Mandatory and Voluntary Labeling Effects*

Aaron Adalja† Jūra Liaukonytė‡ Emily Wang§ Xinrong Zhu¶

January 21, 2021

Abstract

In 2022, all foods for sale in the US will be required to carry disclosure labels if they contain ingredients with genetically modified organisms (GMOs); yet, a lack of understanding of how such labels affect consumer demand remains. Most prior studies on consumer preferences for GMO foods have relied on surveys or lab experiments. We utilize the passage and temporary implementation of a mandatory GMO labeling law in Vermont in 2016 as a quasi-natural experiment and use observed retail transaction data to study the impact of GMO and non-GMO labels. Leveraging a novel dataset from the Non-GMO Project Verified program, we find that *voluntary* non-GMO labels, rather than *mandatory* GMO labels, matter more for consumer choice. Synthetic-control and difference-in-differences estimates suggest that market share of non-GMO products significantly increased and the market share of GMO products decreased in Vermont relative to other states. A close analysis of the timeline reveals that these changes are tied to a nationwide expansion of products with voluntary non-GMO labels, which surfaced several months *before* implementation of the law. The *mandatory* GMO label itself had no additional, direct impact on demand. We provide evidence that campaigning and the informational environment surrounding the law in Vermont primarily explain our results.

Keywords: GMO Labeling, Difference-in-Differences, Synthetic Control, Policy Evaluation

---

*The author names are listed in alphabetical order. The authors thank Cornell University Business of Food Initiative. We also thank Chris Barrett, Omid Rafieian, Tim Richards, and Alminas Žaldokas for their helpful comments. Researchers own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

†Cornell University, S.C. Johnson College of Business, aaron.adalja@cornell.edu

‡Cornell University, S.C. Johnson College of Business, jurate@cornell.edu

§University of Massachussets-Amherst, emilywang@resecon.umass.edu

¶University of Wisconsin-Madison, xzhu245@wisc.edu

1 Introduction

Since its introduction, the technology and use of genetically modified organisms (GMOs)[1] have been the subject of contentious political debates and attracted considerable attention in the media, often fueled by health and environmental concerns raised by consumer advocacy groups. According to the Pew Research Center (2018), about half of US adults (49%) believe that foods containing ingredients with GMOs are less healthy than foods without them. A much larger group, nearly 88% of American consumers, have strong preferences for labeling this credence attribute[2] and (Annenberg Public Policy Center 2016). At the same time, most consumers are unaware of the scientific consensus that there is no substantiated evidence showing that GMO foods are less healthy or unsafe (National Academies of Sciences 2016), which industry groups contend obviates the need for labeling.

The discrepancy between consumer perceptions and scientific consensus has prompted a vigorous debate about the consequences of GMO labeling on consumer choices. These debates sparked widespread industry concerns about detrimental consumer demand response—one reason that the food industry spent more than $100 million to oppose numerous state-level mandatory labeling bills. Meanwhile, voluntary provision of *non*-GMO labels has emerged in the US marketplace to satisfy consumer preferences for this type of information. A number of states have considered legislation to require GMO labeling, but Vermont was the only state that successfully passed and implemented a mandatory GMO food labeling law. The Vermont law remained in effect until it was preempted by the 2016 National Bioengineered Food Disclosure Standard (NBFDS) law, which established a national disclosure standard for GMO foods to be implemented at a later date. As a result of the NBFDS law, beginning January 1, 2022, all foods for sale in the US will be required to carry disclosure labels if they contain GMO ingredients.

Even as the national mandatory compliance date approaches, food manufacturers, policymakers and researchers lack a clear understanding of how such credence labels will ultimately affect consumer choices. There exists an extensive literature on public policy initiatives designed to facilitate healthier consumer choices on product attributes for which there is a scientific consensus, e.g., soda taxes to discourage consumption of highly sweetened beverages (Rojas and Wang 2017, Seiler et al. 2020, Kim et al. 2020) or nutrition-signaling labels to facilitate more nutritious choices (Bollinger et al. 2011, Hobin et al. 2017, Bollinger et al.

[1]GMOs are plants whose genetic material has been altered using genetic engineering techniques, such as recombinant DNA technology. The term GMO is used to describe agricultural crops produced from seed stock that employs this technology and food products that contain ingredients derived from these crops.

[2]Credence attributes are those that cannot be observed through search or experience, making it difficult for consumers to ascertain or verify their existence *ex ante* or *ex post*. Organic status or presence of GMO ingredients are examples of credence attributes.

2020). However, the effects of labels indicating the presence or absence of GMO ingredients on consumer demand have not been evaluated in a revealed preference setting with market data, arguably because the mandatory GMO labeling regime has never existed in the US, aside from one short-lived exception in Vermont. In this paper, we utilize a quasi-natural experiment provided by the Vermont law passage to study these questions.[3].

The goals of this paper are threefold. First, we seek to quantify the impact of mandatory GMO and voluntary non-GMO labeling on consumer demand. Second, we strive to highlight the critical role that firms' supply decisions play in shifting consumer purchase behavior. Lastly, we aim to document the heterogeneity in changing demand patterns across geographic locations, and relate such patterns to local information environments that were potentially linked to the GMO law's passage and implementation efforts. To address these objectives, we study the ready-to-eat (RTE) cereal market, which comprises a significant portion of food manufacturing and is an important downstream market for GMO agricultural commodities such as grains, sweeteners, additives, and preservatives. To determine each product's GMO status, we augment the market sales data with a novel dataset of products certified and labeled through the Non-GMO Project Verified (NGPV) program, the marketplace standard for the third-party verification for non-GMO ingredients in the US.

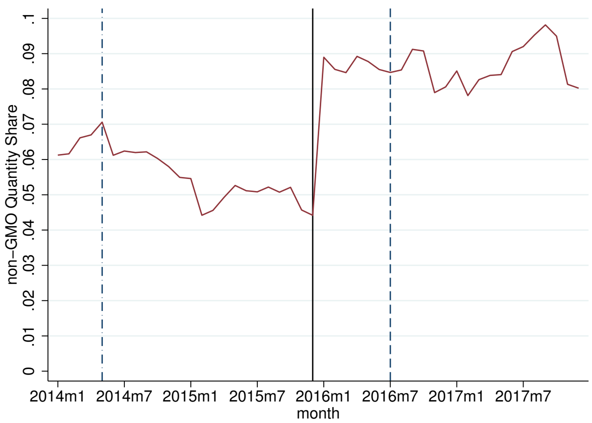
Our identification strategy relies on two key sources of data variation. First, we utilize the heightened information environment unique to Vermont following the passage of the GMO labeling law. Second, we take advantage of a non-GMO supply expansion, specifically, Kellogg's corporate decision to expand national distribution of Kashi cereal. Notably, this non-GMO supply expansion occurred across the nation and preceded Vermont's law implementation, and the expanded selection of products with non-GMO labels occurred well before any products with mandated GMO labels arrived at stores in Vermont; however, it coincided with the heightened information inflow surrounding GMOs in Vermont. Tied to annual distribution contract renewals at the beginning of the year, on January 1, 2016, this supply expansion generated an over 50% increase in the number of available non-GMO products in an average store in our sample across the nation. As Figure 1 illustrates, this greater availability translated into notable changes in consumption patterns in Vermont; the market share of labeled non-GMO cereal increased, and the market share of not-yet-labeled GMO cereal decreased right after the expansion. We employ synthetic control (SC) and difference-in-differences (DiD) methods to find that Vermont's consumption response was

[3]This study focuses on the US marketplace. According to Grocery Manufacturers Association (2014), 75 to 80 percent of conventional processed food contains GMO ingredients in the US. Outside of the US, 64 countries require GMO food labeling, including the EU, Japan, Australia, Brazil, Russia and China. However, these countries have much lower, or (in the case of EU) nearly non-existent GMO ingredient supply chain. For example, the majority of the EU states do not allow cultivating GMO crops on their soil (European Green Capital 2020)

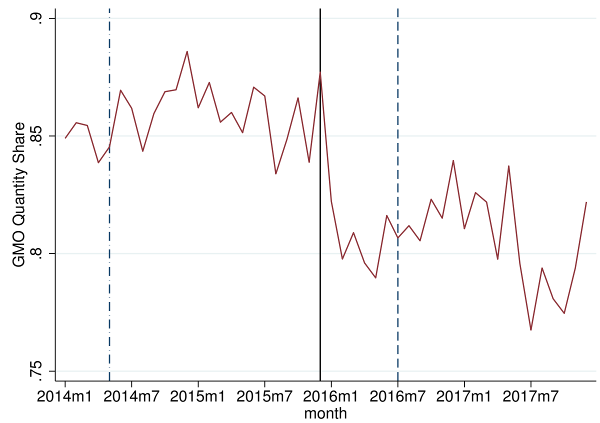
much more substantial compared to other locations in the US that experienced similar scale non-GMO supply expansion. The results are robust to multiple alternative specifications.

Figure 1: non-GMO and GMO Quantity Share in Vermont

(a) non-GMO Quantity Share



(b) GMO Quantity Share



Notes: This figure depicts non-GMO and GMO quantity shares of RTE Cereal in Vermont. The blue dashed vertical lines indicate the months when Vermont mandatory labeling law was passed (April 2014) and implemented (July 2016), respectively. The black vertical line indicates the nationwide expansion of non-GMO product distribution. The sample includes cereal from the Big 3 parent companies: Kellogg's, General Mills, and Post, which together constitute around 90% of overall market share.

Next, we formally explore whether any additional demand changes occurred after products began carrying mandatory GMO labels in July 2016. We find no statistically discernible impact on demand in Vermont attributable to the implementation of mandatory GMO labels. This result indicates that many consumers receptive to altering their consumption to avoid GMO ingredients already made use of alternative labels such as "Non-GMO Project Verified" or "USDA Organic" to facilitate those choices. The mandatory GMO label itself did not have any direct effect on demand.

We then examine the underlying reasons for this response pattern by analyzing additional evidence and conducting additional empirical tests. Our findings suggest that the information environment, spurred by the legislative process, was a main driver of change. We build our argument on several grounds: evidence from survey data, the Google Search Volume Index (SVI) data, empirical tests utilizing Vermont border areas, and interviews with Vermont GMO labeling law campaigners.

