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Do Labels Make A Difference: Estimating The Impacts Of Vermont’s Gmo Labeling Law On Perceptions And Prices

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DO LABELS MAKE A DIFFERENCE: ESTIMATING THE IMPACTS OF VERMONT'S GMO LABELING LAW ON PERCEPTIONS AND PRICES

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ABSTRACT

Vermont is the first and only state in the US to establish mandatory labels for food containing genetically modified organisms (GMOs). This thesis investigates the impact of the mandatory labeling law as it relates to changes in prices, quantities sold, and opinions of GMOs. First, grocery store scanner data from Vermont and Oregon are compared using triple difference (difference-in-difference-in-difference) models. Next, Vermont, Oregon, and Colorado survey response data are compared using difference-in-difference models. The findings reveal that there is a general price premium for non-GMO goods of $0.05/oz across all states and times, that mandatory labeling laws do not result in a short-term change in quantities sold or prices of GMO products, and that both mandatory labeling laws and failed mandatory labeling referendums cause an increase in support for GMOs in the food supply. The implications of this research are that mandatory GMO labels did not impact short-term prices or sales and increased the level of support for GMOs.

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CHAPTER 1.

Introduction

Ever since the release of the first Genetically Engineered Organisms (GMOs) into the consumer food market in the 1980s, the economic, ecological, social, and health impacts of the products have been debated. Many people and organizations are involved in the debate: agri-food and chemical companies, academics from disciplines ranging from natural and food science to the humanities, consumer information environmental and health advocates, and non-profit organizations. In July 2016, Vermont became the first state in the US to pass as a mandatory GMO labeling law. Although the law was only in place until August 2016, it is the only natural experiment that has occurred in the US. The focus of this thesis is not to make claims about the value or harms of GMOs, but instead to focus on consumer reactions to the GMO and GMO-free products when information is mandatory and when it is not available. Specifically, the intent is to see if the law in Vermont and failed referendums elsewhere resulted in changes in prices, units sold, and opinions of GMOs.

The goal of this research is to evaluate survey responses and consumer reactions to GMO labeled products in the marketplace. The reason why such research is important is that it can help resolve the debate of whether GMO labels serve as a "warning" or as a "guidepost" for consumers. The null hypotheses tested is that in response to the passage of a mandatory labeling law in Vermont, H.112, there has been no negative impact on the price, units sold, or opinion of GMOs in Vermont. If we do not reject the null hypothesis, it suggests that the law does not harm the economy and instead simply increases transparency.

The implications of this study primarily relate to future labeling practices. In august of 2016, the federal law, Public Law 114-216, established a mandate that a national GMO labeling regime should be established and implemented by 2020. However, if no national labeling regime is established within a reasonable period of time, then individual states may once again work toward establishing their own regulations. The findings of this study can serve as a guide for the national or state labeling regimes.

This organization of this theses will be as follows: (1) Introduction – a general introduction about the topic, (2) Expanded Literature Review – A detailed exploration into the labeling and a background examination of the theoretical and methodological approaches to the data used herein, (3) Article 1 – Do Mandatory GMO Labels Expand non-GMO Niche Food Markets: A Vermont and Oregon Case Study, (4) Article 2 – Do Mandatory Labeling Laws and Referendums Affect Opinions on GMOs?, (5) General Conclusion and Policy Implications.

CHAPTER 2.

Expanded Literature Review

Generic Labeling Impacts

While humans have always had some concerns about the food they eat, concern about the impact on food of recent technologies has been increasing in recent decades. Technological innovation ranging from pesticide use to fishing practices has led consumers to be more concerned about the impact of what they are eating for their bodies and on the planet. Trends such as the "clean label" movement indicate a desire for more transparency in the contents of food, directly on the product's label (Clean Label, 2018). Increasingly, younger consumers are becoming more concerned about the social and environmental impacts of their food purchase decisions (Cargill, 2017). The issue of labeling food products has been a matter of public debate for decades in the U.S. where it is structured as the right of companies to highlight the beneficial aspects of their products or efforts by consumers with the help of legislators to try to comprehend and use label information (Kolodinsky, 2012).

Impacts of Label Introduction

The introduction of labeling regimes can result in drastically different outcomes. Some labels such as Recombinant bovine somatotropin (rBST)-free or fair trade can result in a price premium whereas geographic labeling of products such as regional Spanish beef has no effect on units sold or price (Kolodinsky, 2008; Loureiro & McClusky, 2000; Verbeke & Ward, 2006). rBST is an early version of a GMO with unique labeling. Between September 1995 and August 1996, the labeling of products containing rBST was mandatory in Vermont. In studying the impacts of voluntary rBST labels on price and sales, Dhar and Foltz (2005) found that rBST free labels resulted in greater demand and higher prices for non-rBST products. Mandatory labeling of rBST products did not have the intended effect of communicating information to the public (Kolodinsky *et al.,* 1998). The confusing labeling practice of small stickers accompanied by fliers posted nearby was not a simple enough way to effectively transmit the intended interpretation. Mandatory rBST labels are only one example of packaging that attempted to create a transparent signal to enable customers to make their own purchasing decision (Kolodinsky, 2008).

Products that use labels such as fair trade or environmentally friendly have better sales and price premiums after the labels are adopted. When consumers consider coffee purchases, they are willing to pay a premium for fair trade and shade grown coffee more than for organic products (Loureiro & Lotade, 2005). The sales of tuna dropped markedly after it was discovered that fishing practices were killing dolphins. The introduction of Dolphin-Safe labels not only corrected for a drop in demand, after controversy emerged, but also increased both units sold and prices (Teisl *et al*., 2002). Similarly, when customers were offered labels indicating lower CO2 emissions to produce the products, they were willing to pay a small premium and consistently chose the lower CO2 products when prices were held equal (Vanclay *et al*., 2010). The conclusion that greenhouse gas (GHG) emission labels are effective was questioned by subsequent empirical studies using UK grocery store scanner data (Kortelainen *et al.*, 2016).

Different label types lead to different willingness to pay for GMO products (Huffman *et al*., 2003). For example, Noussair, Robin, and Ruffieux (2002) found that when GMO labels are placed on the back of a container consumers ignore the information. Given the different responses that labels can produce, it is valuable to study the way in which people respond to GMOs outside the context of a lab experiment.

GMO Labeling

The USDA defines GMOs as “an organism produced through genetic modification” where genetic modification can be “manipulation of an organism’s genes by introducing, eliminating or rearranging specific genes using the methods of modern molecular biology, particularly those techniques referred to as recombinant DNA techniques” (USDA, 2018). Typically, GMO products are made by having a gene from a different species inserted into the DNA of the target plant or animal. Farmers use GMO species typically because the plants are resistant to specific weed killers, allowing for larger doses of the chemicals to be applied without harming the principal crop. In 2016 U.S. farms devoted 72.9 million hectares (MHA) to GMO or biotech crops account for approximately 23% of all principal crops nationally (ISAAA, 2016; USDA, 2017). The primary GMO crops are corn, soy, cotton, alfalfa, papaya, canola, and sugar beets. GMO corn has increased from 25% of all corn acreage in 2000 to 92% in 2017 (USFDA, 2018). GMO soybean cover has increased from 54% to 94% and cottonseed from 61% to 96% in the same period (USFDA, 2018). As of 2017, GMO canola accounts for 90-91% of total canola acreage, alfalfa 14-18% of the total, GMOs account for 100% of sugar beet acreage (ISAAA, 2016; USDA, 2017). GMO potato, papaya, and squash crops account for less than .01% each in 2017 but are expected to increase in the future (ISAAA, 2016).

New technological methods for developing GMO products are rapidly emerging. Scientific techniques currently used to produce GMOs include Agrobacterium, Biolistic Transformation, Electroporation, and Antisense technology (Maghari & Ardekani, 2011).[1] With the advent of Clustered Regular Interspaced Short Palindromic Repeats (CRISPR) countless new varieties of

[1] Agrobacterium is a bacterium that uses horizontal gene transfer between itself and plants. Biolistic Transformation is the use of a gene gun that delivers exogenous DNA to a target nucleus. Electroporation applies an electrical field that permeates a membrane permitting the introduction of DNA. Antisense technology synthesizes strands of DNA or RNA to create “off” switches for specific genes.

genetically engineering crops are expected to be developed. However, ever since the European Union decided to include CRISPR under the GMO umbrella there has been some ambiguity as to what to consider GMO (Abbott, 2018).

The GMO Labeling Debate Thus far

Two main paradigms surround the GMO labelling debate. On one side, there are labeling opponents who believe that any GMO label will be perceived as a warning, in much the same way that a label informing consumers about the increased risk of lung cancer tied to smoking is warning. On the other side of the debate are consumer rights and environmental groups, small farmers, and health advocates who see labels as an information signal. Modern consumers tend to believe that GMO technology is meaningfully different from earlier forms of selective breading. Surveys show that approximately 92% of Americans believe that GMO products should be labeled (Consumer Reports National Research Center, 2014).

While there are many arguments that emerge from those who oppose labeling, the two most frequent are (1) GMO labels will scare and confuse consumers who will view labels as warnings, and (2) labels will drive up the prices of both GMO and non-GMO foods. The "warning camp" believes that consumers do not have a good enough understanding of genetic engineering to make smart decisions about the food they eat (Kolodinsky *et al.,* 2004; Scientific American, 2013). The price argument focuses on the fact that changing labels costs money, that segmenting the market creates premiums that may price lower income consumers out of buying non-GMO goods if GMO goods are labeled, and that generating fear forces farmers and companies to spend more to reassure consumers, resulting in lower profit margins and potentially higher prices to cover the costs (Lesser & Lynch, 2014; Scientific American, 2013). The fear of higher costs has actually resulted in multimillion-dollar campaigns to sway consumers to accept GMO foods without mandatory labeling laws (Coleman, 2016).

Arguments in favor of labelling have also emerged. The most frequent and one even shared by many proponents of GMO technology is the consumers' right to know (Just Label It, 2018). Those who advocate for labeling tend to view labels as an answer to information asymmetry present in the marketplace (Golan *et al.,* 2001, Kolodinsky, 2012). The logic behind the information asymmetry is that producers know more about the products, prices, manufacturing practices, and markets than do consumers. As such producers are able to disproportionately increase the amount of producer surplus as compared to consumer surplus in market transactions. Access to perfect information, one of the economic assumptions for well behaving markets is thus violated. This argument is primarily rooted in consumer rights advocacy. In addition, many supporters of labelling focus on the potential health or environmental impacts.

Credence characteristics are those that cannot independently be verified by a typical consumer without the information being explicitly available, such as organic, place of origin, nutritional value, etc. The application of signaling credence attributes can have various effects; it can create separate markets for labeled products, simultaneously lowering the price of the perceived inferior good and creating a price premium for the superior good (Grolleau & Caswell, 2006; Larson, 2003; Mattoo & Singh, 1994). In the case of GMO goods, where between 10% and 20% would prefer to never consume them, this would likely indicate a decrease in price of GMO goods and an increase in price for non-GMO goods (Buhr *et al*., 1993). If the end goal is maximizing consumer utility, then this could be beneficial for the consumers who are indifferent between GMO and non-GMO foods. However, differences in the pricing of the two types of goods could also price out consumers who would like to purchase non-GMO foods but could not afford to purchase them at the higher price point.

Test and Experiments

The majority of data about GMO preferences in the labeling debate has been from surveys and experimental auctions (McCluskey & Loureiro, 2003). Mail and phone surveys tend to reveal that messaging and language impacts consumer willingness to pay (WTP) for GMO and non-GMO foods (Han & Harrison, 2007; Lusk, 2003). Student surveys including Bernard *et al.* (2009) show a general decrease in WTP for GMO goods. Surveys highlighting the beneficial aspects of GMOs revealed a \$0.006 to \$0.087 higher WTP for GMO tomatoes, and \$0.33 premium for corn chips (Loureiro & Bugbee, 2005; Lusk *et al.,* 2001a). Surveys that did not highlight beneficial traits resulted in a \$0.056 to \$0.39 higher WTP for GMO free products (Brun & Campbell, 2016; Bukenya & Wright, 2007; Loureiro & Hine, 2002; Lusk *et al.,* 2001a; Onyango *et al.,* 2006; Rickertson *et al*., 2017).

