degree, the decrease is 0.7 percentage points. Neither the individual point estimates nor the difference between them is statistically significant.

We next test for differences by sex. We find that information disclosure by Starbucks led to virtually no change in the probability that women visited Starbucks: an increase of 0.1 percentage point, which is not statistically significant. However, after disclosure, the probability that men visited Starbucks fell by 1.4 percentage points (15.2%), which is statistically significant. The difference in the point estimates for men and women is statistically significant at the 5% level.

We next investigate the possibility of heterogeneous treatment effects by consumer weight classification. Those whose BMI is below the overweight range are 0.1 percentage point less likely to visit Starbucks, and those whose BMI is at or above the overweight range are 1.0 percentage point less likely to visit Starbucks. Neither the individual point estimates nor the difference between them is statistically significant.

Intensive Margin of Visits

In Table 4 we present results for the intensive margin of visits; that is, among those who do visit the chain in the last 30 days, how often do they visit: with low frequency (1-5 times) or with high frequency (6 or more times). The first row, which corresponds to the entire sample, indicates that there is no statistically significant change in the intensive margin of Starbucks visits after information disclosure; the point estimate is consistent with a 1.9 percentage point increase in the probability that patrons visit with high as opposed to low frequency, but the estimate is imprecise.

We again test for the possibility of heterogeneous effects. Subsequent rows of the table show that the probability of being a high frequency visitor increases by 2.4 percentage points (9.1%) among those without a college degree, which is greater than the estimate among those with a college degree (0.8 percentage points), which is not statistically significant. However, the difference in estimates across the two education groups is not statistically significant. Subsequent rows of Table 4 indicate that there is no significant difference in the impact of information disclosure on the intensive margin of visits across sex or BMI category.

Discussion

There has long been interest in economics in how consumers respond to information, particularly as relates to health. In this paper we examine how consumers responded to the voluntary disclosure of calorie information by the Starbucks chain in 2013. We find that, overall, disclosure had no detectable impact on the probability that consumers patronized Starbucks in the past month relative to the probability that they patronized a rival chain, Dunkin Donuts. Specifically, we find that disclosure was followed by a 0.5 percentage point reduction in the probability that consumers visited Starbucks in the last 30 days, a change that is not statistically significant. The estimate is relatively precise; based on the 95% confidence interval, we can rule out that the impact of calorie disclosure was to increase the probability of visiting Starbucks by 0.7 percentage points or lower it by 1.6 percentage points.

There is some evidence of a transitory negative impact. The event study indicates that the first year after disclosure, the probability of patronizing Dunkin fell by a statistically significant 0.8 percentage points (6.8%), but in subsequent years the estimated effects were smaller in absolute magnitude.

We test for heterogeneity in these effects by education, sex, and BMI. We find evidence of heterogeneity by sex; there is no change in the probability of a visit to Starbucks by women after disclosure, but the probability that men visit falls by 1.4 percentage points (15.2%). The difference between men and women is statistically significant. The difference by sex could be due to several factors; for example, men may have had less accurate calorie information than women prior to disclosure, and may have previously underestimated the calories in Starbucks items. Men may be more likely to exhibit information aversion (Andries and Haddad, 2020) or strategic self-ignorance (Thunstrom et al., 2016), preferring not to know the number of calories they are consuming, or may experience the reminder of calorie content as a hedonic tax (Sunstein, 2021).

In contrast to the significant difference in impacts between men and women, we cannot reject the null hypothesis that the treatment effect is the same by education or BMI.

On the intensive margin, we find that information disclosure raised the probability that patrons without a college degree were high frequency (6 or more visits per month) versus low frequency visitors (1-5 visits per month) by 2.4 percentage points (9.1%); however, the difference in estimates between those with and without a college degree was not statistically significant. There were no significant differences in this effect by sex or BMI.