First, we show that in consumer surveys conducted over multiple years overlapping with our study period, concerns about GMO products peaked in Vermont during the time leading up to the labeling law's implementation. Such temporal change in consumer opinion was absent in national surveys conducted at the same time. Second, we use state-specific Google Trends indices for the keyword "GMO" to show that a larger index correlates with a larger increase in non-GMO consumption and a larger decrease in GMO consumption. We also find that nearby states that also considered GMO labeling legislation in the past saw consumption changes similar to those experienced in Vermont, albeit significantly smaller in magnitude.[4] Furthermore, we conduct a series of tests based on DiD specifications utilizing geographic areas surrounding Vermont borders. The results of these tests suggest that informational campaigns *within* Vermont had the largest impact on consumer choice. This interpretation is also supported by our interviews with campaign organizers whose actions generated the signature informational environment in Vermont.

Overall, our revealed preference results based on retail transaction data indicate that implementation of GMO labeling did not *directly* impact demand. Rather, a heightened level of awareness in Vermont and a significant national change in supply composition *before* the law took effect drove substitution from not-yet-labeled GMO products to voluntarily-labeled non-GMO products. These results sharply contrast with results from previous studies (discussed in the next section) that suggest GMO labeling itself has a large direct effect on demand. By construction, these previous studies relied heavily on stated preference data and hypothetical scenarios, and, thus, they failed to capture the complexity and existence of alternative information signals that exist in the marketplace.

Our work highlights the importance of accounting for complex relationships between labeling laws, new and existing information signals, and firm product strategies when analyzing policy effects—particularly when many changes occur simultaneously or in close sequence. Implementation of the GMO labeling law in Vermont had no direct effect, but it had an indirect effect in shifting consumer preferences via greater information flow that coincided with expansion of non-GMO product availability. Our results therefore provide the most realistic indication to date of how implementation of the national mandatory GMO label will affect consumer choice. Labeling the GMO credence attribute alone may not suffice to change consumer behavior, even in markets with strong initial preferences for labeling. What matters more, potentially, is the voluntary provision of non-GMO labels and availability of such products, rather than mandatory GMO labels.

Our results have important marketing and management implications for firms as well. Instead of expending resources to oppose consumer movements and campaigns, companies can and should view them as opportunities to respond to potential consumers' preferences. While Kellogg's supply expansion of Kashi products was likely a response to evolving national consumer preferences, it coincided with Vermont's GMO legislation process and the wave of anti-GMO informational campaigns in Vermont. Based on our estimates, Kellogg's total revenue increased by 8% in Vermont relative to the control areas primarily due to heightened

[4] Connecticut and Maine were two other states in the region that passed GMO labeling laws, but never implemented them; in those states, the implementation was contingent on other states passing similar laws.

anti-GMO information environment in Vermont. At a time when consumer preferences are rapidly changing, this is an important lesson. Firms can potentially preempt adverse market effects from evolving consumer preferences and future legislation by reconfiguring their product portfolios, particularly in the markets where such preferences are more pronounced and information is more intense.

2 Related Literature

Broadly, this paper investigates the role of information disclosure in a market characterized by asymmetric information. In particular, the use of GMO technology in food production is a credence attribute (Darby and Karni 1973); quality disclosure via food labeling can correct this asymmetry between consumers and firms and generate efficiency gains (Dranove and Jin 2010). A stream of empirical literature has examined the role of policy-mandated quality disclosure for credence attributes on market outcomes. Jin and Leslie (2003) find that public disclosure of restaurant hygiene inspection grades lead to restaurant-level hygiene improvements, better public health outcomes, and greater consumer responsiveness to such information. Moorman (1998) examines the effects of market information in the context of mandatory nutrition labeling resulting from passage of the Nutrition Labeling and Education Act (NLEA), and finds strong evidence of strategic firm response across product quality, variety, and level of price promotion. Moorman et al. (2012) further explores heterogeneous firm response to the NLEA and finds that the impact of the NLEA on the brand's nutritional quality depends on firm behavior. Rao and Wang (2017) measure the consequences when firms are caught making false health claims on consumer demand and characterize heterogeneity in consumers' responses to misleading information. Our paper contributes to this stream of literature by showing that mandatory disclosure (i.e. labeling) of credence attributes itself does not directly affect demand; but, in fact, the information environment generated by the associated policy process, the presence of alternative voluntary information signals, and contemporaneous supply-side changes in product availability induce an appreciable demand response.

Over the past two decades, hundreds of studies have attempted to understand the effects of the disclosure of a specific credence attribute—presence of GMO ingredients in food. Most of these studies suggest a substantial reduction in consumer demand for GMO products following *hypothetical* GMO labeling, with average willingness-to-pay (WTP) premiums for non-GMO over GMO products exceeding 40%, albeit with a substantial dispersion across studies (for meta analyses, see Lusk et al. 2005, Dannenberg et al. 2009). However, the vast majority of these prior studies rely on stated preference (survey) or lab experiment data rather than actual market transactions. In an attempt to understand the reasons behind the vast dispersion in valuations, Dannenberg et al. (2009) conduct extensive analysis of over 114 valuations across 51 studies and conclude that the valuation depends more on how you ask than on who you ask: the WTP elicitation method and the elicitation format are the key drivers in explaining the variation of the WTP estimates across studies. A related concern regarding the usefulness and interpretability of stated preference results is that there might be an intention-behavior gap, whereby stated preferences may not map onto revealed preferences: actual purchasing behavior might substantially diverge from perceived consumer attitudes (Sunstein 2020). Indeed, prior studies show that sentiments expressed in opinion and attitude surveys can be poor predictors of actual behavior (Smith 1991, Kahneman et al. 1999). Moreover, *ex ante* WTP estimates may not be informative when consumers face asymmetric information or when the preferences for labeled attributes are endogenous to the existence of labels (Sunstein 2020). Our study circumvents issues with stated preference or hypothetical scenario and provides a more realistic estimate of the effects of GMO labeling, as we base our analysis on actual retail-level consumer purchase data. By doing so, we account for several complex mechanisms beyond GMO labeling that shape consumer demand response in differentiated product markets. These mechanisms include the roles of supply responses by multi-product firms, alternative food labels, and the information environment facing consumers.[5]

Lastly, our paper contributes to a long history of economic studies in the RTE cereal industry examining various non-price marketing strategies such as new product introductions (Schmalensee 1978, Thomas 1999), portfolio depth (Scherer 1979, Nevo 2001), advertising (Thomas 1999, Nevo 2001), and couponing (Nevo and Wolfram 2002). Our study adds to this literature by studying the demand effect of voluntary quality disclosure of credence attributes coupled with distributional expansion of existing product lines in the RTE cereal industry.

[5] There are two studies that have utilized the Vermont GMO labeling law as a quasi-natural experiment: Kolodinsky and Lusk (2018) use yearly survey data and find a 19% reduction in stated opposition to GMO food after the Vermont law was passed; and Carter and Schaefer (2019) look at the impact on commodity prices and find that GMO labeling in Vermont led to 1% premium for non-GMO cane sugar and 13% discount for GMO beet sugar at the refiner-level.

3 Background and Institutional Setting

3.1 The Vermont Labeling Law as a Natural Experiment

In this section, we describe the Vermont GMO labeling law in more detail, and argue that it provides a good setting to study the labeling effects. We present summary of the timelines of campaigns and other educational efforts surrounding the Vermont labeling law that contributed to an information-rich environment unique to Vermont. We then give background information about Kellogg's decision to expand non-GMO product distribution nationwide. Lastly, we provide evidence that the three largest cereal companies responded by changing their product labels to comply with Vermont's law.

Timeline of the Law. In the past two decades, a patchwork of state-level legislation in 25 states has been proposed on mandatory GMO labeling, with the public debate becoming considerably more mainstream around California's Proposition 37 in 2012 (Bovay and Alston 2016). Vermont, however, was the first to pass an unconditional mandatory GMO labeling law in May 2014; H.112 (Act 120) became effective on July 1, 2016. Act 120 required food manufacturers to label products sold in Vermont with a GMO label if they contained greater than 0.9% GMO ingredients, by weight. Failure to do so would result in fines of $1000 per day, per product. To avoid a GMO label, manufacturers would have needed to either obtain sworn statements from their suppliers indicating that the ingredients were non-GMO, or undergo third-party non-GMO verification of the final products. Unlike the hotly debated public referenda that accompanied similar labeling bills proposed in states such as California, Oregon, and Washington, the initial proposal and passage of Vermont Act 120 attracted less media attention. The bill originated in the Vermont state House of Representatives in January 2013, passed both the House (99-42 in May 2013, 114-30 in April 2014) and the Senate (28-2 in April 2014) with overwhelming support, and was signed into law by the governor in May 2014, with an implementation date of July 1, 2016. In response, the Grocery Manufacturer's Association (GMA) filed a request in federal district court for a preliminary injunction to halt the law, but the request was rejected in April 2015.

During this time, several attempts to preempt the Vermont law at the federal level also failed. In March 2015, the US House of Representatives introduced the Safe and Accurate Food Labeling Act of 2015, which would have banned all mandatory GMO labeling and established a national *voluntary non-GMO* label. Though it passed the House in July 2015, the bill never left the Committee of Agriculture in the US Senate. Subsequently, in a slightly different tack, a national *voluntary GMO* labeling bill originated in the Senate, but failed to pass in March 2016. Just days later and about three months prior to the seemingly imminent implementation of Vermont Act 120, numerous national food brands (e.g., General Mills, Kellogg's, Mars, ConAgra Foods, and PepsiCo) unexpectedly announced that they would begin *nationwide* GMO labeling, despite the fact that the jurisdiction of the mandatory GMO labeling law was limited to Vermont (Brasher 2016b). This nationwide change in GMO labeling for the major RTE cereal brands began in April 2016 and persisted at least through 2017 — the end of our sample period. The Vermont mandatory GMO labeling law went into effect as scheduled on July 1, 2016. Just 28 days later, however, President Obama signed into law the National Bioengineered Food Disclosure Standard (NBFDS), a compromise deal establishing a national mandatory GMO labeling standard. Enforcement was originally slated to begin in 2020, but the passage of the national law immediately preempted all state-level labeling, thereby overturning the Vermont law after it had been in effect for only 29 days (for more information on NBFDS, see Bovay and Alston 2018).

The procedural context and timing of the Vermont GMO labeling law, coupled with the industry response from major food manufacturers, provide us with a unique natural experiment by which to identify the effect of mandatory GMO labeling on demand for RTE cereal products. First, given that Act 120 was passed in the legislature rather than by referendum, it failed to garner significant media attention prior to its passage in 2014.[6] As such, we do not expect changes in consumer purchasing behavior for GMO foods attributable to information coverage prior to the law's passage. In the time period after the law passed leading up to the law's implementation in July 2016, however, Vermonters *did* experience a unique positive shock to the information environment surrounding GMO topics, as the rule-making process for Act 120 garnered significant local attention in Vermont. This legal process of developing specific requirements to implement the labeling law involved solicitation of considerable public input, which was also spurred on by grassroots informational campaigns. We provide details on the extent of the information shock in Vermont in the period after the law passage but before the implementation in Appendix A, which summarizes the rule-making process and the accompanying information campaigns.