In bid experiments conducted in Europe, researchers founder that consumers preferred to pay 37% less for GMO products compared with non-GMO products when neither beneficial nor detrimental aspects of the technology were highlighted (Noussair, Robin, and Ruffieux, 2001). When GMO labels were present, but attention to them was not emphasized, they resulted in a 2% price discount, as opposed to a 25% discount when they were emphasized (Noussair, Robin, and Ruffieux, 2002). In one auction students were not willing to pay a premium for non-GMO chips (Lusk *et al.*, 2001b). When asked to bid for beneficial GMO vs no GMO traits, students had a higher willingness to pay for GMO lean meat and other beneficial GMO features (Buhr *et al.,* 1993; Colson *et al.,* 2011a; Colson *et al.,* 2011b). Using mixed auction item and information design, different information can drastically change the discount rate for GMO products (Colson & Huffman, 2011; Rousu *et al.,* 2007).

Experiments on volunteers were conducted by Huffman *et al.* (2003) using an auction model where participants bid on products to estimate price levels. These experiments produced a

14% discount for GMO labeled products compared with non-GMO equivalents. Other student auctions revealed a $0.02 to $0.06 greater WTP for non-GMO products (Wachnheim & Vanwechel, 2004).

Who Eats GMO

A challenge to many of the surveys on who is more WTP for GMO food is the assumption that individuals actually purchase the products in the first place. When surveyed, there was a smaller difference of WTP for GMO vs non-GMO when individuals were asked about processed food and a larger difference in WTP when asked about produce (He & Bernard, 2001). However, produce is much less likely to contain GMOs than processed foods that would include ingredients such as corn derivatives, beet sugar, and canola oil. If a household does not purchase processed foods, then its likelihood of interacting with GMO products is much lower. Therefore, surveys and experiments have some limitations. In addition, because many of these experiments and surveys were conducted on small populations, students, and required artificial stimuli (such as hearing pro or anti GMO messaging before being asked about their opinion), the pure effect of GMO labels on price and demand is uncertain. Studies that seek information about WTP and acceptance of GMOs tend to control for age, gender, income, and other demographic variables when applicable.

In general, the acceptance of GMO products is linked to risk-benefit analysis where consumers who perceive benefits to themselves and society are more willing to consume GMO goods, and those who do not, are less likely (Han & Harrison, 2007; Lusk & Coble, 2005). Individuals who believe GMOs are safe for consumption are more likely to buy GMOs (Han & Harrison, 2007). And those who believe biotech benefits society are more likely to buy (Han & Harrison, 2007). More educated consumers are also more likely to support GMOs (Han & Harrison, 2007; Heiman, Just, & Zilberman, 2000). Individuals with a greater trust in the FDA are more willing to buy GMO products (Han & Harrison, 2007).

Support for GMOs varies across income groups. A higher income tends to be correlated with a greater level of support for GMO products in the market place but a lower personal willingness to purchase the foods (Bukenya & Wright, 2007; Colson *et al.,* 2011b; Kolodinsky & Reynolds, 2014; Loureiro & Bugbee, 2005). Wealthier and more educated consumers are less likely to be supportive of GMO (Kolodinsky & Renolds, 2014; Loueiro & Hine, 2002). Those earning less than $30,000 are more likely to buy GMOs but also tend to be more opposed to such products (Han & Harrison, 2007; He & Bernard, 2011).

Those with strong opinions about GMOs or those who believe GMOs are a morally wrong are less likely to buy them (Bernard *et* al., 2009; Bukenya and Wright, 2007; Colson *et al.,* 2011b; Han & Harrison, 2007; He & Bernard, 2011; Kolodinsky, 2008). Those who read more labels or are in favor of GMO labeling are less likely to buy as well (Colson *et al.,* 2011a; Colson *et al.,* 2011b, Han & Harrison, 2007).

Demographic characteristics also play a role in purchase decisions. Larger households tend to be more likely to purchase GMOs, for example (Colson *et al.,* 2011b). Individuals who identify as ethnically white are less likely and blacks are more likely to purchase GMOs (Bernard *et al.,* 2009; Colson *et al.,* 2011b). Individuals over the age of 55 are also less likely to buy GMOs but at the same time are more likely to support such products (Colson *et al.,* 2011b; Han & Harrison, 2007). Individuals with farming experience are less supportive of GMOs (Colson *et al.,* 2011b). Although one study indicated greater support toward GMOs by females (Loureiro & Bugbee, 2005), a larger number of studies indicated the opposite (Bernard *et al.,* 2009; He, Bernard, 2011; Kolodinsky & Reynolds, 2014).

GMO Labeling Law History

On May 8th, 2014 Vermont became the first state in the U.S. to successfully pass a GMO labeling law H.112 (Vermont General Assembly, 2014). The act took effect in July of 2016 on a backdrop of approximately 70 unsuccessful attempts at legislation elsewhere in the country, including failed referendums in Colorado, Prop-105, and Oregon, Measure-92, both in November 2014 (Colorado General Assembly, 2014; National Conference of State legislatures, 2016; Oregon Secretary of State, 2014). While many companies in Vermont and in the U.S. voluntarily began labeling products that contained GMOs, others actively lobbied against any state-based regulations. This opposition led to the passage of the national Public Law 114-216, which overturned Vermont's initiative in August 2016 and shifted the obligation of labeling regulation to the U.S. Congress (U.S. Congress, 2016). In preparation to a federal policy requiring new nutritional labeling in 2020, a national debate is once again emerging between companies and regulators about the best labeling practice for GMO goods.

Economic Theory

In order to evaluate the implications of a large-scale survey on the impact of the GMO labeling law, it is necessary to outline the logical steps that led to a response resulting in an acceptable reading of preference. Following Fishbein's (1963) theory of attitudes, an attitude is a function of what an individual believes about an object and the evaluative aspect of those beliefs. Beliefs such as opposition to or support for GMOs, retrieved from surveys, are proxies for the individual intentions and purchase predictors (Grobe *et al.*, 1997). The attitudes individuals hold with relation to an object (or idea) are correlated with the actions that individuals will demonstrate with regards to that object (Han & Harrison, 2007). As such, if a survey question asks an individual about their preference for a particular product, such as "Do you strongly support, support, are neutral toward, oppose, or strongly oppose the use of GMOs in the food supply," then the individual's response serves as a valid predicter for that individual's purchasing intentions with regards to GMO food.

A key assumption for markets to generate efficient outcomes is that information is perfect. Under the assumption of perfect information buyers and sellers possess the same amount of information about the products in the market place. This assumption seems reasonable in many real-world settings. In a globalizing economy with ever-longer and more complex product chains, even the country of origin of a product can be difficult to determine. Accordingly, in many environments, sellers have an informational advantage over buyers regarding various dimensions of product quality, especially if those dimensions of quality are difficult for consumers to discern after purchase.

The existence of informational asymmetries in many instances creates an incentive for sellers to signal that they are producers of higher quality goods, if doing so allows them to obtain higher prices for their products. In these cases, market asymmetries are voluntarily removed by producers to create niche markets for their goods. In the case of GMO products, the Non-GMO project encourages producers to voluntarily disclose that they do not use GMO products and in exchange receive the right to use the organization's logo, incorporate a price premium, and enable the company to target a higher paying market (Non-GMO Project, 2016).

Voluntary disclosure of product information is typically reserved for product attributes that can increase the value of the product. If, instead, an attribute segments the market in an inferior direction, producers will tend to conceal the attribute. Akerlof's (1970) research provides critical insights regarding the impact of asymmetric information on product quality. Akerlof's model uses two products, "reliable automobiles" and "lemons", where the former are more desirable and command a higher willingness to pay from consumers. According to Akerlof, if consumers are unaware of whether a particular car is "reliable" or a "lemon" but only know the probability distribution of reliable cars vs. lemons, it is possible that only lemons will be sold if the probability that a randomly chosen car is reliable is sufficiently low. If most cars are lemons, and the probability of a lemon being reliable is sufficiently low, then there is no incentive to include reliable cars in the market as the buyers will apply the discount to all of the cars in the market. If the probability of a random lemon being a reliable car is sufficiently high, then the average price for lemons would increase as buyers see a higher probability that the purchase of a random car will result in a desired product.

The interpretation of lemons can be extended to the market for foods. If there is a group of consumers who would prefer to not purchase GMOs, then for those consumers, buying a random unlabeled product is much the same as buying a lemon. There is a chance the consumers are going to randomly select a product that is GMO-free, if the probability of this is great enough, then they will tend to have a higher willingness to pay for the unlabeled food. However, if the probability of a product being GMO-free is sufficiently small, then they will assume that all products in the market place are GMOs and therefore will have a lower WTP for any unlabeled product.

Asymmetric information therefore provides a potentially market making role for mandatory product labeling regulations. A law requiring manufacturers to disclose whether or not their foods contain GMOs reduces information asymmetry about perceived product quality. As a result, separate equilibria can emerge in which both GMO using and GMO-free products are sold, and in which GMO-free products command higher prices than GMO using products.

Data

This study focuses on Vermont, Oregon, and Colorado. Two distinct data sets are used in this study. The first includes prices and sales of products in Vermont and Oregon before and after Vermont's legislation took effect. The products are juices, juice drinks, cereals, and fruit sauces.

About half of the products included are GMO. The data are segmented into the unit of product/week/state. A total of 10 weeks of data are available in each period covering the same set of weeks one year apart. The second sat of data are surveys collected in Vermont and nationally. These surveys also cover the time before and after the execution of Vermont's GMO labeling law. The key dependent variable in these surveys is a Likert scale question pertaining to level of support or opposition to GMOs in the food supply. Demographic variables collected from the survey are included in the analysis. In both data sets, the independent variable of interest is the interaction term of Time and State, and in the case of the prices and sales set, GMO.

With regards to the sales and price data of GMO and non-GMO goods, the original aim was to use a state with similar characteristics as Vermont in order to have a strong control. New Hampshire or Maine would have been ideal candidates. However, after discussions with company representatives who were involved in labeling, it became clear that most products have regional markets that share a label. Vermont is not a large enough state to justify unique labels. As a result, all of New England is in the same labeling market. The rationale for using Oregon is that it is not in the same marketing region as Vermont but shares many of the same characteristics. Given that beliefs and ideology are considered among the most influential components of predicting attitudes towards GMO foods, Oregon was selected for the project as it has a relatively similar ideological makeup and is a relatively small coastal state not in the Northeast. The edge for Democratic presidential candidates exceeded 10% in the last three elections in both Oregon and Vermont. Both states have over one-third of the population living in a single metropolitan statistical area. Both states are within 6 hours of a major Canadian city. Finally, both states had major campaigns pertaining to GMO labeling.

For the survey component, Oregon and Colorado are used because they had some sort of referendum and as such these states can be compared with Vermont. National data are available for the needed time period also. Additionally, including Oregon in both data sets creates additional demographic controls.

Many of the products used in this study can be considered breakfast food. Breakfast is the most likely meal to be consumed at home and, therefore, accounts for the lowest average expenditures, with only 28.2% of families eating breakfast away from home in a given week compared with 60.7% and 55.1% for lunch and dinner, respectively (Paulin, 2000). Bernard *et al.* (2009) used milk and cereal to model the presence of GMOs and preferences. Since breakfast is the most frequent meal eaten in the home, consumers would be most likely to know the ingredients of the breakfast foods they consume. Onyango *et al.* (2006) uses corn flakes, a GMO breakfast food, to estimate consumer WTP for genetically modified goods.

The study uses data on breakfast-oriented foods. All of the products included are sold nationally and include both GMO and non-GMO items. None of the products included an organic label. The products used in this analysis include breakfast cereals, applesauce products, fruit juices, and fruit drinks.

Logistic Models

Binomial and ordinal logit models will serve as the methods of interpretation for the survey data. The Likert Scale question pertaining to support for and opposition to GMO labels will be analyzed in a few different ways as a binary, truncated model, and as pseudo continuous (censored) model. The truncated and binary models are such that: Support + Strongly Support = Support, Oppose + Strongly Oppose = Oppose, and Neutral = Neutral.