The findings of this paper have several implications. Although some restaurants have been concerned that posting calorie counts could hurt their business (e.g. Kruse, 2019), we find, overall, no detectable impact of disclosure on the probability of customer visits. This suggests that, at least for that outcome, voluntary information disclosure did not result in a competitive disadvantage for the disclosing firm. However, it is important to keep in mind that there was a significant reduction in visits the first year after disclosure, and among men in general during the post-disclosure period.

A novel contribution of this paper is that we are able to study an outcome that previous studies could not: the probability that consumers visit the chain. This complements the previous research which has studied how disclosure of calorie information affects what people order when they do visit restaurants (e.g. Cawley, Susskind, and Willage, 2020, 2021; Bleich et al., 2017; Cantor et al., 2015; Bollinger et al., 2011; Elbel et al., 2009).

An important comparison is Bollinger et al. (2011), which examined detailed internal transaction data from Starbucks as a means of evaluating the New York City menu label law that applied to all chains. Bollinger et al. (2011) compare transactions at Starbucks in New York City (the treated city) versus Boston and Philadelphia (the comparison cities) and estimate that calories per transaction fell 6%, with all of the decrease coming in food, not beverages. Note that both Starbucks and Dunkin Donuts had to disclose calorie counts under the New York City law, so Dunkin Donuts is not a comparison firm in their context. Bollinger et al. (2011) also estimate that the New York City menu labeling law increased daily transactions at New York City Starbucks by 1.4%. However, when they analyze a smaller sample of loyalty card holders' purchases, they find no detectable impact of the New York City law on the frequency of cardholders' purchases in New York City relative to the comparison cities. Bollinger et al. (2011) stress that their findings concern a *mandatory* disclosure law, and they emphasize that *voluntary* posting by a single chain could result in substantially different outcomes, especially with respect to competitive effects (Bollinger et al., 2011, p. 93). Our paper, which studies voluntary disclosure by the same firm, thus complements their work.

This paper also complements the broader literature on how disclosure of calorie information affects what consumers order at restaurants. Several studies of the New York City menu label law found no detectable change in the number of calories ordered by consumers at fast food restaurants (Elbel et al., 2009; Cantor et al., 2015). In full-service restaurants with hand-held menus, Cawley, Susskind, and Willage (2020) found in a randomized experiment that calorie labels reduced the number of calories ordered at dinner by 3%, with no significant difference by sex. Because they have menu boards rather than hand-held menus, Starbucks and Dunkin Donuts may be more similar to the fast food restaurants studied by Elbel et al. (2009) and Cantor et al. (2015) than the full-service restaurants studied by Cawley et al. (2020).

More generally, this paper contributes to the economic literature on the effects of information disclosure relating to health (e.g. Bederson et al., 2018; Bedard and Kuhn, 2015; Dupas, 2011; Wisdom et al., 2010; Jin & Leslie, 2009; Variyam, 2008; Jin, 2005; Dranove et al., 2003; Mathios, 2000). Even more broadly, this paper contributes to the economic literature on how consumers respond to information disclosure even unrelated to health (e.g. Luca and Smith, 2015; Conlin et al., 2013; Lewis, 2011; Suijs, 2007; Akerlof, 1970).

Limitations of this paper include that our data provide no information about what items people ordered when they visit, although previously-mentioned studies have already examined that as an outcome. We study a single pair of disclosing and non-disclosing firms, which may limit generalizability. However, much can be learned from studying one or two firms (e.g., Charness & Gneezy, 2009; Finkelstein & Poterba, 2004; Royer, Stehr, & Sydnor, 2015; Bollinger et al., 2010; Bedard and Kuhn, 2015). An important direction for future research is to examine how consumers have responded in other cases in which firms have voluntarily disclosed important information.