3.2 Non-GMO Product Distribution Expansion

One of the key components of our identification strategy is utilizing the national non-GMO supply expansion, which coincided with, but was not triggered by, the Vermont mandatory GMO labeling law implementation.[7]

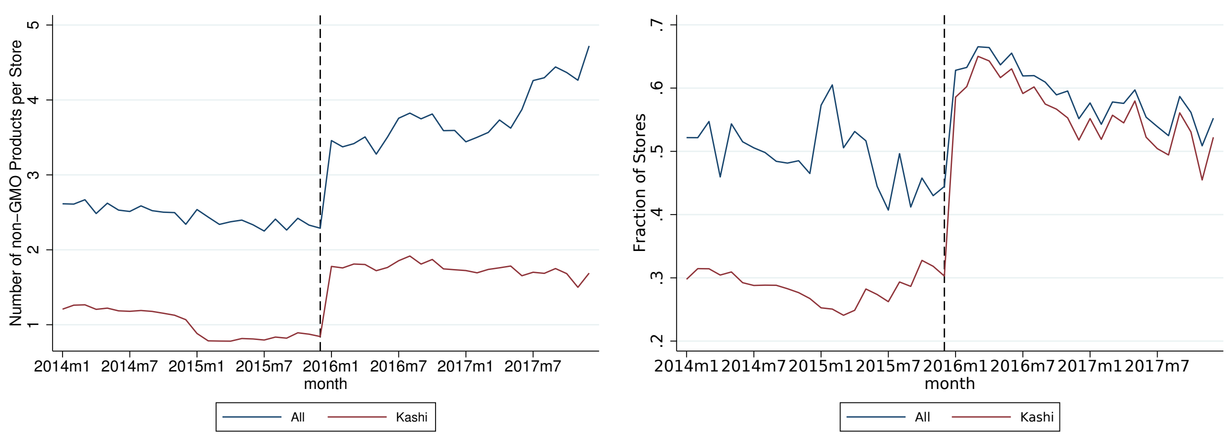
[6] While there were some localized grass roots initiatives in Vermont, the media attention surrounding these events was much smaller in scale than had been the case in California, for example, where millions of dollars were spent in the ad campaign surrounding the Proposition 37 labeling initiative (Bovay and Alston 2016).

[7] An important thing to note is that our identification strategy *does not* rely on the assumption that Vermont law is exogenous to non-GMO product expansion, even though the evidence presented herein suggests that there was

Figure 2 illustrates the intensive (average number of non-GMO products) and extensive (percent of stores carrying at least one non-GMO product) margins of non-GMO supply expansion. Several important details emerge from the figures: First, there is a notable discontinuity in availability of non-GMO products between December 2015 and January 2016. In January 2016, the average number of non-GMO products per store increased by 51% and the number of stores that carried at least one non-GMO product increased by 41%. Second, this spike in distribution was mainly driven by expanded availability of Kashi—a subsidiary brand of Kellogg's that focuses on whole grains, organic, and non-GMO products. Third, the number of products remained relatively stable after the jump in January 2016 and before the labeling law went into effect in July 2016.

Figure 2: Supply Expansion of Non-GMO Products

(a) Number of Non-GMO Products per Store **(b)** Fraction of Stores with $\geqslant 1$ Non-GMO Products



Notes: Panel (a) depicts average number of non-GMO (Kashi) products per store. Panel (b) depicts fraction of stores in our sample that carry at least one non-GMO (Kashi) product.

The graphs in Figure 2 distinctly uncover a strategic brand revitalization story. In 2015, Kellogg's launched several initiatives to re-establish and restore the growth of its then under-performing and declining brand, Kashi. Over the years, Kellogg's alienated many of Kashi's fervent fans with its defensive stance on using GMOs. The controversy peaked when consumers learned that Kellogg's had contributed hundreds of thousands of dollars to a campaign by big US food companies to defeat the California mandatory GMO labeling ballot initiative in 2012 (Wert 2017, Kesmodel and Gasparro 2015). Faced with declining sales, Kellogg's decided to pour its resources into revitalizing the Kashi brand.[8] The brand converted its entire product line to contain only non-GMO ingredients by renovating

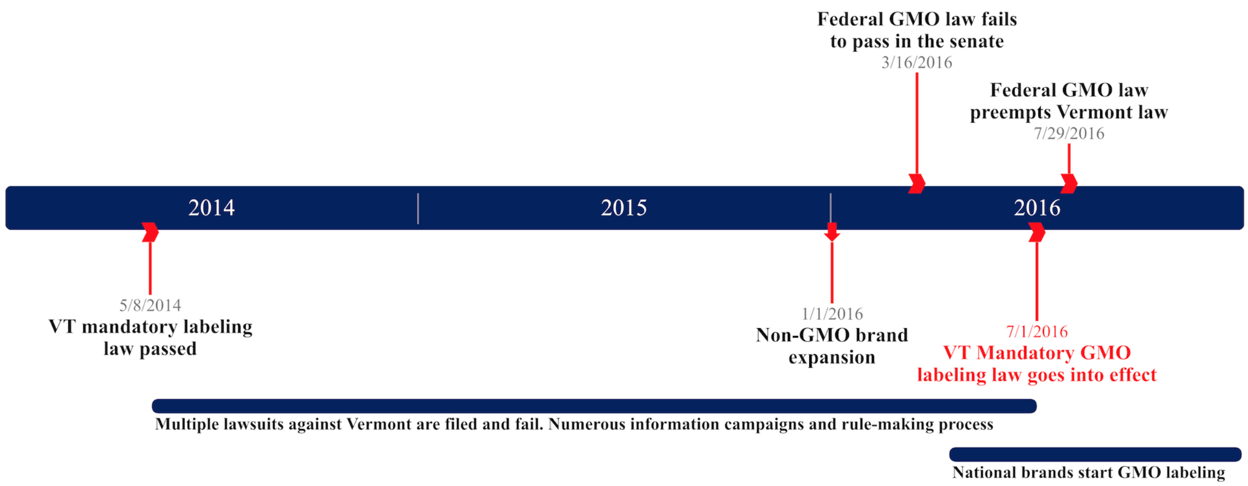
no direct relationship. Our identification strategy *does* rely on this expansion being of similar scale (parallel) across different geographic locations in the US, which we verify in subsection 5.1. In our analysis in subsection 6.2, we also find no evidence that Kellogg's made any supply or pricing adjustments specific to Vermont.

[8]In 2014, Kashi posted about $400 million in sales, about 20% below its peak (Nunes 2020).

the line of existing products, adding some new ones, and creating a supply chain of over 500 *Non-GMO Project Verified* ingredients (Wert 2017).[9] While the revitalization process occurred in 2015, consumers did not experience increased availability or presence of the Kashi products until after January 1, 2016, a timeline consistent with renewed annual distributional contracts.

For clarity, Figure 3 summarizes the full timeline of events that occurred during this period surrounding Vermont GMO legislation.

Figure 3: Vermont GMO Legislation Timeline



4 Data and Descriptive Statistics

4.1 Sales Data

Our primary data source is Nielsen Retail Scanner ("RMS") data provided by the Kilts Center for Marketing at The University of Chicago Booth School of Business. Our sample spans four years, from 2014 to 2017, a period that includes the non-GMO supply expansion (January 2016) in RTE cereal and the Vermont mandatory GMO labeling law implementation (July 2016). The RMS data records weekly quantities sold, revenue, and product information for about 30,000 stores across the 48 contiguous states in the US. Product information

[9]Paul Norman, Kellogg's president, told investors in February 2015 that Special K and Kashi had been its "growth engines for many years" in the competitive US cereal category and fixing the two brands "is critically important". At the time, the ongoing revitalization attempt had been noted by investors. On November 23, 2015, an equity analyst at Credit Suisse upgraded his outlook for Kellogg's Company stock to "outperform," stating, "We expect Kellogg's cereal business (45% of sales) to return to growth in 2016 behind the revitalization of the Kashi and Special K brands" (Wert 2017). Furthermore, a review of Kellogg's 10-K Annual Reports, which requires that publicly listed companies disclose what kinds of risks it faces, reveals that their decision to revitalize the Kashi brand was driven by consumer trends in the RTE cereal category. We did not find any mention relating to increased risks due to potentially changing GMO labeling legislation environment (Kellogg Annual Report 2015, 2016).

includes UPC (universal product code), product description, brand name, organic status, package size (in ounces), and flavor variant. We use these data to calculate quantity sold and to determine prices according to standard definitions used in the literature. Quantity sold is defined as number of units sold multiplied by package size of each unit (in ounces), and price is calculated on a per-ounce basis by multiplying the unit price by the number of units sold and dividing by quantity sold for a given time period. We observe four different types of stores: grocery, drug, convenience stores, and mass merchandisers. Similar to DellaVigna and Gentzkow (2019), we exclude stores that are in our sample for fewer than 48 months. To ensure that some products in smaller stores do not artificially enter and exit the sample over the four year time span, we aggregate the data to the monthly level. Our final data set contains quantity and price information for products in store i at month t.

To track and verify the GMO status and labeling decisions with respect to Vermont mandatory GMO labeling legislation, we need to restrict our analysis to the products and parent companies for which we have such verifiable information. Therefore, we focus our analysis on the three largest parent companies (hereafter, Big 3) in the RTE cereal category: General Mills, Kellogg's, and Post, whose combined market shares account for over 90% of national market share in the RTE cereal category. Each of the Big 3 cereal firms has a complex brand structure that includes several companies under its corporate umbrella, each with a portfolio of products.[10] We are able to accurately verify labeling decisions and timelines for all of RTE cereal products under the umbrella of the Big 3 companies by reviewing official company announcements (Harmening 2016) and press releases (Brasher 2016a,b) made in 2016.[11] We use this information to construct a temporal indicator of nationwide GMO labeling status for the Big 3 cereal firms to use in our empirical analysis. We couple this with an indicator of GMO ingredient status for all Big 3 RTE cereal products in our data, as described in the following section.