Using Wooldridge (2009), I start with the simple model for a logit regression to explain the probability of an event. This form is based on a binary response with a limited probability model.

$$P(y=1|\boldsymbol{x}) = P(y=1|x_1, x_2, \dots, x_k),$$

and

$$P(y=1|\boldsymbol{x}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon,$$

Where $P(y=1|\boldsymbol{x})$ is the logit function of P, P is the response probability of an event y given a set of β_k coefficients for x_k independent variables, ε is the error term.

This model can be transformed into a predictive model:

$$\hat{y} = \widehat{\beta_0} + \widehat{\beta_1} x_1 + \cdots + \widehat{\beta_k} x_k + \varepsilon,$$

Where $\hat{y}$ is the predicted value for the dependent variable, $\widehat{\beta_k}$ is a set of predicted coefficients for the k independent variables, and ε is the standard error.

Interpreting the outcome of the model results in a simple model that captures a single effect of a binary output within the model.

$$\varphi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k) - \varphi(\beta_0 + \beta_2 x_2 + \cdots + \beta_k x_k),$$

where φ is the transformation logit function.

The resulting difference, when viewed as an odds ratio, can then be interpreted as a percentage point increase in probability. However, for our study, the primarily focus is on sign and significance, and less so on percentage of probability change. When interaction terms exist within the model, partial derivatives can be taken to isolate the partial effect of the interacting variables. The interpretation derived from a simple multinomial logistic model is parallel to that of Han and Harrison (2004) who used the model in earlier GMO preference studies.

In addition to the binomial context, this model can be applied to ordinal variables as well. This will be done in the second part of the analysis of survey data.

Ordinal Regression

Given the structure of the survey data, which uses a Likert scale, it is sensible to analyze the data using an ordered choice model. Following Greene (2012) the inferences can be made for interpreting an ordered choice model. Assuming the data are censored where each response indicates some level of utility greater than the previous response, then

$$R_{im} = 1 \; if -\infty < U_{im}^{*} \leq \mu_1,$$

$$R_{im} = 2 \; if \; \mu_1 < U_{im}^{*} \leq \mu_2,$$

$$R_{im} = 3 \; if \; \mu_2 < U_{im}^{*} \leq \mu_3,$$

$$R_{im} = 4 \; if \; \mu_3 < U_{im}^{*} \leq \mu_4,$$

$$R_{im} = 5 \; if \; \mu_4 < U_{im}^{*} < \infty,$$

where R_{im} is an event, U_{im}^{*} is the utility gained, and μ_j are the censored boundaries. Following McKelvey and Zavonia (1975) the ordinal model can be defined as

$$\Pr[U_{im}^{*} = 1] = \varphi[\mu_k - \sum_{i=0}^{k} \beta_i x_{ij}] - \varphi[\mu_{k-1} - \sum_{i=0}^{k} \beta_i x_{ij}].$$

where x_{ij} represents the independent variables in the model. Then we can estimate the utility as a linear function

$$U_{im}^{*} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \varepsilon_{im} .$$

Following Angrist and Pischke (2009) it is slightly more complicated to create a difference in difference estimation of a non-linear function. In order to be able to fully regress the model it has to be transformed into the function using Agresti (2010):

$$\log[Prob(y \leq j)] = \log\left[\frac{P(y \leq j)}{P(y > j)}\right]$$

$$= \beta_j + \sum_{m} \beta_m x_{im} + \varepsilon, \quad j = 1, 2, \ldots, J-1 ,$$

where β_j is the intercept for each censored level.

Difference in Difference

The difference-indifference estimator (DiD) is a regression model that normally compares the means of four different outcomes by a value and a time period. The goal of this estimation is to isolate the impact of a target event. In the case of this model the event is the passage of Vermont's GMO labeling law. It is compared to the same time span as Oregon for price and to failed parallel events in Oregon and Colorado. By using the DiD estimator, it is possible to isolate the effect of the event without confounding it to other unobserved variables. This outcome is commonly referred to as the average treatment effect (ATE), where it is computed in one of two ways: (1) as a difference in averages taking the form of

$$\delta_1 = (y_{1,E} - y_{1,C}) - (y_{0,E} - y_{0,C}),$$

s.t δ_1 is the ATE, y is the average given time period T {0,1} and treatment category, state or GMO, D_i {E,C}

or (2) as the averages over time for each group given different time periods (Wooldridge, 2009).

$$\delta_1 = (y_{1,E} - y_{0,E}) - (y_{1,C} - y_{0,C}).$$

Both of these methods produce the same result as each is simply differencing a different aspect of the equation first but to the same end.

The simplest linear DiD estimation model can be presented as

$$y_i = \beta_1 + \beta_2 D_i + \varepsilon_i,$$

where D_i is a value equal to one or zero depending if the event occurred or not and y is the dependent variable of price or sales. The value of β_2 is thus the coefficient of the test event (Greene, 2012). The model can then be expanded to include all of the four variables of space and time, including an interaction term.

$$y_{it} = \beta_1 + \beta_2 T_t + \beta_3 D_i + \beta_4 T_t * D_i + \sum(\beta_k X_{ik}) + \varepsilon_{it},$$

s.t. $\sum \beta_k X_{ik}$ represents all other time constant and time varying covariates along with their parameters.

Differencing the model results in the isolation of the treatment effect with

$$(y_{i2} \mid D_i = 1) - (y_{i1} \mid D_i = 1) \; = \; \beta_2 + \beta_4,$$

and

$$(y_{i2} \mid D_i = 0) - (y_{i1} \mid D_i = 0) \; = \; \beta_2.$$

The final step of differencing isolates the interaction term β_4 with:

$$((y_{i2} \mid D_i = 1) - (y_{i1} \mid D_i = 1)) - ((y_{i2} \mid D_i = 0) - (y_{i1} \mid D_i = 0)) \; = \; \beta_4.$$

The model depends on the same assumptions as traditional least squared estimators (OLS). The additional assumptions needed to justify DiD are: (1) "Stable Unit Treatment Value Assumption," where treatments are completely present and there is no interaction between populations, (2) "Erogeneity" such that the components of X are not influenced by the treatment e.g.

$$X_0 = X_1 = X, \forall x \in X,$$

(3) "No Effect on Pre-Treatment Population," where the treatment is uncorrelated with the pretreatment population, and (4) "Common Trend," where the expected non-treatment outcomes are independent of the treatment effect or that the biases in each are consistent (Lechner, 2010).

Ordinal Regressions in DiD

Following the logic of Kim and Lee (2017) it is possible to develop a DiD model for ordinal dependent variables. Assuming that variables are ordinal:

$$P(Y = j \mid X, \beta_d) - P(Y = j \mid X, 0), \quad j = 0,1,2,3,4\,,$$

where Y is the dependent variable with j categories, X is all covariates, and β_d is the differencing parameter. The model can be further expanded into:

$P(Y_1 = j \,|X_1, Q = 1) - P(Y_0 = j \,|X_0, Q = 1) - \{P(Y_1 = j \,|X_1, Q = 0) - P(Y_0 = j \,|X_0, Q = 0)\}$,

where Q = 1 for treatment and 0 otherwise.

When this model is transformed into a regression form, then β_d can be interpreted as a ratio in ratios such that the true value of β_d = X/σ_u, where X is the returned value of the derivation that is then divided by the standard error (Lee, 2016) and where β_d is the β that references the differencing variable.

Courtemanche and Zapata (2013) use interpretations of β on ordinal variables to be equal to the percentage point difference from the control when a continuous variable is used and then use a decrease in the standard deviation for ordinal variable outcomes.

Logit in DiD

While a DiD model cannot be estimated perfectly within a logistic function due to the violation of the common trend assumption, there are ways to resolve the issue (Angrist & Pischke, 2009). One approach is to treat the model as a linear probability model as in Ai and Norton (2003):

$$\Pr(Y = 1|\, X = x) = x'\beta.$$

If a model uses a limited dependent variable expressed in a standard DiD distribution, then a probit or logit model can be justified with the form

$$Y_i = 1[Y_i^* > 0], Y_i^* = \beta_1 + \beta_2 T_t + \beta_3 D_i + \beta_4 T_t * D_i + \sum(\beta_k X_{ik}) + \varepsilon_{it} \,.$$

In this case β_4 can still be interpreted as a DiD estimator because β_4 is a logarithm of the "ratio in ratios" effect or odds ratio (Lee, 2016 p.143). The exponent of the coefficient of the differencing parameter, β_4, can be interpreted as:

$$\left(\frac{\exp(\beta_1 + \beta_2 + \beta_3 + \beta_4 + \sum \beta_k)}{\exp(\beta_1 + \beta_3 + \sum \beta_k)}\right)/\left(\frac{\exp(\beta_1 + \beta_2 + \sum \beta_k)}{\exp(\beta_1 + \sum \beta_k)}\right) = \exp(\beta_4)$$

Both the interaction term, $T_t * D_i$, and the time dummy,T_t, can be accurately interpreted using this model. However, the other coefficients cannot be (Puhani, 2008). The most important interpretation is that the statistical significance of the β_4 coefficient and its sign can be interpreted as directional even if the magnitude is harder to decipher (Puhani, 2012). This finding is simplified by Karaca-Mandic *et al.* (2012), which shows a probit difference in difference variable for a binomial variable. While some authors state that this model is not appropriate for a binomial logit DiD analysis, there are peer reviewed examples that make an interpretation. Athey and Imbens (2002) replace the language of DiD to "Change-in-Changes" to interpret binary dependent variables with DiD methods. Mayer *et al*. (2014) use a logit DiD variable to isolate the impact of lending policies and interpret the coefficient for significance and sign, but do not attach an explicit value to the differencing coefficient. A second alternative to interpreting binomial dependent variable is by treating it like and OLS estimation as is done by Sun and Yannelis (2016).

Multiple Controls DiDiD or Triple Difference

Difference in difference in difference (DDD) or Triple Difference (TD) is a model that includes another layer of control. In the case of the grocery store data, this is the non-GMO products. In this way we can isolate the effect of the law on only the products that were impacted by controlling for the non-impacted products.

The TD model can take the form of either a simple linear model:

$$y_{its} = \beta_1 + \beta_2 T_t + \beta_3 D_i + \beta_4 S_s + \beta_5 S_s * D_i + \beta_6 S_s * D_i * T_t + \sum(\beta_k X_{ik}) + \varepsilon_{its},$$

where S_s is a subset of the population affected by the policy. In the case of the GMO labeling law, T is time, D is State, and S is GMO.

The fully saturated TD model taken from Lee (2016) is:

$$y_{its} = \beta_1 + \beta_2 T_t + \beta_3 D_i + \beta_4 S_s + \beta_5 S_s * D_i + \beta_6 S_s * T_t + \beta_7 D_i * T_t + \beta_8 S_s * D_i * T_t + \sum(\beta_k X_{ik}) + \varepsilon_{its}.$$

In this case, β_6 and β_9 serve as the key interpretive variables.

CHAPTER 3.

Do Mandatory GMO Labels Expand non-GMO Niche Food Markets? A Vermont and Oregon Case Study

Abstract

This study examines the short-term impact of Vermont's GMO labeling law on prices and units sold using grocery store scanner data. Using a triple difference or difference-in-difference-in-difference model, we find that having mandatory GMO labels has neither an impact on the price nor units sold of a select set of GMO or non-GMO foods. We investigate reasons for these results and postulate the reasons for the lack of statistically significant impacts of the labels. We do find a consistent price premium for non-GMO foods at a rate of $0.05 per ounce regardless of place, time or label.

Abbreviations

DiD – Difference-in-Difference

GE – Genetically Engineered

GMO – Genetically Modified Organism

MHA – Million Hectares

TD – Triple Difference

WTP – Willingness to Pay

Introduction

Genetically modified organism (GMOs) have existed in the United States consumer food market since 1994 with the introduction of the Flavr Savr Tomato. In the past few decades, GMOs have become ubiquitous in many major US crops, with farms devoting 72.9 million hectares (MHA) to modified products as of 2016, accounting for 23% of all principal crops nationally (USDA 2017). Specifically, 92% of all corn, 94% of all canola, and 100% of sugar beet acreage are now genetically modified (ISAAA 2016). With the expansion of GMO technology into more food products, a debate about the social, environmental, and health impacts of the technology ensued with proponents of the technology claiming there is no scientific basis for criticism and skeptics advocating for a precautionary approach. Vermont passed a GMO labeling law that took effect on July 1st of 2016 (Vermont General Assembly 2014). The law required that all products produced or partially produced with genetic engineering (GE) must include a simple disclosure stating the use of GE (see Figure 1 for examples). The law was short lived as it was overruled one month later by federal law aimed at creating a single mandatory labeling scheme across the U.S. (U.S. Congress 2016).