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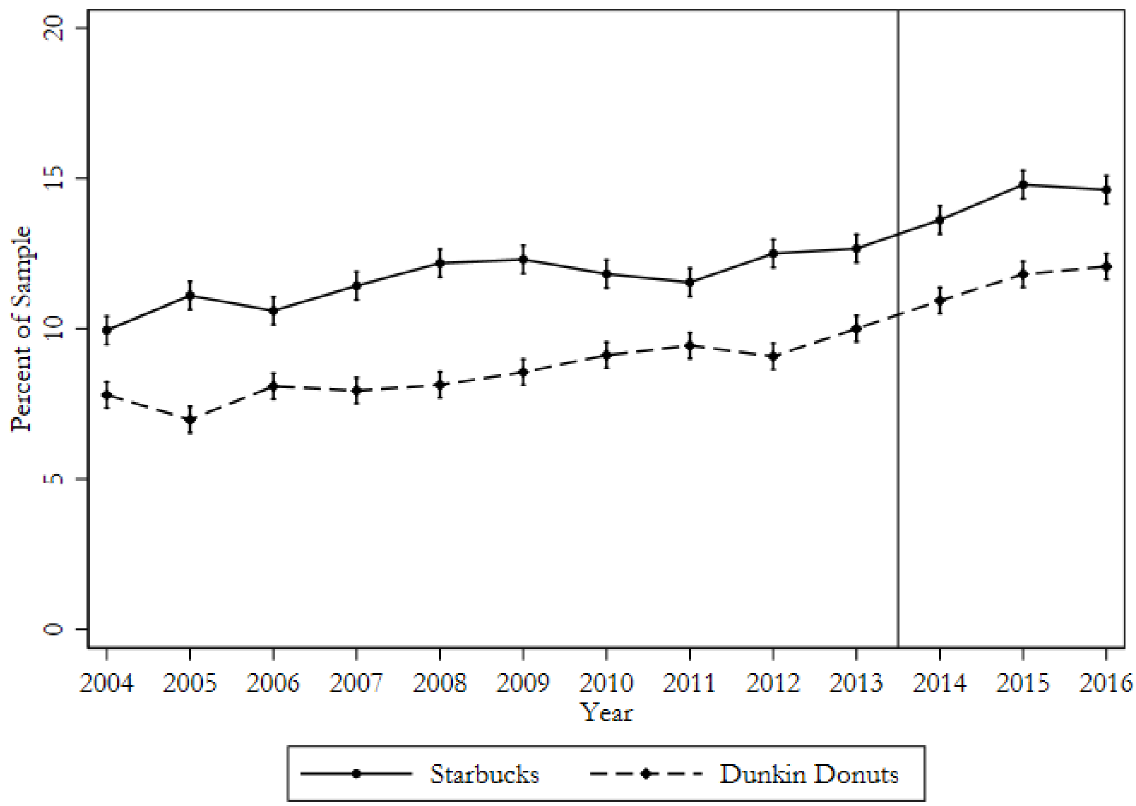
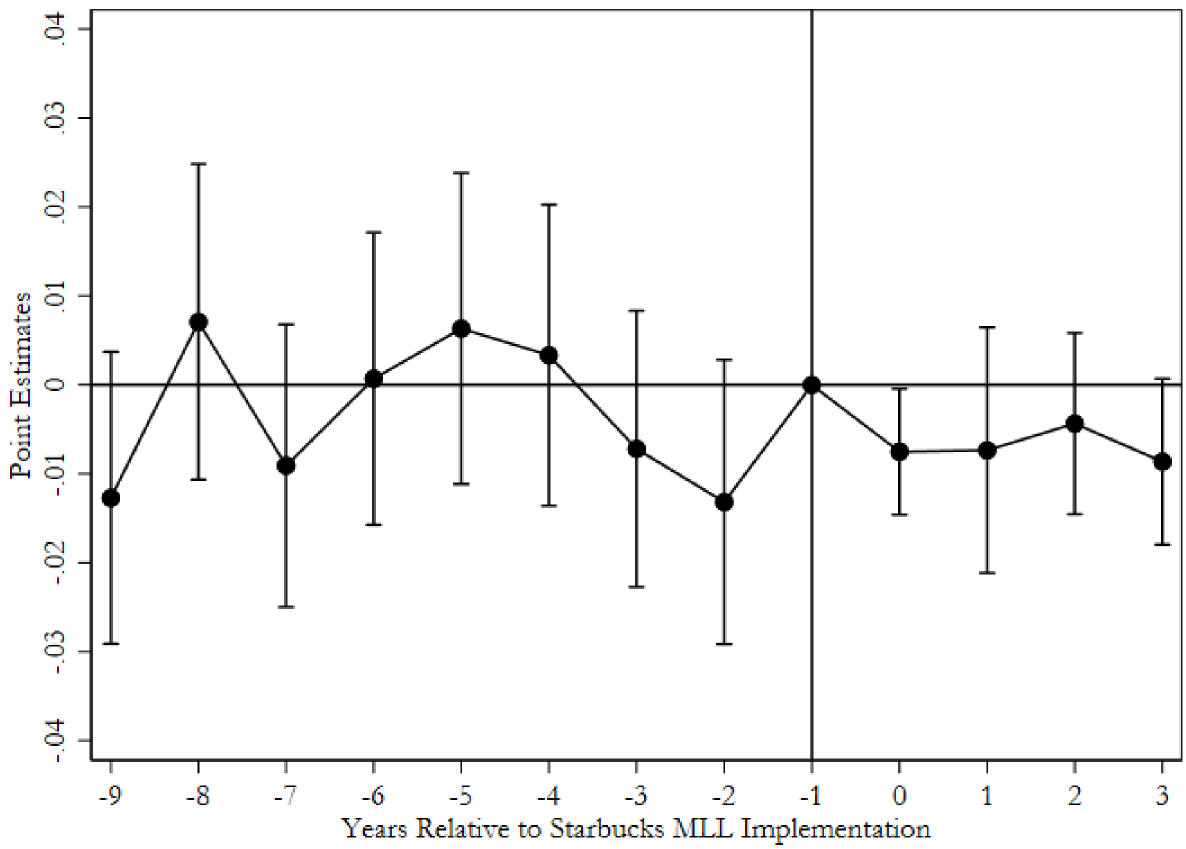
Figure 1: Trends in Consumers Patronizing Starbucks and Dunkin Donuts in Past 30 Days