4.2 Non-GMO Project Verified Data

To determine each product's GMO status, we leverage two types of data: an indicator of organic status provided directly in the Nielsen scanner data, and an indicator of third-party non-GMO certification status obtained from the Non-GMO Project.[12] The Nielsen data do not provide information about whether a given product contains GMO ingredients; thus,

[10] An example would be Kellogg's (parent company), Kashi (company), Organic Promise (product). The variants within each product pertain to different flavor varieties, e.g. Kashi Organic Promise product line includes Berry Fruitful, Cinnamon Harvest, etc. Throughout the paper, we track the number of products.

[11] Section 3.1 provides a detailed recount of the labeling timeline, and Figure 3 provides a visual summary.

[12] USDA Certified Organic products are prohibited from containing GMO ingredients based on the National Organic Program standards.

while we observe USDA Certified Organic information in Nielsen data, we cannot rely on Nielsen data to distinguish GMO status for *non*-organic products. We therefore augment the Nielsen data with a novel dataset of products certified and labeled through the Non-GMO Project Verified (NGPV) program. The Non-GMO Project is a nonprofit organization that began offering third-party verification and labeling in 2010 for non-GMO products that fall under a 0.9% threshold for GMO presence, which aligns with the exemption threshold for the Vermont GMO labeling law. The verification process involves a combination of ingredient traceability standards, supply chain segregation, and laboratory testing and is administered in partnership with several prominent international technical administrators. The NGPV standard is the leading third-party verification program for GMO avoidance in North America, with over 60,000 verified products representing over $26 Billion in annual product sales. These NGPV data includes UPC-level information for all products certified by the project between 2010 and 2017, including the date when each product was certified. This information enables us to precisely track whether a particular product was subject to mandatory GMO labeling in Vermont at a given point in time.[13]

Table 1: Average Annual Store Sales and Revenues of RTE Cereal

	Before 2016		After 2016	
	mean	*sd*	*mean*	*sd*
Overall Quantity	535.14	2385.61	519.24	2779.36
Overall Revenue	106.63	467.74	105.28	561.69
Big 3 Quantity (% of overall)	83.76%		84.13%	
Big 3 Revenue (% of overall)	85.47%		85.67%	
Big 3 Quantity GMO	430.29	1861.79	414.74	2161.31
Big 3 Quantity non-GMO	18.03	103.47	22.14	163.35
Big 3 Revenue GMO	87.38	369.46	85.22	439.86
Big 3 Revenue non-GMO	3.76	22.04	4.97	36.67
Number of Stores	20,946		20,946	

Notes: Quantity is annual quantity of RTE cereal sold in 10,000 ounces averaged across years and stores. Revenue is average revenue in $10,000. Big 3 refers to Kellogg's, General Mills, and Post. "Before 2016" specifies time period from January 2014 to December 2015, whereas "After 2016" — time period from January 2016 to December 2017.

Based on these product level indicators, Non-GMO products in our sample are defined by the union of Organic and NGPV products, while the complement of this union defines GMO

[13] In the vast majority of cases, all UPCs under the same product umbrella will have the same non-GMO certification status. In rare cases in which a product's non-GMO status is not consistent across all UPCs under its umbrella (usually along the flavor dimension), we separate the product into subsets of GMO and non-GMO products.

products subject to mandatory GMO labeling.[14] Figure 4 presents examples of the typical labels that products must carry to be flagged as a non-GMO product in our sample. The product could have one or both of the labels. In creating our estimation sample, we exclude products that underwent NGPV certification during our sample period – this removes less than 1.8% of Big 3 products by quantity and revenue share. Our results are robust to this exclusion. Table 1 summarizes average annual store sales and revenues of RTE cereal by GMO ingredient status in our sample.

Figure 4: Non-GMO Project Verified and USDA Organic Labels

(a) Non-GMO label

(b) USDA Organic label

4.3 Summary Statistics

We present summary statistics for GMO and non-GMO RTE cereal in Table 2. This table summarizes the number of products, quantity share, and revenue share for GMO and non-GMO products in our sample, separately for Vermont and nationwide. Quantity (revenue) share is calculated by dividing total quantity sold (revenue) in a store i and month t by total RTE cereal category quantity sold (revenue) of that store-month. The presented statistics are weighted averages using store-level category sales as weights.

Table 2 shows a declining trend in quantity share and revenue share for GMO products. The trend is present nationwide, but it is particularly pronounced in Vermont. The number of distinct products with GMO ingredients remained relatively stable across all geographies. On the other hand, the right side of Table 2 presents the opposite trend: increasing quantity and revenue share of non-GMO products across the nation, particularly in Vermont.[15] Furthermore, there are some changes in both Vermont and outside of Vermont in marketing mix

[14] Given the added costs associated with securing a non-GMO ingredient supply chain and the credence nature of the non-GMO attribute, it is quite unlikely that a profit maximizing firm producing a non-organic, non-GMO product would choose *not* to obtain NGPV certification in the US, and we are not aware of any of such cases.

[15] GMO and non-GMO quantity shares do not sum up to 1 because these include only products from Big 3 manufacturers. The remaining quantity share of around 0.1 (depending on location) corresponds to non Big 3 products, which we exclude from our analysis due to inability to verify their GMO labeling status.

variables such as prices and assortment. Our formal empirical model, discussed below, is designed to control for these potential confounders. While these simple descriptive statistics present general trends, they do not provide a robust understanding of how these changes relate to the Vermont legislation timeline, which we present in the next section.

Table 2: Summary Statistics of GMO and non-GMO Products (Big 3)

	GMO				non-GMO			
	Vermont		Nationwide		Vermont		Nationwide	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
Pre								
Quantity	6.553	0.047	8.426	4.635	0.471	0.080	0.228	0.144
Quantity Share	0.859	0.000	0.887	0.023	0.056	0.009	0.023	0.010
Price	0.253	0.001	0.242	0.017	0.314	0.019	0.258	0.026
Revenue	1.467	0.020	1.650	0.811	0.124	0.019	0.052	0.033
Revenue Share	0.840	0.004	0.886	0.023	0.064	0.009	0.024	0.011
# of Products	48.976	0.192	45.425	7.714	16.444	1.103	7.968	3.293
Post								
Quantity	6.413	0.319	7.652	4.445	0.735	0.032	0.367	0.241
Quantity Share	0.806	0.007	0.867	0.027	0.087	0.001	0.038	0.014
Price	0.262	0.004	0.244	0.019	0.271	0.034	0.233	0.018
Revenue	1.483	0.069	1.508	0.789	0.191	0.004	0.085	0.056
Revenue Share	0.793	0.009	0.865	0.028	0.095	0.002	0.041	0.015
# of Products	47.756	3.489	46.937	8.916	21.047	1.981	10.974	4.329

Notes: Big 3 refers to Kellogg's, General Mills, and Post. Quantity is weighted average quantity of RTE cereal sold in 10,000 ounces averaged across months and stores. Revenue is average revenue in $10,000. Price is in dollars per ounce. "Pre" specifies time period from January 2014 to December 2015, whereas "Post" is time period from January 2016 to December 2017.

5 Research Design

5.1 Identification Strategy

Our empirical analysis is motivated by the previously identified nationwide supply expansion of non-GMO products in January 2016 (described in subsection 3.2). We examine demand responses to this nationwide supply expansion in Vermont and other locations and link the magnitude of the response to the information environment related with GMO topics in the local markets.

Our identification exploits two ideas: (i) many other states did not pass similar labeling laws and did not have intensified information inflow on GMO related topics (documented in section 3 and Appendix A), and (ii) all localities experienced a supply expansion of non-GMO products, primarily driven by expanded Kashi availability, of a similar scale. Our definition of what constitutes the "treatment" or "intervention" is slightly unconventional in that it is the supply expansion *in tandem* with the heterogeneous information environment across different localities that identify the main effect.[16]

Based on the discontinuity in Figure 2, we specify the start of the treatment window as January 2016, which aligns with non-GMO product supply expansion discussed in subsection 3.2.[17] Figure B1 in Appendix B plots the monthly number of non-GMO products separately for Vermont and the other states, suggesting that the size of non-GMO product expansion in January 2016 in Vermont is parallel to that of the rest of the US. This suggests that the supply expansion in non-GMO cereals was *not* directly triggered by or correlated with any demand factors specific to Vermont, although it may have happened in anticipation of general consumption trends towards more natural and healthier foods. Furthermore, conversations with industry professionals indicate that the Kellogg's supply expansion of Kashi was not directly related to Vermont labeling law. Therefore, we consider the non-GMO product expansion as a quasi-natural experiment within Vermont.

The expansion triggered demand changes and potential substitution between GMO and non-GMO products. We examine how consumers in Vermont—who received significantly more information because of the law's passage—changed their consumption of GMO and non-GMO cereals subsequent to the supply expansion. This difference, however, would also include any other changes that may have occurred absent the local differences in information—via, for example, a general consumption preference trend towards non-GMO products. Therefore, we look for a location (or a set of locations) where the GMO and non-GMO consumption patterns were very similar to those in Vermont prior to January 2016. To do so, we use a synthetic control (SC) method to construct such a composite location. The next subsections explain the SC method and our implementation of it.

5.2 "Synthetic Vermont"

The synthetic control (SC) method has gained popularity in policy evaluations with quasi-experimental designs (Abadie et al. 2010, 2015). Athey and Imbens (2017) refer to SC

[16] One could also consider the treatment as the supply expansion and the differences in response across locations as the heterogeneous treatment effects. This distinction is purely semantic for the purposes of identification.

[17] We also perform a formal structural break test on the monthly number of non-GMO products time series. We run a time series regression first with number of non-GMO products as a dependent variable, and then conduct a Wald test for a structural break at an unknown break date. The test selects January 2016 as the structural break point, with a test statistic equal to 1377.172 and a p-value of 0.0000, rejecting the null that there is no structural break. This treatment window yields 24 months of pre-intervention data and 24 months of post-intervention data in our sample.

as "arguably the most important innovation in the policy evaluation literature in the last 15 years." SC has also emerged as a powerful approach for causal inference in marketing (Narang and Shankar 2019, Pattabhiramaiah et al. 2019, Guo et al. 2020, Kim et al. 2020). The underlying idea is that researchers can construct a "clone" of the treated unit by using a convex combination of control units. This "clone" in our case is what we hereafter refer to as the "Synthetic Vermont," which mimics the pre-period consumption trends of Vermont.

The main logic of identification behind the SC method is that the constructed control follows similar market conditions in prices, product assortments, and consumption trends as those of the treated unit prior to the supply expansion in January 2016. Thus, any deviation that happens post-treatment is caused by the treatment; which, as we assert in section 7, is the difference in the information environment surrounding GMO related topics. Thus, the measured outcome or treatment effect is the differential demand response between locations due to variation in information intensity around GMO topics. In addition, we impose a conventional identification assumption that any unobservables are uncorrelated with the treatment.