Figure 1.
GE Labels in Vermont

To examine if Vermont's labeling law had an impact on the market for GMO and non-GMO goods in the short term, we test whether a change in prices or units sold occurred following the enactment of the law. If the price or sale of non-GMO goods increased in response to the law, then one could argue that the law successfully produced a distinct market for non-GMO goods.

For this study, we examine the possible emergence of a non-GMO premium market using a sampling of grocery store scanner data from major grocery stores located in Vermont and Oregon corresponding to the time before and after Vermont's labeling law. Oregon was selected as a control for this comparison due to its similarity to Vermont demographically and ideologically while being far enough geographically from Vermont to minimize the probability of sharing regional labeling regimes. While a neighboring state like New Hampshire may originally seem as a more appropriate comparison, Vermont's law impacted retailers who produce identical packaging for the entire New England or the East Coast region (Qorpak, 2018). Specifically, we focus on two major categories of products, fruit beverages and breakfast cereals, along with a smaller category of fruit sauces.

All prior studies that assessed the relative prices and sales of GMO and non-GMO goods did so with either surveys or laboratory experiments. As a result, these studies did not have a truly random selection of participants, as a selection bias applies for those who wish to participate in food-related studies or surveys. Secondly, this study is the first example of a non-hypothetical experiment that uses actual data from consumer behavior. This feature reduces the impact of experimental design in influencing the choices that participants made. Instead, the natural experiment was created by the "treatment" of Vermont's law and customers responded in a natural way, as they would respond to any other product labeling change in an actual market place. Collectively, these aspects of our data permit the utilization of more robust econometric methods that are not feasible with data that are structured in survey format or that have too small of a sample size, as is the case with many prior studies (Bernard *et al* 2009; Brun and Campbell 2016; Buhr *et al*. 1993, Bukenya and Wright 2007, Colsen and Huffman 2011; Colsen *et al.* 2011; Han and Harrison 2007; Huffman *et al*. 2003; Loureiro and Hine 2002; Lusk 2003; Lusk *et al*. 2001; Noussair *et al.* 2002; Rousu *et al* 2007; Wachenheim and VanWechel 2004).

The primary methodology utilized in this study is a triple difference (TD) or difference-in-difference-in-difference model. The TD model is useful as it allows us to control for time, location, and product characteristic, controlling for as many available background trends as possible in the estimation of the marginal impact of the labeling law. Product fixed effects are included in the model to prevent a false notion of randomness that would not occur in panel data.

Literature Review and Setting

Labels can have disparate impacts on the demand for consumer products. Before Vermont had a mandatory GMO labeling law, the state experimented with mandatory recombinant bovine somatotropin (rBST) labels. Between September 1995 and August 1996 any product containing rBST had to be labeled. The method for labeling involved the use of small colored stickers along with interpretive flyers. The result of this intervention did not have any meaningful impact on sales, prices, or opinions but did succeed in adding a burden for grocery stores (Kolodinsky *et al.* 1998).

Non-mandatory labels tend to highlight beneficial aspects of products, thus making it easier to justify a price premium. Once the public discovered, for example, that tuna fishing practices were harming dolphins, demand for tuna decreased. Once the Dolphin-Safe labels were adopted by the industry, the demand rebounded to higher levels and prices than before the public outcry (Teisl *et al* 2002). In contrast, when grocery stores in the United Kingdom began including carbon footprint labels that highlighted lower environmental impact on their packages, there was no change in price or demand (Kortelainen *et al.* 2016).

One of the most common forms of labeling that most consumers are accustomed to are nutrition labels. Front of package food labels are intended to inform consumers. Simple labels such as “stop light” color signifiers are the most effective at communicating nutritional value to consumers (Borgmeier & Westenhoefer 2009; Emrich *et al.* 2014). The general impact of nutrition labels is that while about 89% of consumers claim to use them, researchers have found that only about 69% of consumers can accurately decipher their meaning (Rothman *et al.* 2006).

A major topic of study in the GMO debate is the consumer willingness to pay (WTP) for GMO and non-GMO goods when both options exist. WTP is the highest price at which an individual is still willing to purchase a single unit of a product. Using the Bonroy and Constantantos (2015) utility function where labels are both costless and fully reveal product characteristics, we can frame WTP as

$$U(\theta) = \theta q - p,$$

where q represents quantity, p, price, and U(Θ) is the consumer willingness to pay for a given product.

The majority of GMO WTP studies have used either auctions or laboratory style experiments to ascertain the wiliness to pay for GMO and non-GMO goods. The findings of these studies are not very useful in a real-world context because of the way the technology is interpreted. The studies do not tend to produce consistent results as many of them focus on GMOs that have a benefit to consumers, such as lean meat or added nutritional value, neither of which are product features that currently exist in the consumer market (Buhr et al. 1993; Loureiro and Bugbee 2005). The vast majority of GMO technology is oriented around increasing efficiency in agricultural production, not on improving nutritional traits (USDA, 2017).

Some studies that focus on GMO WTP look highly processed leisure foods such as corn chips, potato chips, muffins, and cookies (Huffman *et* al., 2003; Lusk *et al.*, 2001; Noussair *et al.*, 2002, Rousu *et al*., 2007; Wachenheim and VanWechel, 2003). These studies tend to consistently show a higher WTP for non-GMO products. Research by Milkman et. al (2010) shows that consumer decisions about less healthy foods tend to be less thought out than decisions to purchase healthier alternatives.

Of the studies that include less processed food, such as tomatoes, broccoli, potatoes, and salmon, participants were willing to pay a premium between 1% and 21% for non-GMO foods over that of the GMO equivalent (Bruno and Campbell 2016; Bukenya and Wright 2007; Colsen *et al.* 2011; Rickertson *et al.* 2017). The aggregate of these findings indicate that in the marketplace we could expect non-GMO goods to carry a price premium because consumers tend to value them at a higher WTP, but the magnitude of the premium is uncertain. While these studies were able to isolate survey and experimental responses, it is unclear if the same WTP would be reflected in the consumer market.

New technology has expanded the way in which consumer data can be analyzed. With the development of grocery store scanner data, it is easier to track changes in units sold and prices for products in the United States. Grocery store scanner data has been used to analyze a number of consumer economics questions, including that the use of positive nutrition value shelf labels have an impact on quantities sold and prices (Berning *et al.* 2010). Research conducted by Taylor and Tonsor (2013) found that country-of-origin labels do not have a statistically significant impact on sales. Using scanner data, Campbell and Eden (2014) found that the price for new products fluctuates before reaching a stable state. Grocery scanner data has also been used to analyze package size pricing, timing of sales, and predictive models for out-of-stock expectations (Shreay *et al*. 2016; Berck *et al*. 2008; Andres *et al*. 2010).

Theoretical Approach

Neo-classical economic theory indicates that the introduction of mandatory labels into a consumer market would result in product segmentation and premiums. Because GMOs produce additional value primarily to the farmer rather than the consumer and a fear of GMOs exists (Greenpeace, 2018; Just Label It, 2018), the general expectation would be that the introduction of labels would either create a discount for GMO goods or a premium for non-GMO goods. The reasons being (1) that farmers presumably use GMO seeds instead of non-GMO because of a lower cost of production and can thus sell their products for a lower price while still being competitive and (2) for the consumers who fear GMOs, presumably a higher WTP exists for non-GMO products. Akerlof (1970) provides key insights into this model with the impact of asymmetric information in the market for "lemons" and reliable automobiles. While Akerlof's lemons are not inferior goods, reliable automobiles simply have a lower probability of risk, which is valued by a risk neutral and utility maximizing consumer. If consumers are risk-tolerant, then they would be more likely to always select for the lemon, given it has a possibility of being equally valuable to a reliable car but at a lower price. When competitive information market segmentation exists, we would tend to assume that farmers choose to use GMO crops because of a lower cost such that

$$C_{non-GMO} > C_{GMO},$$

and

$$P_{non-GMO} > C_{non-GMO} \quad and \quad P_{GMO} > C_{GMO},$$

then

$$P_{non-GMO} > P_{GMO},$$

where *P* is the price and *C* is the costs of non-GMO and GMO goods.

When access to information is asymmetric, i.e. when producers know which products contain GMOs while consumers do not, then the market for a second good can disappear if the expected value of a randomly chosen food product is less than the marginal cost of a non-GMO item. As per Akerlof's model, assuming a risk neutral, utility maximizing consumer, the market for non-GMO goods will not exist if the probability of

$$\pi < \frac{C_{non-GMO} - P_{GMO}}{P_{non-GMO} - P_{GMO}},$$

where π is the probability threshold. The probability threshold is such that if π is sufficiently small, then there will be a lemon only market known as pooling equilibrium.

Following this logic, if consumers are unable to determine whether a given food product uses GMO and the probability that a randomly chosen food item contains GMO is sufficiently high, then asymmetric information may result in only GMO foods being sold. In this case, price would not serve as a sufficient signal of product differentiation and consumers would assume the probability of purchasing a non-GMO product is sufficiently small as to be improbable. Thus, the price alone would guide consumer decisions precluding the possibility for a non-GMO market.

Asymmetric information therefore provides a potentially market-making role for mandatory product labeling regulations. A law requiring manufacturers to disclose whether or not their foods contain GMOs reduces information asymmetry about product attributes. As a result, a separating equilibrium can emerge in which both GMO and non-GMO products are sold, and in which non-GMO products command higher prices than GMO using products. Past studies on GMOs have shown that separate markets for GMO and non-GMO goods exists with 10-20% of consumers preferring only non-GMO goods (Buhr *et al.* 1993) and 32-65% of consumer unwilling to pay any premium for non-GMO goods (Brun and Campbell 2016; Loureiro and Bugbee 2005; Loureiro and Hine 2002)

Data and Empirical Approaches

Data

For our study we used a data set of grocery store scanner data provided by IRI, a market research company that provides retail market data, that includes a sample of price and units sold data for breakfast foods from major grocery stores in Vermont and Oregon. To accurately assess the impact of Vermont's labeling law, the selection of an appropriate control group is critical. In order to have effective experimental design, control groups serve as the background tend that would have been expected had no intervention occurred in the tests case. Oregon was selected for this study as a control group because it is a demographically, ideologically, and geographically similar to Vermont and that it is in a different product marketing area. The use of a neighboring state such as New Hampshire may have been more appropriate demographically. However, if a food processing company is large enough to have multiple labeling areas, GMO labels could also be found elsewhere in New England or even over a larger area after Vermont's label law was passed. The company would not have had to change the labeling for its West Coast market. Oregon was chosen for a number of similarities to Vermont: both states had GMO related legislation or referendums[2], each state has the smallest population in its region, more than a 10% lead for Democratic presidential candidates in the last four elections, over 34% of the population live in a single metropolitan statistical area, and each state is within 6 hours of a major Canadian city[3].

The data cover two parallel time periods, July 5th through September 12th of 2015 and July 3rd through September 10th of 2016, thus controlling for seasonality. These data include a total of 3,547 samples of week/state/product prices and sales such that a single data point represents one product in a state for a given week. A total of 91 products are included in the set, which are sold in both Oregon and Vermont in both 2015 and 2016, 80 of which are sold in every week of the sample set.

The set is made up of the following products: 55.7% juices and juice drinks, 33.4% cereals, and 10.8% apple sauces. Cereals, apple sauces, juices, and juice drinks were selected as they are often consumed for breakfast, which is the meal most likely to be consumed at home and thus most likely to be purchased from a grocery store (Paulin, 2000). Breakfast being the most likely food

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[2] Oregon had a failed referendum to label GMO goods in November 2014

[3] Historically Vermont is influenced by Quebec just as Oregon is part of Cascadia, which includes British Colombia

consumed from the grocery store is important because it decreases the probability of consumers otherwise getting their meals from restaurants where they would not be exposed to the labeling law.