Note: Partially treated data from Summer 2013 is dropped. Fall 2004 is excluded due to data corruption. Voluntary labeling implemented in June 2013. Vertical line indicates treatment. Each year also show the 95% confidence interval. N=257,493 for Starbucks, N=257,493 for Dunkin Donuts.

Figure 2: Graph of Results from Event Study, Testing Parallel Trends Assumption of DiD Model



Note: The graph plots the point estimates of the coefficients on event time from an event study model, along with the 95% confidence intervals on those estimates.

Table 1: Descriptive Statistics

Variable	Mean	(SE)
Visited Starbucks in Past 30 Days (Extensive Margin)	0.123	(0.330)
Visited Dunkin Donuts in Past 30 Days (Extensive Margin)	0.093	(0.291)
Visited Starbucks 6+ Times (vs 1-5 Times) in Past 30 Days (Intensive Margin)	0.266	(0.442)
Visited Dunkin Donuts 6+ Times (vs 1-5 Times) in Past 30 Days (Intensive Margin)	0.179	(0.384)
% Female	0.562	(0.496)
% Age 30-40	0.152	(0.359)
% Age 40-50	0.188	(0.391)
% Age 50-60	0.202	(0.402)
% Age 60-70	0.167	(0.373)
% Age 70 Plus	0.141	(0.348)
% White	0.784	(0.412)
% Black	0.071	(0.256)
% Asian	0.028	(0.165)
% Other Race	0.117	(0.321)
% Hispanic	0.311	(0.463)
% HS Grad	0.281	(0.449)
% <1 Year of College	0.065	(0.246)
% 1 Full Year of College	0.058	(0.234)
% 2 Full Years of College	0.095	(0.294)
% 3 Full Years of College	0.046	(0.209)
% College Graduate	0.161	(0.367)
% Some Graduate School	0.031	(0.173)
% Graduate School Degree	0.106	(0.308)
% College Degree or More	0.297	(0.457)
% Single	0.193	(0.394)
% Divorced, Separated, or Widowed	0.181	(0.385)
% Full-time Employed	0.461	(0.498)
% Part-time Employed	0.123	(0.329)
% Retired	0.201	(0.401)
% Temporarily Unemployed	0.051	(-0.22)
% Disabled, Not Employed	0.044	(0.205)
% Full-time Student	0.018	(0.131)