We track two main outcomes of interest: (i) the quantity share of non-GMO products and (ii) the quantity share of GMO products. Furthermore, to capture the composite effect of (i) and (ii), we also construct what we henceforth refer to as "differential quantity share", which is the difference between the GMO product quantity share and non-GMO product quantity share.[18]

The SC method performs better if the data are less volatile. Therefore, we aggregate the store-month level data to DMA-month level using store RTE cereal category sales as weights. In our original sample, an average state has 564 stores, and an average DMA has 133.5 stores. Because Vermont is a relatively small state with only 110 stores in the Nielsen data, we match Vermont to other DMAs (and not states) to ensure maximum variation across donor markets.[19] To eliminate possible contamination on the main effect via information spillovers, we exclude from the donor pool all neighboring region states: all DMAs in Connecticut, Maine, Massachusetts, New Hampshire, and New York.[20] In sum, the donor pool for Vermont consists of the 192 DMAs across 42 states. In section 7, we include the neighboring states in our analysis to better explore the information environment mechanism.

We include four types of predictive variables in the construction of the Synthetic Ver-

[18]For example, if treatment resulted in 4% decrease (-0.04) in GMO quantity share, and 2% increase in non-GMO quantity share (+0.02), then the *differential quantity share* will be = -0.04-(+0.02) = -0.06. In other words, differential quantity share is a single metric that captures both quantity share changes. We report all three metrics, but, for ease of comparison, we focus on the differential quantity share in follow up robustness tests.

[19]We also conduct state-to-state synthetic matches with very similar results. See Appendix D.5.

[20]We also exclude the DMA associated with Washington, DC, due to insufficient number of stores in the Nielsen sample.

mont: (i) pre-treatment GMO and non-GMO consumption patterns (to ensure that the parallel trends assumption in the pre-treatment is satisfied); (ii) pre-treatment and post-treatment trends in assortment (to ensure that the expansion of assortment and supply is as close as possible to the expansion in Vermont); and (iii) pre-treatment and post-treatment prices (to ensure that changes in demand in the post-period are not attributable to divergence in pricing).[21] We conduct the synthetic match procedure using demeaned time trend variables (except for the variables that relate to the supply expansion) by subtracting the pre-treatment location-specific average from all the time trend variables, thereby removing any level differences specific to geographic locations. Demeaning is inconsequential in the DiD setting; however, Ferman and Pinto (2021) show that a demeaned version of the SC method can substantially improve efficiency and reduce bias and variance. Indeed, in our setting demeaned SC estimator results in better matching (RMSPE=0.0178 vs. RMSPE=0.0365 without demeaning).

The resulting Synthetic Vermont is constructed as a weighted average of DMAs from the donor pool that minimizes root mean squared prediction error (RMSPE). Table 3 presents the geographic locations (DMAs) selected by this procedure and the resulting optimal weights. The list of the selected DMAs is quite intuitive, as it includes a number of college towns that tend to have very similar GMO vs. non GMO demand patterns to those of Vermont.

Table 3: Synthetic Control Weights for Matched DMAs

DMA Name	Weight
Charlottesville, VA	0.398
Erie, PA	0.302
Terre Haute, IN	0.257
Fargo-Valley City, ND	0.027
Eureka, CA	0.016

Our SC procedure does a good job constructing a measurably reliant control for Vermont. Panels (a) and (b) in Figure 5 depict demeaned time series of non-GMO and GMO consumption trends in Vermont and Synthetic Vermont. Panel (c) depicts the differential quantity share defined above.[22] Visual inspection of the time trends in Panels (a), (b), and (c) in Figure 5 highlights the fact that pre-trends are very similar (parallel) in the pre-period

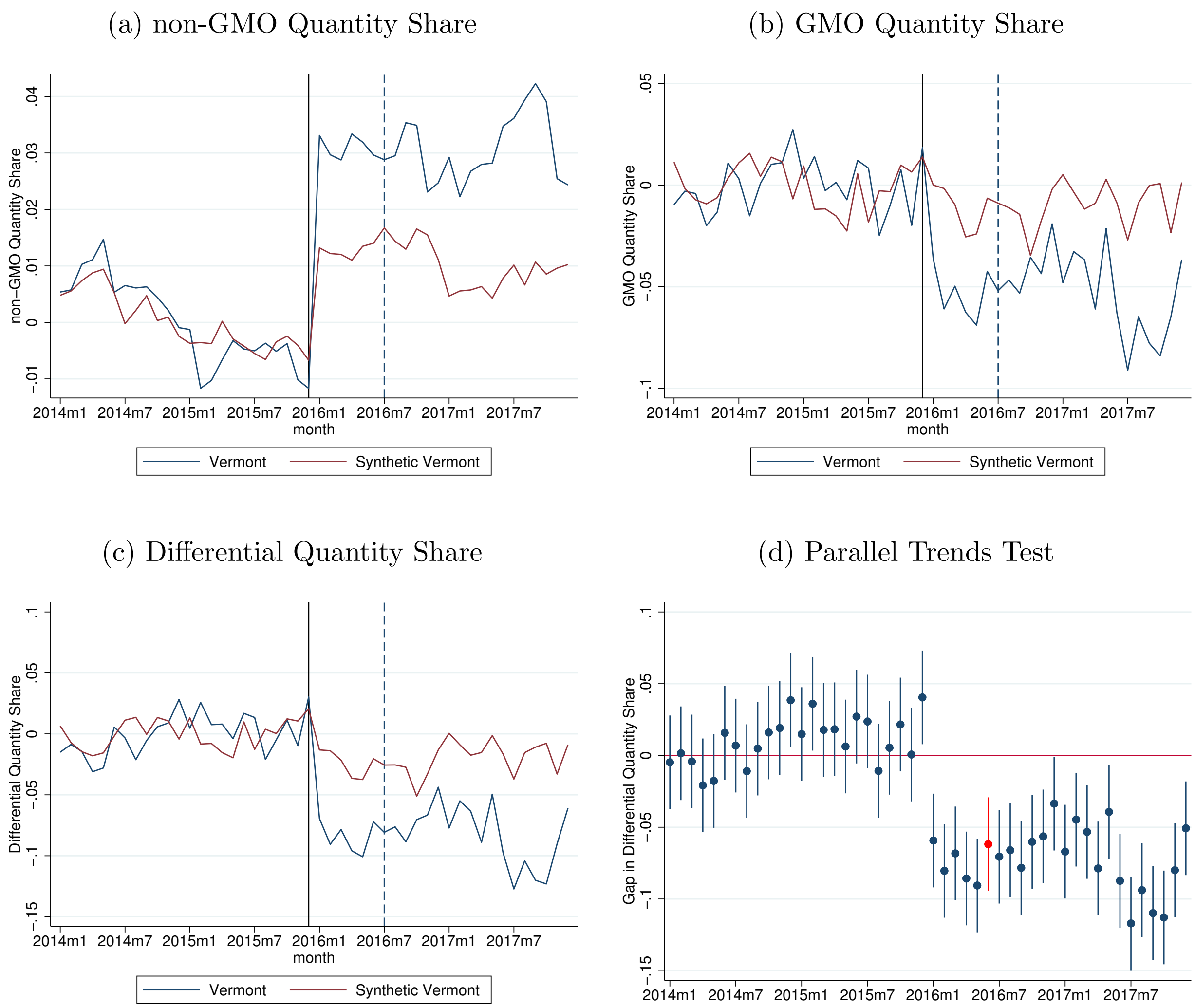
[21]The complete list of the controls is the following: pre-treatment difference between GMO quantity share and non-GMO quantity share, pre-treatment difference between GMO revenue share and non-GMO revenue share, average number of non-GMO products, average number of non-GMO UPCs, difference between number of GMO and non-GMO UPCs, difference between number of GMO and non-GMO products, increase in number of non-GMO products from December 2015 to January 2016 (supply expansion), and difference in prices of GMO and non-GMO products.

[22]The respective time trends prior to demeaning are presented in Appendix D.1.

and they diverge substantially after January 2016. Panel (d) in Figure 5 depicts the formal parallel trends test with 95% confidence intervals following Autor (2003).[23] The vast majority of the pre-period coefficients are not significantly different from zero, which indicates that our SC procedure succeeds in constructing a Synthetic Vermont that satisfies the parallel trends assumption. In the next section we also show that none of the marketing mix variables such as prices, assortment, and advertising levels show divergence between Vermont and Synthetic Vermont; thus these factors are not confounders that could explain the divergence in the quantity share.

[23] To conduct this test we estimate the following rolling treatment window regression: $\mathrm{Y}_{lt} = \sum_{t=1}^{T} \beta_t I_{VT} \times I_t + \varepsilon_{lt}$; where Y_{lt} stands for the monthly differential quantity share for Vermont and the Synthetic Vermont. I_t is an indicator variable which equals to one only in the relevant month t. I_{VT} is an indicator that switches to one if the observation is in Vermont. β_t are variables of interest, which capture whether and by how much Vermont's differential quantity share differs from Synthetic Vermont in each month. Panel (d) in Figure 5 plots the estimated β's along with their confidence intervals.

Figure 5: Demeaned GMO and non-GMO Quantity Shares
in Vermont vs. Synthetic Vermont



Notes: This figure depicts demeaned non-GMO and GMO quantity shares of RTE Cereal in Vermont and Synthetic Vermont. In panels (a)-(c) the black vertical line indicates the nationwide expansion of non-GMO product distribution (the treatment). The blue dashed vertical line marks July 2016, the month when Vermont mandatory labeling law was implemented. Panel (d) illustrates how much Vermont's differential quantity share is different from the Synthetic Vermont's in each month with corresponding confidence intervals. The red dot and whisker indicate July 2016.

With Synthetic Vermont constructed, we zoom into the main identifying data variation upon which our identification strategy is built. We focus on the non-GMO products whose supply distribution significantly expanded after January 2016. This presents a quick yet clear check on the uniformity of the supply expansion and the contrast in the demand response across both the control and the treatment. By construction, the quantity share of previously unavailable products is zero before the supply expansion.

Figure 6 displays time series of these newly expanded non-GMO products separately for Vermont and Synthetic Vermont. Specifically, panel (a) highlights the fact that the scale of supply expansion between Vermont and Synthetic Vermont was remarkably similar. However, as panel (b) illustrates, the consumption rate of these newly added non-GMO products in Vermont was about a third higher than that of Synthetic Vermont. Therefore, the differential demand response between Vermont and Synthetic Vermont partly stems from this differential consumption of newly added non-GMO products and potential substitution away from GMO products.