Table 1
Summary Statistics

Variable	Mean	Std. Dev	Min.	Max.	N
Vermont	0.506	0.5	0	1	3,547
T2	0.494	0.5	0	1	3,547
T2 * Vermont	0.253	0.435	0	1	3,547
GMO	0.477	0.499	0	1	3,547
T2 * Vermont * GMO	0.123	0.328	0	1	3,547
Juice	0.557	0.497	0	1	3,547
Cereal	0.334	0.472	0	1	3,547
Units Sold Normalized	255.79	363.194	0	3,808	3,547
Price ($0.01 per Oz)	15.34	18.01225	2.093	113.245	3,547

Notes: Vermont = 1 if sample is from Vermont, T2 = 1 if sample from is 2016, T2 * Vermont = 1 if sample from Vermont and in 2016, GMO =1 if a sample contains GMOs, T2 * Vermont * GMO =1 if a sample is from Vermont, in 2016, and contains GMOs, Juice = 1 if a sample is a juice or juice drink, Cereal = 1 if a sample is a cereal, Units Sold Normalized is continues variable representing the number of units of a products sold in a state and week. Price is the per OZ price at the $0.01 level for an individual product.

To have a balanced data set, approximately an equal amount of GMO and non-GMO products were included in the study with 47.7% of products GMO. Additionally, a similar amount of GMO and non-GMO products of each type, cereal, juice, and fruit sauce were used in the study. To account for different product volumes and normalize prices, all prices were divided by volume in ounces. To account for the different population size of Vermont and Oregon, 623,600 and 4,143,000 respectively, all units sold in Oregon were divided by 6.64, the factor by which Oregon's population exceeds Vermont's. All the products are from companies that sell in both the Vermont and Oregon markets. Products that were made with GMO ingredients were labeled as such only in Vermont's 2016 dataset. Any product with "organic" or a GMO-Free label was excluded from the study in order to remove effects unrelated to the passage of the GMO labeling law on consumer behavior. The inclusion of "organic" or GMO-Free labeled products would add an additional variable that signals product traits to consumers for which we did not have the resources to focus on in this particular study. Table 1 includes the summary statistics for variables in this study.

Triple Difference Regressions

The aim of our research is to test the null hypothesis that mandatory GMO labels did not lead to a price premium for non-GMO foods or decrease the units sold of GMO foods. The primary method used in our analysis is the Triple Difference (TD) regression, which is an expanded version of a traditional difference-in-difference (DiD) estimation. The DiD model not only controls for factors that impact the sales or price by creating dummies out of GMOs, but allows us to use the relative times to understand the impact of a targeted intervention. This approach allows us to gain a causal inference and not simply derive a correlation.

Because our data include time periods before and immediately after the introduction of the GMO labeling regime, we are able to treat the labeling law as a natural experiment. By measuring the change in units sold and prices we are able to see what would have happened had the labeling regime not been implemented. The model is dependent on an assumption of independence for the assignment of the treatment and other unobserved variables. If independence does not hold, then there is bias in the model and it cannot be universalized. Because all included GMO products were labeled in Vermont and no products were labeled in Oregon, this assumption holds.

The TD model used in this study originates primarily from the work of Lee (2016). The model elaborates on Greene's (2012) framing of a DiD model with product fixed effects as was done by Kortelainen *et al.* (2016).

$$y_{it} = \beta_0 + \beta_{T2}T_t + \beta_{VT}S_i + \beta_{VT,T2}T_t * S_i + \delta_i + \sum(WeekDummies)_t + \varepsilon_{it},$$

where y_{it} is the dependent variable representing price or units sold, T_t is the time dummy (2016 = 1), S_i is the state dummy (Vermont = 1), δ_i represents the product fixed effects, and $\sum(WeekDummies)_t$ represents a weekly dummy for 19 of the 20 included weeks. We include the week dummies in order to prevent weekly product fluctuations that may be caused by promotional events or sales as was done by Kortelainen *et al.* (2016).

Following Lee's model, we elaborate from a single differencing effect to a triple difference

$$y_{its} = \beta_0 + \beta_{T2}T_t + \beta_{GMO}D_i + \beta_{VT}S_s + \beta_{VT,GMO}S_s * D_i + \beta_{VT,T2}S_s * T_t + \beta_{GMO,T2}D_i * T_t + \beta_{VT,GMO,T2}S_s * D_i * T_t + \beta_{Price}P_{its} + \delta_i + \sum(WeekDummies)_t + \varepsilon_{its} \quad ,^{4}$$

such that y_{its} is the dependent variable, either prices or units sold depending on the model, T_t is the binary event-time variable (2016 = 1), S_s is the binary state variable (Vermont = 1), D_i is the binary GMO variable (GMO = 1), P_{its} is the price variable in the sales regression. The variable δ_i controls for product fixed effects in the model. A weekly dummy $\sum(WeekDummies)_t$ is included to control for exogenous time trends in either prices or units sold during the sample period. This model evaluates the marginal effects of each of the included variables and interactions terms to isolate how each influenced the dependent variable.

Results

The results of the TD regressions are included in Table 2. From left to right, the first column contains the variables used in the model, as well as the model tests of significance. The second column defines the variables reported. The third column (1) Price Dependent Regression with fixed effects, contains the results of the TD model using dollars per oz. as the dependent variable. The forth column, (2) Units Sold Dependent Regression with fixed effects, contains the results of the

[4] $\beta_{Price}P_{its}$ is only used in sales model.

TD model using normalized units sold[5] as the dependent variable. All results are very short-term economic effects on sales and prices, since the research focuses only on the 10-week period immediately after passage of Vermont's GMO labeling law. Figure 2 and Figure 3 show the general trends of price change and units sold changes in Vermont and Oregon. Weeks 1-10 account for the time period in 2015, while weeks 11-20 account for the time period after the law's implementation in 2016.

[5] Units sold are considered in terms of Vermont, with Oregon normalized to Vermont's population. The relative difference between Vermont and Oregon must be taken lightly because it is not clear if the exact same proportion of stores were sampled in each state with regards to the population and the information if proprietary to the IRI, the data seller.

Table 2
Price and Units Sold regressions

	Definition	(1) TD - Price Dependent (SE)	(2) TD - Unit Dependent[6] (SE)
Constant		0.106*	406.689*
		(0.005)	(35.987)
Vermont	From Vermont	0.000	72.412*
		(0.002)	(12.567)
T2	In 2016	-0.007	-39.131
		(.004)	(23.150)
GMO	Contains GMO	-0.047*	-323.099*
		(.008)	(48.006)
VT*T2*GMO	In Vermont, 2016, and contains GMO	-0.002	-11.532
		(.004)	(25.973)
VT*T2	In Vermont and 2016	-0.003	27.156
		(.003)	(17.908)
GMO*VT	In Vermont and contains GMO	-0.016*	18.615
		(.003)	(18.3)
GMO*T2	In 2016 and contains GMO	-0.003	2.460
		(.003)	(18.494)
Price ($0.01 per Oz)	Price per oz of unit sold at $0.01		-11.011*
			(1.0476)
Fixed Effects	Product fixed effects	Yes	Yes
Week Dummies	Dummy for each week	Yes	Yes
N		3547	3547
F-Test		995.1*	79.87*
Adj-R2		0.9697	0.7189

Notes: Price dependent regressions are normalized by dollars per Oz where total price was divided by weight in Oz. Sales dependent regressions area normalized by Vermont's population where sales in Oregon are divided by a factor of 6.64 to account for the relative population of the two states.

Significance at * $p < 0.001$.[7]

In the price dependent model if a product is non-GMO, we can expect the price to be approximately $0.047 per oz. higher than its GMO equivalent. The trend of price difference is

[6] Running a log(units sold) regression produced similar results with regards to sign and significance when testing for semi elasticity.

[7] No variables were found significant at the .01 significance level

reflected in Figure 2, illustrating the difference between the prices of GMO and non-GMO food in Oregon and Vermont. Products made with non-GMO ingredients tend to carry an additional premium of $0.016/oz in Vermont before and after the law came into effect based on the significance of the Vermont dummy variable. Perhaps most interesting, is the TD treatment of Vermont * T2 * GMO has no statistical significance, indicating that the passage of mandatory labeling of GMOs in Vermont did not create an additional premium for non-GMO products.

Figure 2

Ave. Price of GMO & non-GMO Food in VT & OR

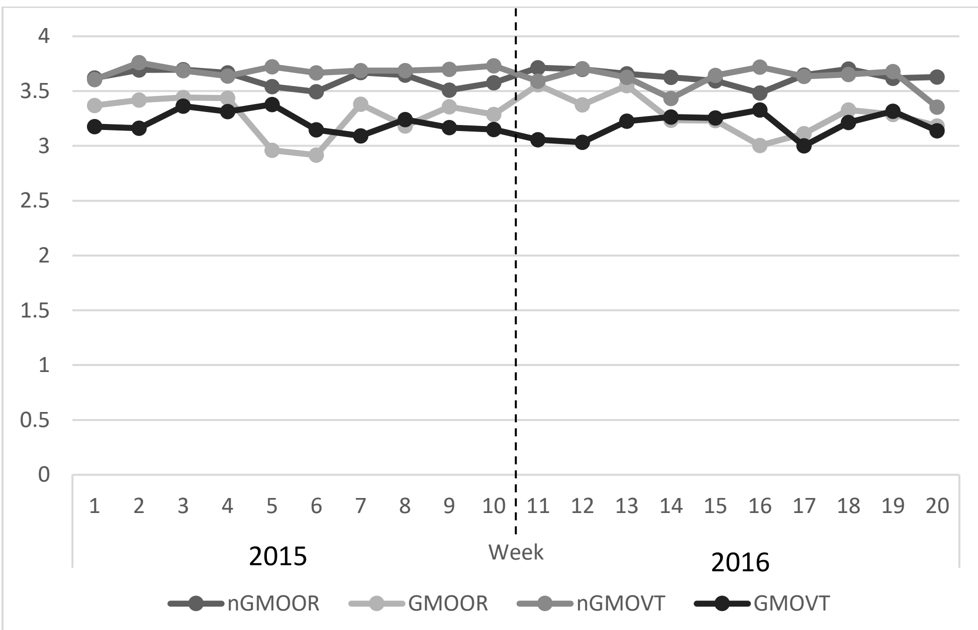
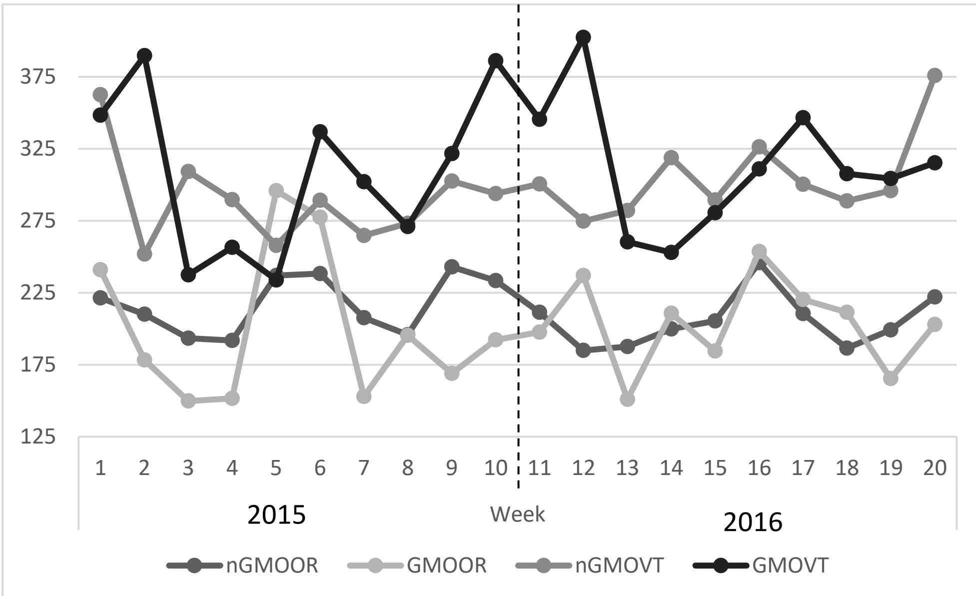


Figure 3

Ave. Units Sold of GMO & non-GMO Food in VT & OR



For the unit dependent model, it is important that the units listed do not carry an exact value but should be viewed only in relation to one another. This is because we do not know how many stores are in each state or what percent of stores in each state was sampled relative to the state population. For this reason, while Vermont has a statistically significant and positive value of 72.412 additional units sold than Oregon, it is difficult to accurately assess if Vermont consumers purchase more food from grocery stores than their Oregon counterparts.