% Homemaker	0.086	(-0.28)
% 2 People in HH	0.333	(0.471)
% 3 People in HH	0.181	(0.385)
% 4 People in HH	0.183	(0.387)
% 5 People in HH	0.11	(0.313)
% 6 People in HH	0.055	(0.228)
% 7 People in HH	0.025	(0.155)
% 8+ People in HH	0.025	(0.155)
% HH Income: $30,000-$49,999	0.186	(0.389)
% HH Income: $50,000-$74,999	0.185	(0.388)
% HH Income: $75,000-$149,999	0.285	(0.451)
% HH Income: $150,000+	0.146	(0.353)
% in Midwest Region	0.253	(0.435)
% in South Region	0.439	(0.496)
% in West Region	0.24	(0.427)
% in DMA that passed but not implemented a MLL	0.116	(0.321)
N	514,986	

Data are from 2004-2016. Starbucks is the treatment firm and Dunkin Donuts is the control firm. The data are unique at the Person ID-Firm level, with one observation per person, per firm. N listed (514,986) is for the extensive margin of visits; the N for the intensive margin (high or low frequency of visits) is N=55,843. When sample is divided by BMI category, the sample size is smaller due to non-response to the questions about weight and height; N=474,730 for the extensive margin of visits and N=52,542 for the intensive margin of visits.

Table 2: Results of Event Study Model

Treatment Firm:	Starbucks					
Control Firm:	Dunkin' Donuts					
Interaction	Coefficient	Robust SE	T-statistic	P-value	95% Confidence Interval	
Starbucks * 2004	-0.013	0.008	-1.53	0.128	-0.0291145	0.0036967
Starbucks * 2005	0.007	0.009	0.79	0.432	-0.0106507	0.0248159
Starbucks * 2006	-0.009	0.008	-1.13	0.261	-0.0249602	0.0067931
Starbucks * 2007	0.001	0.008	0.08	0.934	-0.0157325	0.0171233
Starbucks * 2008	0.006	0.009	0.71	0.477	-0.0111605	0.0238061
Starbucks * 2009	0.003	0.009	0.39	0.698	-0.0135936	0.0202545
Starbucks * 2010	-0.007	0.008	-0.91	0.362	-0.0227115	0.00833
Starbucks * 2011	-0.013	0.008	-1.62	0.106	-0.0291481	0.0028125
Starbucks * 2012			(omitted)			
Starbucks * 2013	-0.008	0.004	-2.09	0.038	-0.014593	-0.000426
Starbucks * 2014	-0.007	0.007	-1.05	0.295	-0.021619	0.0064634
Starbucks * 2015	-0.004	0.005	-0.84	0.401	-0.0145383	0.0058419
Starbucks * 2016	-0.009	0.005	-1.83	0.069	-0.0179562	0.00069
Joint Test of Significance	Interactions Tested: 2004-2012					
F-statistic:	4.24					
P-value:	0.000					
Joint Test of Significance:	Interactions Tested: 2013-2016					
F-statistic:	1.93					
P-value:	0.107					

Table 3: Results of Difference-in-Differences (DiD) Models, Extensive Margin

Sample	Sample Size (N)	DiD Coefficient	Standard Error
Full	514,986	-0.005	0.006
With college degree	153,280	-0.004	0.007
Without college degree	361,706	-0.007	0.006
Test of equality of DiD coefficient across education groups: Chi-Squared=0.508 (p=0.476)			
Females	289,492	0.001	0.008
Males	225,494	-0.014***	0.004
Test of equality of DiD coefficient across sex: Chi-Squared =8.199 (p=0.004)			
BMI < 25	206,846	-0.001	0.008
BMI >= 25	267,884	-0.01	0.005
Test of equality of DiD coefficient across BMI categories: Chi-Squared=2.439 (p=0.118)			