Figure 6: Number and Quantity Share of non-GMO Products Added

(a) Number of Added non-GMO Products (b) Share of Added non-GMO Products

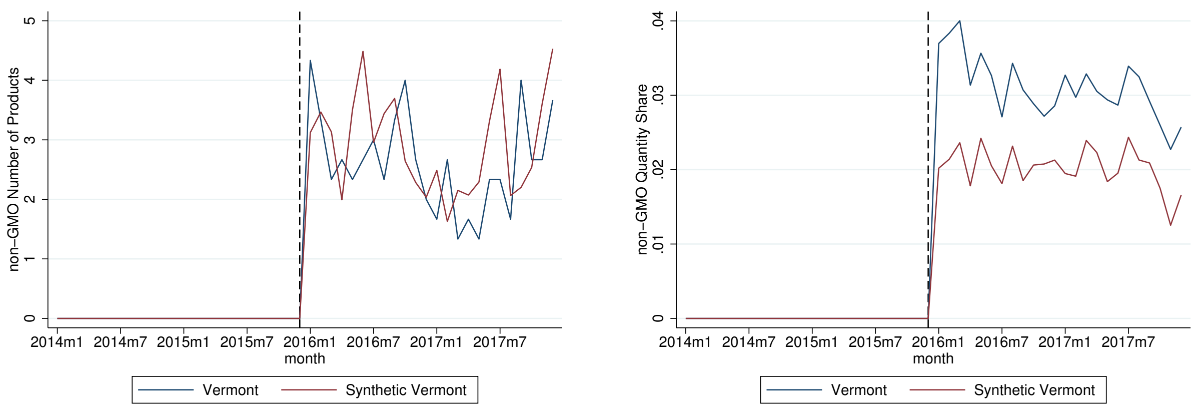


Table 4 reports the pre/post descriptive statistics behind Figure 5 and Figure 6 for non-GMO and GMO quantity shares in Vermont and Synthetic Vermont.

Table 4: Quantity Share of Newly Added non-GMO Products and Overall Products in Vermont vs. Synthetic Vermont

		(A) Non-GMO Products Added		(B) All Products	
		Before	*After*	*Before*	*After*
non-GMO	Synthetic Vermont	0.000	0.020	0.026	0.037
	Vermont	0.000	0.031	0.055	0.087
GMO	Synthetic Vermont	-	-	0.882	0.872
	Vermont	-	-	0.858	0.806

5.3 Baseline Specification

To quantify how the consumption patterns differ between Vermont and Synthetic Vermont after the non-GMO supply expansion, we specify the following baseline regression:

$$Y_{lt} = \delta I_{VT} I_t + I_{VT} + \lambda_t + \varepsilon_{lt} \tag{1}$$

where l denotes location (Vermont or Synthetic Vermont), t denotes month. Y_{lt} is one of the three main outcome variables (non-GMO quantity share, GMO quantity share, differential quantity share). I_{VT} is an indicator variable for Vermont and I_t is a post-treatment indicator that equals one for months on or after January 2016. λ_t is month fixed effects.

The main coefficient of interest, δ, captures the quantity share differential between GMO and non-GMO demand in Vermont relative to Synthetic Vermont.

6 Main Results

6.1 Baseline Specification Results

We quantify the treatment effect on non-GMO and GMO quantity shares depicted in Figure 5 by estimating the regression in Equation 1 on Vermont and Synthetic Vermont. We consider three post-treatment time periods: three months, six months and 24 months. In all three post-period cases considered, the main estimated treatment effect is strikingly similar. It ranges from -0.0624^{***} (three months) to -0.0607^{***} (six months) to -0.0625^{***} (24 months), suggesting that the treatment effect was nearly immediate and persisted throughout our sample period of 24 months.

We choose to focus on the six-month post-treatment window (from January 2016 through June 2016) as our baseline. By focusing on the time period *after* the non-GMO supply expansion but *before* the mandatory GMO label implementation, we ensure that the estimated effect is not confounded with that from the label. For robustness, we also consider a three-month post-treatment window because press releases from the RTE cereal companies indicated the possibility that labeled GMO cereals might arrive at stores ahead of the law's implementation (see discussion in section 3). This shorter window allows for a more conservative measure of the treatment effect.[24] Lastly, we explore the long term effects by focusing on the entire post-period in our sample — 24 months. We report our baseline specification

[24] The press releases indicated that the companies started considering labeling only after the proposed Federal GMO legislation failed to pass in the Senate at the end of March 2016. Based on the content of these releases, the earliest plausible availability date was the end of April 2016.

(six-month post-period) results in Table 5. Three-month and 24-month post-period results are reported in Table D1 and Table D3 in Appendix D, respectively.

Table 5: DiD Estimates for Quantity Shares
(6 Months Post-Treatment)

	(1) non-GMO Quantity Share	(2) GMO Quantity Share	(3) Differential Quantity Share
After × Vermont (δ)	0.0184***	-0.0423***	-0.0607***
	(0.00171)	(0.00699)	(0.00768)
Vermont (I_{VT})	0.0291***	-0.0232***	-0.0522***
	(0.000764)	(0.00313)	(0.00344)
Constant	0.0293***	0.880***	0.850***
	(0.000483)	(0.00198)	(0.00217)
Month FE	Yes	Yes	Yes
Observations	60	60	60
R-squared	0.992	0.913	0.964

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

The baseline specification results reported in Table 5 quantify the general patterns that we discussed above. Overall, we find strong evidence of consumption substitution from GMO cereals to non-GMO cereals in both Vermont and Synthetic Vermont. However, the substitution pattern is much more pronounced in Vermont. The results in columns (1) and (2) of Table 5 indicate a substantial increase in non-GMO quantity share, and a sizable decrease in GMO quantity share in Vermont compared to Synthetic Vermont; the increase in the non-GMO quantity share in Vermont is bigger than that of Synthetic Vermont by 0.0184, which constitute a 33.45% increase over the average non-GMO quantity share in Vermont before January 2016. The decrease in GMO quantity share in Vermont is larger than that of Synthetic Vermont by 0.0423, a 4.93% decrease from the average GMO quantity share in Vermont before January 2016.

6.2 Marketing Mix Stability Tests

Next, we formally check whether any of the outsized differential demand effect in Vermont can be attributed to differential changes in marketing mix variables: prices, assortment, or advertising. Our main result can be consistent with a variety of alternative explanations, such as GMO (non-GMO) prices increasing (decreasing) more in Vermont relative to Synthetic Vermont, or local advertising expenditures for non-GMO products being higher in Vermont. Thus, we conduct stability tests using the same regression specification as in Equation 1 for assortment, prices, and advertising levels. We report them in Table 6.[25]

The results show no significant divergence in assortment composition, prices, or advertising expenditures post-treatment in Vermont compared to Synthetic Vermont. Even if there were any prices or assortment changes, they were parallel in Vermont and Synthetic Vermont, and, thus, would be differenced out.[26] The stability tests provide reassuring evidence that the main effect cannot be explained by any of the aforementioned marketing factors that could drive demand.[27]

Interestingly, the results of the stability tests also suggest that retailers and manufacturers were not engaging in intertemporal price or assortment discrimination given observable shifts in local demand. DellaVigna and Gentzkow (2019) document a related phenomenon showing that multi-state retailers do not price discriminate, and that they charge nearly uniform prices across stores, despite a wide variation in local demand conditions. In our case, we find similar lack of price discrimination, but on the intertemporal dimension. Furthermore, the stability results also provide further evidence that the Kashi expansion was not correlated with changing consumer preferences in Vermont, as Kellogg's did not engage in any local adjustment in pricing or assortment decisions.

Table 6: Stability Tests for Assortment, Prices and Advertising Levels (6 Months Post-Treatment).

	(1) non-GMO Product	(2) GMO Product	(3) non-GMO Price	(4) GMO Price	(5) Total Ad	(6) GMO Ad
After × Vermont (δ)	0.0330	-0.436	-0.00335	0.00343	4540.301	3586.87
	(0.401)	(0.610)	(0.00608)	(0.00337)	(2968.93)	(2866.336)
Vermont (I_{VT})	6.058***	2.455***	0.0350***	0.00222	7557.537***	8510.969***
	(0.179)	(0.273)	(0.00272)	(0.00151)	(2149.439)	(2132.899)
Constant	10.97***	46.74***	0.275***	0.251***	24790.07***	27234.12***
	(0.113)	(0.173)	(0.00172)	(0.000954)	(1374.786)	(1348.904)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60	60	60	60	60	60
R-squared	0.984	0.854	0.911	0.707	0.848	0.869

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

[25] To implement advertising tests, we use Nielsen AdIntel data, which reports advertising spending for all cereal products nationally and locally. We manually flag whether each advertised product contains GMO ingredients. Nielsen AdIntel data indicates that the majority of RTE cereal advertising expenditure is spent nationally, and, specifically, on national TV. Only a tiny fraction of advertising is spent locally (e.g., total local advertising targeting Vermont DMAs comprised only 0.03% of national advertising expenditures). None of the non-GMO products advertised locally in Vermont during our sample period. In synthetic Vermont, non-zero non-GMO advertising spending is observed for only three months during the pre-period; thus we can not identify the coefficient for local non-GMO advertising.

[26] Our main specification results remain virtually unchanged if we condition on these covariates in Equation 1.