The relative units sold of non-GMO goods to GMO goods, 323.099 more units of non-GMO goods, initially indicates that more non-GMO goods tend to be sold. However, the sampling intentionally included a balanced set of GMO and non-GMO products, whereas an actual grocery store shelf would have a much larger percentage of products with GMO than non-GMO products. This difference could be explained by a relative preference for non-GMO goods for the specific subset of products included in the data set. The significance of price with a coefficient value of -11.011 cents per oz. indicates that this model follows basic economic principals in so far as increasing the price of a good results in lower demand. The treatment term of Vermont * T2 * GMO is not statistically significant even at the .1 level indicating that the law had no effect on relative units sold, and therefore we fail to reject the null hypothesis of no impact.

Discussion and Further Research

In our effort to isolate the impact of a mandatory GMO labeling regime on the price premiums and units sold of non-GMO goods, several plausible explanations support the statistical significance and insignificance of the results of the econometric modeling work. When developing our experiment, our primary goal was to isolate the effect of our interaction term of Vermont, GMO, and the time period after Vermont's GMO labeling law was implemented. The theory behind this interaction term is that it should isolate the impact of labeled and unlabeled products. This study adds to food consumption and labeling literature in a few major ways. Our main finding is that the labeling law had no effect on the prices or units sold of non-GMO products. We do not reject the null hypothesis that the creation of simple GMO labeling requirements has no effects on the units sold or prices of GMO products. It is important to remember that in this study, we only have the data for the 10 weeks that the law was in place and the 10 control weeks from the prior year. As such, it is possible that a more significant impact could have developed over time as prices can be "sticky."

This study adds to the growing, but still limited, collection of empirical work, which focuses on the impact of GMO product labeling. While a large selection exists that uses survey and laboratory style experiments, there is a marked lack of peer reviewed articles using real world consumption data as it relates to GMO and non-GMO prices and units sold. One policy implication of our study is that simple labeling could be implemented without affecting either units sold or consumer prices, especially because 92% of Americans support labeling according to a Consumer Reports National Research Center survey from 2014.

Perhaps the most interesting statistical finding is a fixed number for the price premium of non-GMO goods. That non-GMO products can sell for \$0.05/oz. more than their GMO counterparts provides valuable information for producers. This is the equivalent of a family size (19.5oz) box of non-GMO cereal costing about \$1 more than the GMO containing substitute. Following Akerlof's (1970) theories of secondary markets, it becomes safe to say that if the two products are differentiable, one can be sold for a higher price. The major implication for this may be for products that are labeled as "Organic," which according to the USDA definition cannot contain GMOs, or Non-GMO Project Verified (Non-GMO Project 2016; USDA 2013). Producers of products that carry these explicit designations of Non-GMO may be able to successfully inform consumers that they are justified in charging an additional \$0.05/oz.

Units sold were included in this model in order to see if the law resulted in a change in the quantity sold due to mandatory labels. If any of the coefficients that were dependent on the 2016 variable were statistically significant, then we would have been able to infer general time trends. The potential trends would be those of purchasing food from the grocery stores of time, a general regarding GMO foods over time, a general trend regarding purchasing food in either state over time, and most importantly a trend about GMO foods in Vermont. The time trend about GMO food in Vermont would indicate that the law had an effect on the units sold.

An important limitation of our research is that we intentionally used a balanced set of GMO and non-GMO foods in our study so that the size of each state/week/products group was roughly consistent. The implication is that while comparing the probability of a single GMO product to a single non-GMO product may show a relative change, it does not reflect the coverage of an average grocery store shelf. This limitation specifically impacts the findings from the unit dependent model as it relates to the 323.099 additional units sold. If the set of GMO and non-GMO products was reflective of the actual number of each product on a standard grocery store shelf, then this number would carry greater significance.

A second limitation in our study is that we only worked within the very short period after the law was enacted. It is possible that prices are much stickier and would have taken longer to adjust. Unfortunately, we were only able to work with the natural experiment that occurred and later data would no longer have been required to carry the key differencing variable as producers are no longer required to include simple labels in Vermont. A second aspect of this is that we focused only on products that existed in all available time periods and states. As such it is possible that some products left or entered the market in response to the law.

Our analysis focused exclusively on the relationship between GMO and non-GMO labeled goods. We did not include either Organic or Non-GMO project verified in our study. Future research should compare the findings of the study that we completed with additional data that codes for "Organic" and "Non-GMO Verified Project" to see if the GMO-Free labels generate an additional premium above that which is already captured by not including GMOs.

Despite limitations, the potential impact of a GMO labeling law is a consistent outcome of all the models. This study utilized a real-world natural experiment and market data, an approach that has not been used in prior studies.

Conclusions

We studied the effect of Vermont's mandatory GMO labeling law, which was in effect in 2016, on price premiums and units sold for non-GMO goods. In order to do so we used grocery store scanner data from Vermont and Oregon for two parallel seasonally adjusted time periods in 2015 and 2016, with Oregon as out control group. Based on our regressions, the mandatory GMO labels had no statistically significant impact on the units sold or prices of either GMO or non-GMO goods. We did find that the average premium for non-GMO goods is about \$0.047/oz. relative to a similar GMO good, which was consistent before and after the law. When controlling for important variables such as price, we found that our data reflect fundamental economic principals where higher prices result in fewer units sold.

Once the GMO labels appeared consumer decisions that existed prior to the law persisted; the labels did not cause more consumers to switch to non-GMO products. A secondary market already exists that is satisfied by Organic and Non-GMO Project labeling.

Since prices and units sold of the labeled products were not impacted, this research serves as support for mandatory labeling by protecting consumer choice and facilitating symmetric information in the marketplace. An additional implication is that the food industry need not be concerned about mandatory GMO labeling laws as they relate to prices or units sold. This would allow companies to spend fewer resources challenging potential laws, thus increasing their overall profits.

The mandatory labeling law did not raise prices of food included in the study nor cause a drop in the units sold of GMO foods. Both conclusions have been asserted by opponents to labeling. In the short-run, under a mandatory labeling scheme, neither occurred.

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CHAPTER 3.

Do Mandatory Labeling Laws and Referendums Affect Opinions on GMOs?

Abstract

A debate about the impacts of mandatory Genetically Modified Organisms (GMO) labeling laws has existed since the introduction of the products. Vermont is the only state to have successfully passed a mandatory labeling law before it was overridden by federal policy one month later. The objective of this research is to evaluate if the successful law impacted opinions differently than failed referendums in Colorado and Oregon. This study uses Vermont and national survey data and analyzes it using a series of differencing models. The key findings are that Vermont became more supportive of GMOs after the passage of the law and that states with referendums became more supportive of GMOs than those without. The implications of this study are that both labeling laws and failed referendums increase the level of support for GMOs in the food supply.

Introduction

Vermont was the first and only state in the US to implement a mandatory genetic engineering labeling law, VT H112, which was in effect July 2016 before being overridden by federal policy one month later. While Vermont's law was in place, all products produced or partially produced with genetic engineering (GE) were required to have simple labels on their packaging. Prior to the passage of Vermont's law, as many as 70 bills and referendums in 25 states were introduced that attempted to mandate the labeling of genetically modified organisms (GMOs) (Farquar, 2016). Colorado and Oregon are two states that had referendums in November 2014, prior to Vermont's law.

GMO food tends to be a contentious issue in the United States with many individuals falling into the extremes of strong support or strong opposition to their presence in the food supply (Huffman and McCluskey, 2014). Willingness to pay (WTP) experiments found that 10-20% of consumers would refuse to purchase GMO goods while 32-65% would refuse to pay any price premium for non-GMO goods (Bruno and Campbell, 2016; Buhr *et al*., 1993; Loureiro and Bugbee, 2005; Loureiro and Hine, 2002). Manufacturers and retailers of GMO food claim that mandatory labeling of GMO products would result in greater opposition to GMOs (Messer, Constanigro, and Kaiser, 2017).

A null hypothesis that would help resolve this debate is to see if opinions about GMOs change in response to mandatory GMO labeling laws or failed referendums. To test this hypothesis, a natural experiment is used with Vermont as a test case and Oregon and Colorado as controls. These two states are used because data are available for a sufficiently robust time period before and after their referendums. To further test the hypothesis, a second evaluation is conducted where Vermont, Colorado, and Oregon are combined as the experimental group and compared to a control of the rest of the country, excluding a few states that had referendums but for which sufficient data were not available. In all cases, the goal is to evaluate if the introduction of a mandatory labeling law or referendum resulted in a change in opinions pertaining to GMOs in the food supply.

For this analysis a combination of methods is used to analyze the way in which Vermont's GMO labeling law impacted the opinions of Vermonters with regards to their perception of GMOs. Following Kolodinsky and Lusk (2018), a survey-based approach that combines data from a Vermont poll and a national poll is used in this study. The analysis focuses primarily on a survey question pertaining to the level of support or opposition to GMOs in the food supply consistent with the methodology used by Kolodinsky and Lusk (2018). The area of focus in this study is the interaction term that combines the state or states that had interventions with the time periods after the interventions occurred. The goal of grouping Colorado, Oregon, and Vermont is to identify if GMO related laws and referendums cause a change in opinions of GMO in the food supply.

Background and literature

Products using GMO technology have exponentially proliferated since the introduction of the Flavr Savr tomato in 1994. As of 2016, many principal crops in the US use GMO technologies including 92% of corn, 94% of canola, and 100% of sugar beets by acreage (ISAAA, 2016). Farmers in the US dedicate approximately 72.9 hectares accounting for 23% of all principal crop cover nationally (USDA, 2017). As the prevalence of GMO crops becomes commonplace, a growing percentage, about 92%, of Americans support mandatory labeling (Consumer Reports National Research Center, 2014).

Proponents of GMO technology are resistant to the mandatory labeling of GMO products for two frequently cited reasons: (1) GMO labels will scare and confuse consumers who will view labels as warnings, and (2) labels will drive up the prices of both GMO and non-GMO food. The "warning camp" believes that consumers do not have a good enough understanding of genetic engineering to make the correct market place decisions (Kolodinsky *et al.,* 2004; Scientific American, 2013). The fear of mandatory labeling has resulted in a multimillion-dollar campaigns aimed at swaying consumers into accept GMO foods without mandatory labels (Coleman, 2016). This approach has been effective in preventing any state with a proposed law, voted on via referendum, from passing (Farquar, 2016).

Kolodinsky and Lusk (2018) tested if the opinions in Vermont changed in response to the new law, VT H112, using difference-in-difference estimators. The findings of the study revealed that a 19% reduction in opposition occurred in Vermont relative to the rest of the country, after the labeling regime was implemented. Using subsets of the data from the Kolodinsky and Lusk (2018) study, this research tests whether opinions changed in other states with similar proposed laws.

The theory driving this study builds on Fishbein's (1963) idea about attitudes, where attitudes are a function of an individual's belief that is focused on maximizing utility. Beliefs such as opposition to or support for GMOs, retrieved from surveys, are proxies for individual intentions and therefor predictors for consumer behaviors (Grobe *et al.*, 1997). The attitudes individuals hold with relation to an object (or idea) are correlated with the actions that individuals will demonstrate with regards to that object (Han & Harrison, 2007). Thus, the opinions an individual espouses about GMOs reflects their actions as they relate to the products. If opinions about GMOs shift in a positive direction, it would indicate that there is greater support for the products in the market place, and vice-versa.