Note: asterisks indicate statistical significance: * 10% statistical significance, ** 5%, *** 1%. Dependent variable is an indicator for having visited the chain in the past 30 days.
Note: Total sample size for model estimated by BMI classification (N= 474,730) is smaller than the total sample size of the main model (514,986) due to non-response to the questions about weight and height.

Table 4: Results of Difference-in-Differences (DiD) Models, Intensive Margin

Sample	Sample Size (N)	DiD Coefficient	Standard Error
Full	55,843	0.019	0.011
With college degree	21,529	0.008	0.017
Without college degree	34,314	0.024*	0.01
Test of equality of DiD coefficient across education groups: Chi-Squared =1.411 (p=0.235)			
Females	34,873	0.017	0.012
Males	20,970	0.019	0.013
Test of equality of DiD coefficient across sex: Chi-Squared =0.014 (p=0.905)			
BMI < 25	24,055	0.023	0.012
BMI >= 25	28,487	0.01	0.015
Test of equality of DiD coefficient across BMI categories: Chi-Squared =0.558 (p=0.455)			

Note: asterisks indicate statistical significance: * 10% statistical significance, ** 5%, *** 1%. Dependent variable is an indicator for having a high number of visits (6+) versus a lower number (1-5) in the past 30 days. Sample includes only those who visited the chain in the past 30 days.
Note: Total sample size for model estimated by BMI classification (N= 474,730) is smaller than the total sample size of the main model (514,986) due to non-response to the questions about weight and height.

Appendix Table 1:

United States Demographic Distribution v. Regression Sample Distribution

Demographic Characteristic	U.S. Census (2010)	Simmons NCS Regression Sample (2003-2016)
% Male	48.50%	43.80%
% Female	51.50%	56.20%
% White	81.00%	78.40%
% Black	11.90%	7.10%
% Asian	4.70%	2.80%
% Other Race	2.40%	11.70%
% Hispanic	13.90%	31.10%
% Non-Hispanic	86.10%	68.90%
% Age 18-30	24.10%	15.00%
% Age 30-40	17.20%	15.20%
% Age 40-50	18.80%	18.80%
% Age 50-60	17.90%	20.20%
% Age 60-70	12.30%	16.70%
% Age 70 Plus	11.60%	14.10%
% Less than HS Grad	13.70%	15.70%
% HS Grad	31.00%	28.10%
% College Graduate	18.00%	16.10%
% Graduate School Degree	9.30%	10.60%
% Married	54.10%	62.60%
% Single	26.90%	19.30%
% Divorced, Separated, or Widowed	19.00%	18.10%
% Full-time Employed	47.30%	46.10%
% Part-time Employed	12.40%	12.30%
% Temporarily Unemployed	6.70%	5.10%
% 2 People in HH*	42.70%	33.30%
% 3 People in HH*	22.50%	18.10%
% 4 People in HH*	20.00%	18.30%
% 5+ People in HH*	14.80%	21.50%
% HH Income: $0-$29,999	31.50%	19.80%
% HH Income: $30,000-$49,999	19.10%	18.60%
% HH Income: $50,000-$74,999	17.70%	18.50%
% HH Income: $75,000-$149,999	23.40%	28.50%
% HH Income: $150,000+	8.30%	14.60%
% in Northeast Region*	18.40%	6.80%
% in Midwest Region*	21.80%	25.30%
% in South Region*	36.70%	43.90%
% in West Region*	23.10%	24.00%

Note: All percentages are for Simmons or Census respondents aged 18 years or older unless otherwise noted.
Asterisk (*) indicates that, due to Census Data availability, the U.S. percentages are based on adults aged 20 years or older.