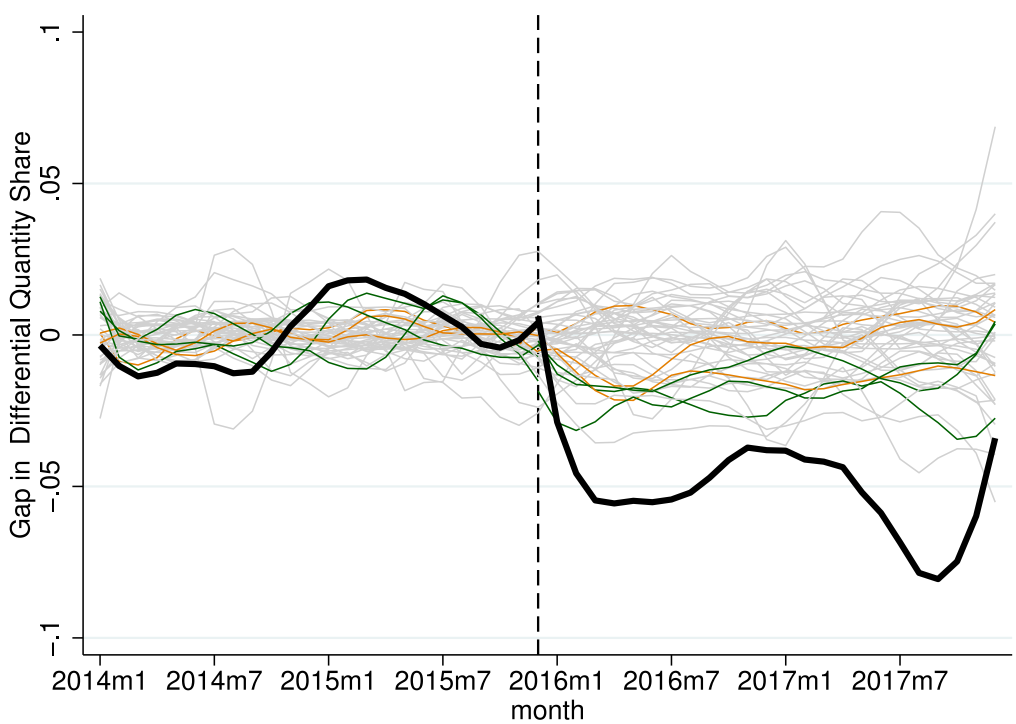
[27] The results of the three-month post-period also pass the assortment, prices, and advertising stability tests; however, for the long-term (24-month) effect we find evidence of slight assortment adjustment in Vermont relative to Synthetic Vermont. Both GMO and non-GMO product assortment increases in Vermont relative to Synthetic Vermont. Table D2 and Table D4 in Appendix D present the results.

We conduct a similar exercise in which we consider revenue share instead of quantity share as the dependent variable. We use the same weights in Table 3 to construct the same Synthetic Vermont, and then run equivalent regressions. The conclusions from revenue share results largely follow the quantity share results, and are reported in Appendix D.4.

6.3 Placebo Test

To assess the significance of our main results, we conduct a placebo test similar to Abadie et al. (2010). This test is intended to answer the following question: If one were to randomly select a state that has neither a similar GMO labeling law nor a similar information environment, how frequently would one observe a result of similar magnitude to the estimated treatment effect? To that end, we apply the same SC method iteratively to every state. In each iteration, we reassign the intervention associated with the non-GMO supply expansion to one of the 48 contiguous states in our sample. For each placebo state, we create its own synthetic state. Figure 7 plots the results of this placebo test.

Figure 7: Placebo Test



Notes: This figure depicts the gap in differential quantity shares between any given state and its synthetic counterpart. Vermont line is bolded black. Green lines are 3 states with the next largest Google SVI for the term "GMO" — Connecticut, New Hampshire and Maine. Orange lines are the 3 states with the lowest Google SVI — Mississippi, Alabama, and Louisiana. We apply locally weighted scatterplot smoothing to the curves with bandwidth 0.14.

All the time series displayed in the figure are constructed by subtracting the differential quantity share in the synthetic placebo state from differential quantity share in the treated placebo state; that is, each time series depicts the gap between the two time series. This generates a distribution of the estimated gaps for states where no interventions happened. The bold black line denotes the estimated gap for Vermont, which corresponds to the difference between the two lines illustrated in Figure 5(c). As the figure clearly illustrates, none of the states exhibits a change as drastic as Vermont's.

The green (orange) lines correspond to top- (bottom-) three ranking states excluding Vermont in Google Trends Search Volume Index (SVI), and the gray lines correspond to the remaining 41 states. We discuss the mechanisms behind these results and how Google SVI relates to the location specific estimates in greater detail in section 7),

The placebo test provides compelling evidence that the demand response in Vermont after the non-GMO product expansion differed quite notably from the other states in the US that did not undergo a similar rule-making process or undertake educational campaigns during that period.

6.4 Alternative Specifications

In a comparable alternative to the SC method discussed above, we examine the demand response in Vermont by estimating a series of DiD models. Instead of pooling across or aggregating over distinct locations to construct Synthetic Vermont, we iterate over each location as a control. In this specification, the observation is at the store (i)–location (l)–month (t) level and thus allows for a more disaggregated analysis than that in the SC specification. For each non-neighboring Vermont state (DMA) we estimate:

$$Y_{ilt} = \delta I_{VT} I_t + I_{VT} + \lambda_t + \varepsilon_{ilt} \tag{2}$$

where Y_{ilt} is our outcome of interest—differential quantity share in store i location l (Vermont vs. control location) and month t. I_{VT} is an indicator that takes a value of one if store i is located in Vermont, and zero otherwise; λ_t is month fixed effects; the main parameter of interest is δ.

We estimate 42 (192) such regressions using each non-neighboring state (DMA) as control. We specify the pre- and post- periods in the same way as the SC specification and we weigh each store observation by overall RTE cereal sales in that store.

Panel (a) of Figure 8 presents the histogram and density plot of estimated DiD coefficients for 42 state level regressions. Panel (b) presents the histogram and density plot for each of 192 DMA level regressions. We highlight several findings: First, the DiD estimates for differential quantity share are all negative and statistically significant. The average DiD coefficient for state level regressions is -0.0760^{***} (-0.0806^{***} when weighted by the number of stores in each control state), and the average DiD coefficient for DMA level regressions is -0.0792^{***} (-0.803^{***} when weighted). The absolute magnitude of the average DiD coefficient is larger than the corresponding coefficient from the SC specification presented in section 6 (-0.0607^{***}). However, the totality of the results is largely consistent with the SC results.[28]

The main advantages of this state-by-state (DMA-by-DMA) approach include the ease of interpretation and the additional statistical power harnessed through variation across stores in the store-month level data. The average number of observations in each regression is around 32,000 depending on the state (DMA), compared to 60 for the SC specification. However, this specification also has its downside; the parallel trends assumption is not likely to hold for all control states (DMAs). Indeed, we find that the majority of control states (DMAs) do not pass the strict parallel trends test we describe in footnote 23.

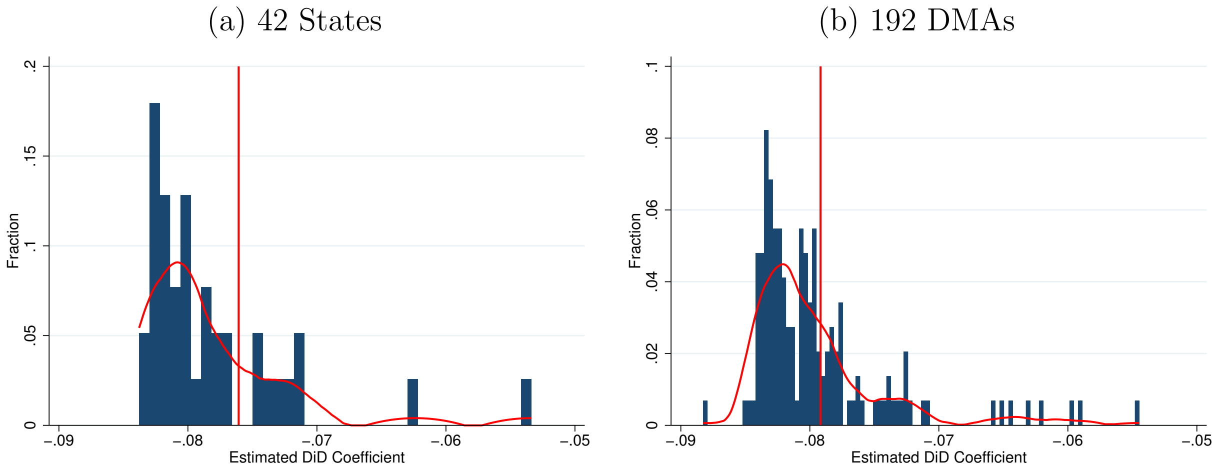
In another specification, we re-estimate the same model (Equation 2) with a narrower window: pre- six months and post- six months. The results are very similar. The state-level weighted average DiD coefficient is -0.0816^{***}, virtually the same as -0.0806^{***} from the 24 month pre-period specification, and the DMA-level weighted average DiD coefficient is -0.0801^{***}.[29] With this shorter pre-period, significantly more state (DMA) pairs get closer to satisfying the parallel trends assumption, but the majority of states (DMAs) still fail the test. Restricting to only those states (DMAs) that have the best performance in passing the parallel trends test, gives the average DiD coefficient of -0.0620^{***} and -0.0732^{***} for states and DMAs, respectively. A general pattern emerges: the better any given control location is in satisfying the parallel trends condition, the more conservative the coefficient estimate is. The SC approach provides the best performance in pre-trend matching and the most conservative estimate.

Nevertheless, the relative consistency of the treatment effect estimates across the variety of the DiD specifications explored above corroborates the robustness of our main result. Our preferred specification, however, remains the SC method described in section 6, because it uses a combination of distinct geographic markets to construct a control state that is more similar to Vermont than any state (DMA) individually.

[28] In another specification, we also control for potential confounders such as differential prices and assortment. The DiD results are similar, with a mean of -0.0801*** (states as control) and -0.0795*** (DMAs as control).

[29] The equivalent coefficient for the SC method using pre- six months is -0.0582^{***}.

Figure 8: Density Plot of DiD Coefficient Estimates for Differential Quantity Share Looping Over Non-Neighboring States and DMAs as Control Locations



Notes: Panel (a) plots the histogram and density plot of all 42 DiD regressions, where in each regression the treated location is Vermont and the control location is one of 42 non-neighboring states. Panel (b) represents parallel results for 192 non-neighboring DMAs. All 42 state-level regression coefficients are estimated to be statistically significant at $p = 0.001$. Only three out of 192 DMA-level coefficients are insignificant. The vertical red lines indicate unweighted means: -0.076 for state regressions and -0.079 for DMA regressions. We winsorize state-level coefficients at 5% and DMA-level coefficients at 1% level.

In another robustness test, we zoom in at multi-state retailers that operate in Vermont, and compare the demand changes within the same retailer across Vermont borders, using DiD specification. Though the within-retailer comparison places a strict restriction on parallel supply expansion and includes comparisons with neighboring regions, we still find a bigger demand response in Vermont. We report the results in Appendix C.

6.5 Mandatory GMO Labeling Effect in Vermont

The visual inspection of Figure 5 panels (a)-(c) indicates that there were no significant changes in GMO and non-GMO product consumption patterns in Vermont (or Synthetic Vermont) immediately after July 2016 (dashed blue line), the date of the mandatory law implementation in Vermont. In this subsection, we explore this formally. Specifically, we test whether the implementation of the Vermont labeling law had any direct impact on GMO and non-GMO product quantity shares.