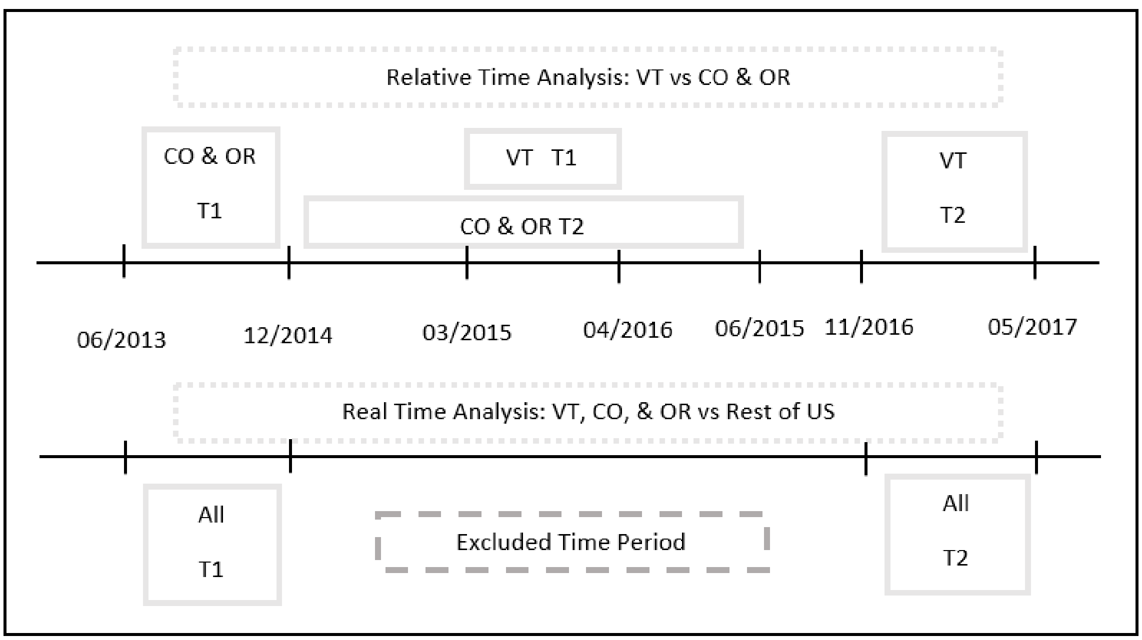
Methods

Data

Data for this project was obtained from two separate surveys. Vermont data were obtained from phone surveys that occurred in March 2013, March 2014, March 2015, March 2016, November 2016, and March 2017. The data were merged with a second set of online nationwide surveys over the same time periods. Vermont data were removed from all national surveys so that the state's responses would not be double counted. Connecticut, Maine, California, and Washington were removed from this study because all four states had referendums pertaining to mandatory GMO labeling. Both the national and Vermont data collection protocols were approved by the respective institutional review boards of the participating institutions.

The structure of the questions in the two surveys follows the methodology of Kolodinsky and Lusk (2018). Preliminary analysis presented by Pazuniak and Kolodinsky (2017) revealed that similar enough questions about GMOs are accurate predictors for other GMO related questions, such that a specific question about a particular GMO trait will have a similar response as one about GMOs in general. Participants in Vermont were asked, “Overall, do you strongly support, somewhat support, have no opinion, oppose, or strongly oppose the use of GMOs in the food supply?” In the national survey the questions were framed as “How concerned are you that [genetically modified food poses] a health hazard in the food that you eat in the next two weeks?” In both cases, a value of 1 indicated the least worry or most support for GMOs and the value of 5 indicated the most opposition or concern for GMOs, in both cases a value of 3 indicated neutrality.

Figure 1
Timeline of Regressions: Relative Time and Real Time Analysis



In the first part of the study a comparison is made on the effect of Vermont’s law with Vermont serving as the experimental case and the failed referendums in Colorado and Oregon serving as controls. Instead of using identical time periods, relative time periods corresponding to before and after the different interventions are used, as is depicted in the top half of Figure 1. In order to have a balanced and sufficiently robust set of data before and after the interventions, four time periods from Vermont were used. The T1, or before event, time periods in Vermont were from surveys conducted in March 2015 and March 2016. T2, or after the law, includes surveys conducted in November 2016 and March 2017. Data from Oregon and Colorado was more continues in nature. As such responses between June 2013 and November 2014 were used as the T1 period and survey responses between December 2014 and May 2016 were used at the T2 period.

For the second part of the analysis, Vermont, Colorado, and Oregon are grouped as a test case and compared with the rest of the country, which serves as the control. Surveys conducted in Vermont during March 2013 and March 2014 are grouped with responses from the national survey that were entered between June 2013 and November 2014 to serve as T1, the time before referendums or laws. For the T2, after laws and referendums, Vermont's surveys after November 2016 are combined with national surveys from the same time until April 2017. For this part of the analysis, all responses between December 2014 and October 2016 are removed from the study in order to avoid having dates that would include both a before and after case for the experimental group as can be seen in the bottom half of Figure 1.

Econometric methodology

Different methods are used to analyze the data: OLS, binomial logit, and ordered logit. In the OLS case, the Likert scale questions are treated as a continuous variable from 1 to 5. Two different binomial models are used: (1) combining support and strongly support into one group, and (2) combining oppose and strongly oppose into one group using methods from Wooldridge (2009) to interpret results. The ordered logit model uses the existing value order and is evaluated as a linear model following the methodology of McKelvey and Zavania (1975) and Agresti (2010). The purpose behind cross-referencing the different methods for the same set of data is to focus primarily on sign and significance of the variables, due to the difficulty of accurately interpreting likelihood ratios in a difference in difference setting. For all the models, a simple and a more complex model are used. The complex models include demographic control variables including political party affiliation, household size, number of children, white, female, income more than $40,000 annually, college education or higher, and six age groups. In the second set of regressions that combine Vermont, Oregon, and Colorado, state fixed effects are included. The general models used in the regressions is:

$$y_{it} = \beta_0 + \beta_{T2}T_t + \beta_{State}S_i + \beta_{Interaction}S_i * T_t + \delta_i + \sum(\beta_k X_{ik}) + \varepsilon_{it},$$

where y_{it} is the dependent variable composed of a version of the GMO support or oppose question, depending on the models design, T_t is the time variable where time after the event is set to equal one, S_i is the state with target event(s) is set to equal one, $\beta_{Interaction}$ is the variable of greatest interest as it the interaction of S_i, and T_t representing the law or referendums, $\delta_i$is the state fixed effect when applicable, and $\sum(\beta_k X_{ik})$ are the demographic control variables. In this regression model the goal is to isolate the impact of combined state and time effect that represent Vermont's law in the first set of regression and the combination of Vermont's law with Oregon and Colorado in the second set. By including the individual state and time variables separately, the combined trend can be properly specified.

Results

In this section the different regressions and findings seen in Tables 1 through Table 3 are evaluated. The first half of this analysis looks at the case of Vermont as test case with Oregon and Colorado as Controls The second half of this analysis evaluates the results of combining Oregon, Colorado, and Vermont as the test cases and comparing them with the control of the remaining US states.

Vermont, Colorado, and Oregon

In the comparison of Vermont, Colorado, and Oregon, an analysis is made as to whether having passed a successful law, that regulates the labeling of GMOs, has a different effect than a failed referendum. The before and after periods are relative to the states' own histories such that Vermont's intervention is after July 2016 and Oregon's and Colorado's are after November 2014. The general findings in Table 1, with regards to the preference for GMOs in the food supply in Vermont, show a general decrease in opposition and increase in support. The same trend is visible in Colorado and Oregon but to a lesser degree. This is evident due to the statistical significance and sign of the interaction terms coefficient in Table 2.

Table 1

Descriptive Statistics of Regression Sets Before and After Interventions

	Regression Set 1				Regression Set 2			
	VT		CO OR		VTCOOR		Rest of US	
	Before	After	Before	After	Before	After	Before	After
N	1232	1001	593	569	1811	1206	14893	5098
GMO Pref(avg)	3.9	3.61	3.15	3.04	3.53	3.53	3.21	3.27
GMO Support	13.39%	21.77%	31.70%	33.04%	17.78%	22.97%	28.61%	26.73%
GMO Oppose	68.58%	56.74%	45.69%	42.17%	55.82%	54.64%	46.40%	47.94%
Age								
18-24	2.04%	2.24%	7.08%	12.24%	3.00%	5.78%	10.97%	9.18%
25-34	6.56%	12.04%	15.51%	20.38%	8.29%	10.53%	20.47%	20.53%
35-44	9.20%	11.32%	19.56%	16.16%	14.03%	13.29%	20.06%	17.67%
45-54	17.90%	19.28%	19.05%	14.76%	18.59%	18.29%	18.09%	16.96%
55-64	27.02%	24.82%	15.51%	18.98%	25.05%	23.73%	13.08%	17.59%
65-74	24.21%	18.86%	17.87%	13.18%	21.49%	17.94%	14.13%	14.43%
75+	14.83%	10.90%	5.39%	4.04%	9.52%	9.92%	3.16%	3.58%
Income over								
$40k	50.81%	53.24%	43.17%	55.00%	49.72%	53.81%	42.39%	52.09%
College or More	49.91%	48.95%	22.76%	27.24%	42.57%	44.36%	23.53%	21.79%
Female	52.19%	51.84%	51.09%	53.60%	52.07%	52.57%	51.16%	51.16%
White	90.99%	89.41%	86.17%	88.57%	92.04%	89.55%	74.59%	80.79%
Household Size	2.425	2.434	2.48	2.6	2.49	2.4618	2.632	2.62
Kids	24.45%	28.39%	27.31%	28.47%	26.09%	28.54%	29.64%	30.54%
Democrat	27.67%	27.37%	33.38%	38.31%	29.81%	29.93%	39.56%	39.87%
Republican	14.93%	13.68%	25.80%	23.72%	17.83%	16.41%	23.05%	30.09%

Multiple tests including OLS, binomial logit, and ordinal logit models were used in the analysis because the primary focus is not the magnitude of the difference but a focus on sign and significance of the interventions. If the interaction term representing the law has an impact, it would be visible through the statistical significance of the interaction term and the directional sign of the coefficient. None of the post-event coefficients are statistically significance indicating that a general time trend is not influencing different states opinions. If a general time trend was statistically significant, it would be difficult to interpret as the control and experimental groups are located on different timelines as is evident in Figure 1.

Vermont is consistently more opposed to GMOs in the food supply than Colorado and Oregon. This opposition is irrespective of time and applied to both before and after Vermont's labeling law. Every model produced a similar result with a high degree of statistical significance indicating that it is extremely likely that Vermonters overall have a greater level of opposition.

The most relevant finding of this set of regressions is the interaction term of Vermont and Post-Event. In all the regression models, a general decrease in opposition and increase in support occurred. The directionality of decreased opposition and increased support is evident as both binomial models have movement away from the opposition group. Table 1 shows that the level of support increases, and the level of opposition decreases, meaning that the change is not simply a function of neutral individuals moving towards support but also a movement away from opposition.

Table 2

Estimation Results of OLS, Binomial Logistic, and Ordinal Logistic Regressions Comparing Vermont to Oregon and Colorado

	OLS		Logit - Support				Logit-Oppose				Ordinal Logit			
	Simple	Full	Simple		Full		Simple		Full		Simple		Full	
			Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio
Constant	3.152***	2.805***	0.767***	0.464***	-0.347	0.707	-0.172**	0.041**	-0.832***	0.435***	-	-	-	-
	(0.051)	(0.147)	(0.088)	(0.041)	(0.274)	(0.193)	(0.082)	(0.069)	(0.255)	(0.11)				
Post-Event	-0.106	-0.091	0.061	1.063	0.038	1.039	-0.143	0.866	-0.15	0.86	-0.147	0.863	-0.127	0.881
	(0.073)	(0.072)	(0.125)	(0.133)	(0.13)	(0.135)	(0.118)	(0.102)	(0.122)	(0.105)	(0.105)	(0.091)	(0.107)	(0.094)
Vermont	0.750***	0.701***	-1.099***	0.333***	-1.117***	0.327***	0.953***	2.594***	0.871***	2.389***	1.017***	2.765***	0.967***	2.631***
	(0.062)	(0.066)	(0.122)	(0.041)	(0.133)	(0.043)	(0.103)	(0.266)	(0.113)	(0.27)	(0.091)	(0.252)	(0.098)	(0.258)
VT & Post-Event	-0.178**	-0.194**	0.527***	1.694***	0.690***	1.805***	-0.367***	0.693***	-0.378**	0.685**	-0.247*	0.781*	-0.280**	0.756**
	(0.905)	(0.09)	(0.169)	(0.286)	(0.175)	(0.316)	(0.148)	(0.102)	(0.154)	(0.105)	(0.13)	(0.102)	(0.133)	(0.101)
Demographic Vars	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj R2 or PsdR2	0.0689	0.1154	0.0349		0.066		0.0324		0.0666		0.0215		0.0405	
F or Chi2	84.68	26.17	125.76		232.18		150.43		299.44		222.74		406.98	
N	3395	3281	3395		3281		3395		3281		3395		3281	

Note Parenthesis indicate standard errors; levels of significance *** p < .01, ** < .05, * < .10

Colorado, Oregon, and Vermont compared with the rest of the US

The second set of regressions that combine Colorado, Oregon, and Vermont as the test case and compare them to the rest of the US as the control build on the findings from the first set as is evident in Table 3. Additionally, these findings corroborate the findings produced by Kolodinsky and Lusk (2018). This set of regressions is not affected by the relative time constraint as the time periods are consistent for both groups as the period of temporal overlap is removed from the data set as is shown in Figure 1. The second half of Table 1 indicates the same general trend of increased support that was evident in the Vermont, Oregon and Colorado model. In this context, Vermont has the largest growth in support for GMOs followed by Oregon and Colorado, while the rest of the country moves in the opposite direction.

The statistical significance of the Post-Event coefficient indicates that a general time trend is affecting the entire country with regards to opinions on GMOs. This movement can be specifically seen in the OLS, binomial support, and ordinal models where a statistically significant sign indicates a decrease in support for GMOs in the control states. In all of the models, Vermont, Colorado, and Oregon show an overall greater opposition to GMOs in the food supply. This attitude is independent of time and applies to the periods both before and after the referendums were voted on and after the law was passed. This statistically significant trend is corroborated by the general findings from Table 1.

When the time trend is combined with the test states a different picture emerges. In Table 3, the statistical significance of the interactions term indicates that changes occurred in the test states after the law. Because the directional sign is in the opposite direction to the test states overall patterns and the overall time trend it evident that the laws and failed referendums decreased the level of opposition and increased the level of support for GMOs in the food supply, relative to the rest of the country.

Table 3

Estimation Results of OLS, Binomial Logistic, and Ordinal Logistic Regressions Comparing the Grouping of Colorado, Oregon, and Vermont to the Rest of the US†

	OLS		Logit - Support				Logit- Oppose				Ordinal Logit			
	Simple	Full	Simple		Full		Simple		Full		Simple		Full	
			Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio	Beta	Odds Ratio
Constant	3.216***	3.126***	-0.914***	0.4***	-0.761***	0.467***	-0.144***	0.865***	-0.307**	0.735**	-	-	-	-
	(0.01)	(0.082)	(0.018)	(0.007)	(0.148)	(0.069)	(0.016)	(0.014)	(0.13)	(0.096)				
Post-Event	0.056***	0.052**	-0.093***	0.910***	-0.085**	0.918**	0.061	1.063*	0.054	1.055	0.074***	1.076***	0.064**	1.066**
	(0.021)	(0.021)	(0.036)	(0.033)	(0.037)	(0.034)	(0.032)	(0.034)	(0.033)	(0.035)	(0.028)	(0.031)	(0.029)	(0.031)
VTCOOR	0.467***	0.545***	-0.743***	0.475***	-0.992***	0.370***	0.591***	1.805***	0.658***	1.931***	0.599***	1.821***	0.697***	2.008***
	(0.026)	(0.0780	(0.052)	(0.025)	(0.145)	(0.053)	(0.04)	(0.073)	(0.124)	(0.24)	(0.035)	(0.064)	(0.109)	(0.218)
VTCOOR & Post-Event	-0.203***	-0.216***	0.541***	1.718***	0.592***	1.808***	-0.322***	0.724***	-0.344***	0.708***	-0.248***	0.779***	-0.248***	0.780***
	(0.049)	(0.049)	(0.091)	(0.158)	(0.095)	(0.172)	(-0.076)	(0.055)	(0.078)	(0.055)	(0.067)	(0.052)	(0.068)	(0.053)
Demographic Vars	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
State FE	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj R2 or PsdR2	0.015	0.0547	0.0083		0.0314		0.007		0.0287		0.0044		0.0176	
F or Chi2	120.45	22.44	232.53		875.31		234.13		959.78		332.18		1329.91	
N	24240	24110	24240		24106		24240		24110		24240		24110	

Note Parenthesis indicate standard errors; levels of significance *** p < .01, ** < .05, * < .10

† The rest of the US does not include Connecticut, Maine, California, or Washington due to lack of data during relevant times of the states' referendums

<u>Discussion</u>

A major implication in this research is that even the idea of transparency eases public opposition to GMOs. The second set of regressions show that Colorado, Oregon, and Vermont all have consistently greater levels of opposition to GMOs before and after the event period. The implication of this greater level of opposition may be why the issue of GMO labeling went further in these states than in the rest of the country.

The general shift in Vermont relative to Colorado and Oregon with regards to opposition to GMOs indicates that after the passage of the law, Vermonters become more comfortable with GMOs in the food supply. This finding would seem to bolster the argument that simple and transparent labels tend to decrease opposition and that the label is not perceived as a warning, contradicting the claims made by opponents of mandatory labels. Instead it is likely that as people see labels on their food, they become more comfortable with the presence of GMO ingredients as they are no longer perceived as something that is intentionally hidden and therefore potentially unwanted.

A national trend of opposition to GMOs in the food supply clearly exists based on the general time trend of the second model and the findings of Kolodinsky and Lusk (2018). Vermont's larger, and Oregon and Colorado's smaller movement in the opposite direction indicate that more information and discourse may increase support for GMOs in the marketplace. This finding supports the hypothesis that transparency and information makes consumers more comfortable with some forms of new technology such as GMOs.

One of the potential shortcomings of this research is that by using relative time analysis where Vermont, Oregon, and Colorado use different time periods the general time trend that existed nationally is omitted. One of the reasons the second set of regressions that included that entire country was included was to give an idea of what the time trend would seem to be.

A second short coming is the overall low R^2 value of the different regression models. While a few of the models such as the Full OLS model in the Vermont vs Oregon and Colorado case did produce a meaningful value, the remainder of the models tended to explain a relatively small portion of the overall story. A possible solution to this problem is to include additional variables in future studies that help explain the remainder of the difference; however, this is not possible with historical data.

For future research, it would be beneficial if survey responses from a longer time period could be analyzed. In this way it would be simpler to include the excluded states of Connecticut, Maine, California, and Washington, specifically as they relate to the relative time analysis. Other future research that would aid in this analysis would be to include sales and price data for the studied states in the same time periods. If purchases of processed foods that include specific ingredients that are commonly known to be GMO are compared with GMO-Free food, then actual consumer behavior could corroborate the survey results.

Conclusions

The passage of Vermont's mandatory GMO labeling law and the failed referendums in Colorado and Oregon provided an opportunity to evaluate the way in which different types of GMO legislations impact opinions of GMOs in the food supply. An expected trend in this context would be to assume that states that chose to reject legislation would have become more supportive of GMOs; however, the findings of this research present the opposite conclusion, where successful passage tampers opposition to GMOs more than failed referendums.

The general finding of increased support for GMOs between Vermont vs Oregon and Colorado holds when compared to the rest of the country, but in an even more extreme context. In aggregate, Vermont, Oregon, and Colorado became increasing supportive of GMOs in the food supply while states that did not have any referendums or successfully passed laws became more opposed. The key implication of this finding is that if retailers and manufacturers of GMO products want to improve the attitudes of consumers as they relate to GMO products, then it is in their best interest to support laws and referendums that require labeling. This trend may already be adopted by many companies that have begun voluntarily disclosing their use of GMO ingredients without any law that mandates the behavior.

The implications of this information are that product transparency increases acceptance of emerging technologies. While it is plausible that the opinions in Colorado and Oregon changed due to an increased amount of spending by pro-GMO sources on advertising prior to the referendum, the same does not hold for Vermont. Given that Vermonters' level of support increased after the implementation of the labeling law would seem to indicate that through increased transparency of food manufacturing processes consumers become more comfortable with GMO technologies.

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CHAPTER 4. CONCLUSION

The aim of this research was to evaluate the impact of Vermont's GMO labeling law to better understand the impacts of GMO legislation. Prior studies tried to evaluate the potential impacts of such intervention primarily through survey and laboratory experiments conducted in limited regions or with small groups of voluntary participants. Unsurprisingly, such approaches led to a variety of results with regards to opinions and willingness to pay (WTP) for GMO and non-GMO food. Given the context of these past studies and the work being conducted by Kolodinsky and Lusk (2018), an approach that focused both on a subset of the Kolodinsky-Lusk data and overlapping IRI grocery store scanner data was adopted. Differencing models and redundant tests that analyze both grocery store data and survey data were evaluated to form a general picture of the short-term economic impacts of Vermont's law.

With regards to the grocery store scanner data analysis, two notable conclusions emerge. The first is that the price premium for food that is non-organic, not "Non-GMO Project Certified", non-GMO, healthy, and processed is approximately \$0.05 per ounce. This finding can help end the debate that has continued with hypothetical WTP experiments and surveys. Past WTP studies have used somewhat arbitrary price levels and starting points to price a product, did not oblige participants to make binding choices (e.g. pay real money for one product or the other), and frequently did not even have a real product available. A result of previous methodologies is that the WTP amount varied significantly. The \$0.05 per ounce derived in this study may not hold for all possible products, as some products are significantly more expensive per unit such as mushrooms or caviar. However, this study provides a better starting point than prior research.

Future research should be conducted to see if other products that contain GMOs or various forms of non-GMO certification have an additional impact on these prices. As a larger variety of products becomes genetically engineered, new questions can be asked with relation to the specific products.

The second important finding of the study is the lack of significance of the key differencing variable as it relates to either sales or prices of GMO and non-GMO goods. The implication of this result is that mandatory labeling laws do not have an impact on consumer behavior. Consumers who want to avoid GMOs may already be doing by purchasing USDA Organic or Non-GMO Project Certified labeled products, may avoid processed foods, and thus implicitly avoid many of the GMO ingredients, or may pay close attention to ingredient lists that contain otherwise ingredients considered unhealthy such as high fructose corn syrup. Thus, they are not be affected by the mandatory label. However, as more products become genetically engineered, avoiding specific ingredients may become increasingly more difficult as more of the products listed on a given ingredient list may have a higher probability of being genetically engineered. This would lend credence to the argument that the labels are a good thing so that the consumers who currently avoid GMO products can do so in the future without being obliged to pay the additional price premium that the USDA Organic and Non-GMO Project may have.

When evaluating the findings of the survey research, the most important conclusion is that both labeling and the visibility of referendums swayed citizens towards becoming more open to GMOs. Much of the past literature, even after Vermont's experiment, voiced concern that labels would scare consumers (Messer, Constanigro, & Kaiser, 2017). This argument can be soundly rejected. Not only did the law in Vermont decrease opposition towards and increase support for GMOs in the food supply, but it also had no impact on the price or sales of GMO foods in relation to their non-GMO counterparts. It is worth noting that in the case of similar referendums in Oregon and Colorado, even though no labeling law was passed, bringing the discussion to public attention had an improved impact on the perception of GMOs.

An interesting finding that emerges from research into both sets of data is how Vermont compares with other states as it relates to GMOs. In the grocery store scanner set it was clear that the price premium for non-GMO goods in Vermont is about $0.016 more per ounce than in Oregon. Likewise, in the survey data set, the level of opposition to GMOs in Vermont was 22% higher before and 14% higher after legislation than in Oregon and Colorado. One conclusion that could be drawn from these combined pieces of information is that Vermonters tend to be more opposed to GMOs and therefore it was more feasible to enact legislation that mandated labeling. An alternative hypothesis could be that it is easier to have an impact on voters than in a legislative context to oppose mandatory labeling and anti-labeling groups were able to exert a greater impact in the referendum states.

To summarize, GMO labeling may not have a large effect on consumer behavior, but it does increase acceptance of new technologies. As such, this study would recommend supporting clear and simple labels on the grounds of transparency and the lack of harmful impacts on prices or sales that labels produce. If companies using emergent technologies want to improve their relationship with the public and the perception of the new technologies, transparency may be the simplest and most cost-effective approach. On the other hand, if food producers wish to avoid the use of GMO ingredients, then by doing so they can charge premiums for their products of various size depending on the state. If demand for such products is relatively inelastic, and the profits from these premiums are greater than the costs incurred by companies in avoiding GMO ingredients, then a non-GMO niche market can comfortably exist.

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