Our hypothesis is that, if implementation of the law made consumers in Vermont more aware of the mandatory GMO label, and if the label provided consumers with any *additional information*, we would find (i) further changes in differential quantity share in Vermont; and (ii) a larger divergence in the gap in differential quantity share between Vermont and Synthetic Vermont after July 2016.

The first test we run addresses the first hypothesis — that is, whether there are further consumption changes *within* Vermont. To isolate the additional GMO labeling effect, we look at the first difference within Vermont (post vs. pre). For this exercise the treatment becomes the implementation of the mandatory GMO labeling law (July 2016). The pre-treatment period is now February 2016 to June 2016, and the post-treatment period is July 2016 to December 2017. Using a t-test, we compare post-treatment GMO quantity share and non-GMO quantity share in Vermont to the respective pre-treatment quantity shares in Vermont. The p-values are $p = 0.5938$ and $p = 0.9982$, respectively; thus, we fail to reject the null that there are no statistically significant changes in consumption patterns for GMO and non-GMO products.[30] Altogether, these first difference tests provide supportive evidence that the consumption patterns in Vermont did not change in any statistically significant way after the implementation of the labeling law.

The second test asks whether the consumption patterns after the law's implementation further diverge between Vermont and Synthetic Vermont. To implement this test, we use the Vermont and Synthetic Vermont time series and estimate Equation 1 with the same pre- and post- treatment periods as in the first test. The results in Table 7 show that the estimated coefficients are all statistically insignificant; thus, we do not find any evidence of a statistically significant additional effect on consumption stemming from label information stating that a product contains GMO ingredients.

In both tests, the null effect is robust to different lengths of post- (and pre-) periods after the supply expansion. These two tests suggest that the implementation of GMO labeling did not have any direct impact on consumer attitudes and behavior in Vermont. Coupled with the main results, our explanation of these test results is that many consumers who were receptive to altering their purchasing behavior to avoid GMO ingredients had already encountered alternative labels such as "non-GMO Project Verified" or "USDA Organic" to facilitate those choices.

[30] The differential quantity share change is also insignificant ($p = 0.6623$). In a follow up robustness test, we specify the treatment window to be April 2016, the earliest possible month when GMO labels could have appeared in the stores. We get similar results, and we are unable to reject the null.

Table 7: Additional Vermont Mandatory GMO Labelling Effect

	(1) non-GMO Quantity Share	(2) GMO Quantity Share	(3) Differential Quantity Share
After × Vermont	0.00269	0.00120	-0.00149
	(0.00331)	(0.00982)	(0.0122)
Vermont	0.0472***	-0.0667***	-0.0616***
	(0.00292)	(0.00868)	(0.0108)
Constant	0.0373***	0.871***	-0.0208***
	(0.000964)	(0.00286)	(0.00356)
Month FE	Yes	Yes	Yes
Observations	46	46	46
R-squared	0.984	0.934	0.898

Notes:*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

7 Mechanism Analysis

The preceding results clearly indicate a disproportionately strong and sustained demand response to the national non-GMO supply expansion in Vermont compared to other states, manifested in reduced quantity shares for GMO cereal and increased shares for non-GMO cereals. However, they do not fully explain the underlying mechanisms. The results of our alternative specifications and robustness tests rule out several obvious potential explanations such as traditional marketing mix factors, and retailer-specific effects. In this section, we provide structured evidence that our results are in fact driven by the rich information environment in Vermont. This information environment was created by the advocacy campaigns and educational efforts leading up to the passage of the Vermont GMO labeling law, along with the subsequent rule-making process that took place prior to implementation of the law.

Consumer Concern Surveys. In the midst of the national GMO debate, Kolodinsky and Lusk (2018) conducted several waves of surveys to assess consumer attitudes toward GMO technology in Vermont and the rest of the US over multiple years, a summary of which is recreated in **??** in Appendix A. A clear trend emerges from these data. Between March 2014 and March 2016, leading up to implementation of the GMO labeling law, Vermonters' level of concern about GMO technology increases, reaching its peak in March 2016, while the level of concern in rest of the US remains flat. Notably, this trend of heightened concern and awareness of GMOs among Vermonters coincides with the educational campaign and rule-making timeline associated with Act 120 in Vermont. This trend provides some externally corroborated evidence that the information environment in Vermont surrounding GMOs was indeed more intense than the information environment in other parts of the US.

Google Search Volume Index Evidence. In this section we explore in detail the heterogeneity of our main effect across states reflected in Figure 7. An interesting question is whether and how the magnitude of substitution from GMO to non-GMO products after the non-GMO supply expansion correlates with consumer interest in GMO and non-GMO topics across different regions.

In the absence of more detailed data on consumer attitudes across states, we instead look to data from Google Trends to measure varying levels of interest in GMO related topics across states, as captured by online searches in the period before implementation of the law. We collect Google Trends indices for the period from January 2015 through June 2016 for all the states in our sample. Our Google Search Volume Index (SVI) queries exclude Alaska and Hawaii, which are not included in the Nielsen Data. We choose this period because it is the period during which the Vermont State Attorney General commenced with the rule-making process and many grassroots organizations also launched informational campaigns. Therefore, inflow of information to the Vermont market about GMO and non-GMO topics was at its peak.

To identify the most relevant keyword for this exercise, we use the search engine optimization tool suite SEMrush. Keyword "GMO" is the most common keyword that is searched among all non-GMO and GMO related keywords. Furthermore, during our study period, the websites that were visited after searching the keyword "GMO" tended to be the same websites that were visited after searching for "What is GMO" and "Is GMO safe", the next most frequent queries. The most frequently visited organic links after searching for these keywords were (1) the Wikipedia page on GMOs; (2) the non-GMO Project Verified page on "What is a GMO" and (3) the currently archived *Nature* page on the use of GMO technology. Overall, these queries and visited websites indicate that searchers have incomplete knowledge about GMO technology, and that they are interested in finding out more information about it, particularly information that pertains to health and safety.

Based on the results above, we opt to document Google Trends for the most common search term "GMO" across all states during the analyzed time period. Google Trends analyzes the popularity of search queries in Google Search across various regions and time. Google identifies the geographical information of the searches based on users' IP addresses. A Search Volume Index (SVI) is created by first determining the number of searches for a particular search term as a share of the total number of searches conducted in each time and place. Google Trends then assigns an index value of 100 for the time/place in which this "relative search rate" is maximized. Other index values are determined by the ratio of the search rate in a particular time/place to the maximum search rate. For example, a time when or the place where the relative search rate is half the maximum value would be assigned an index value of 50.

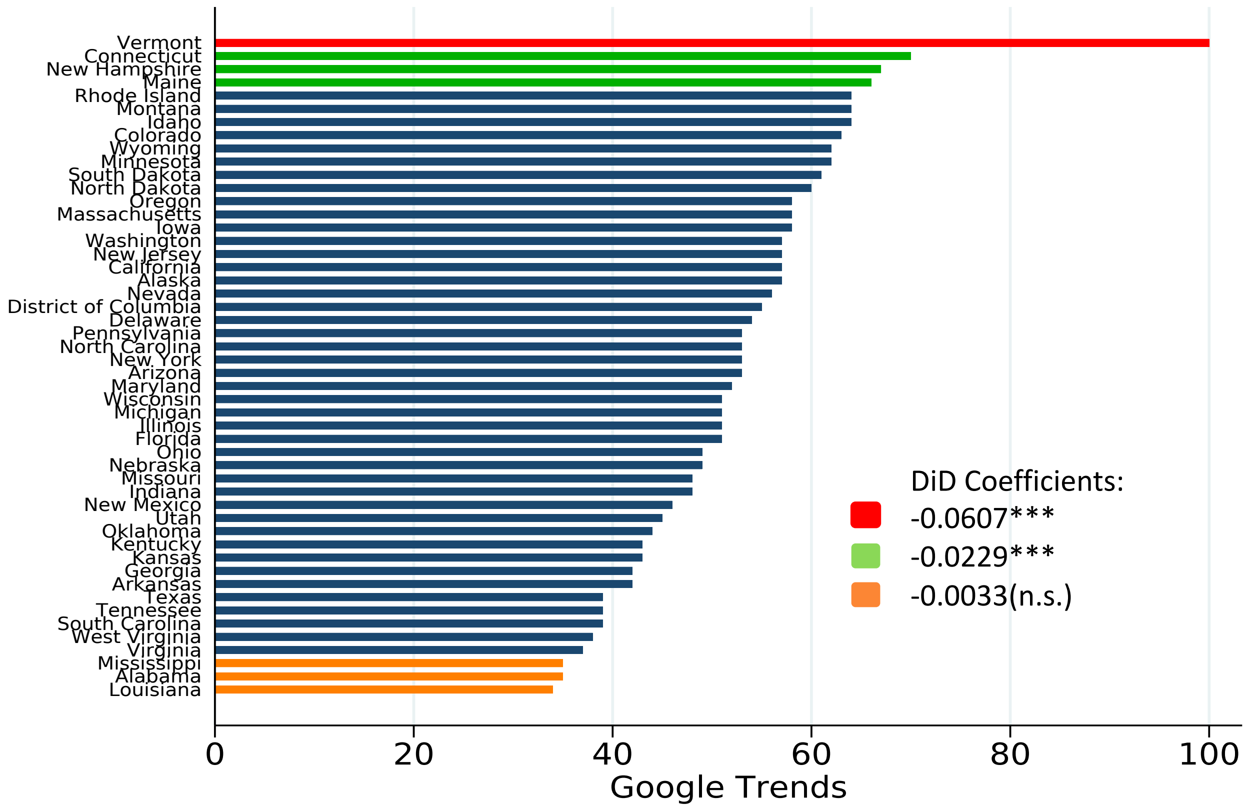
Figure 9 shows the Google Trends SVIs for our focal keyword by state. During this time period, Vermont's score was the highest among all the states in our sample and by a large margin. We also collected the same Google Trends indices from January 2010 to January 2014, the time period before the legislative process began. Vermont ranked ninth during that time period, indicating that consumers' relative awareness and interest in GMOs (as manifested through online search activity) increased during our studied time period. We therefore interpret the Google Trends indices as a measure of consumer interest and information intensity on GMO-related issues.

To further explore the relationship between the informational environment intensity and relative GMO and non-GMO food consumption rates after non-GMO supply expansion, we estimate the SC model using the same specification from Equation 1, separately for the three top-ranking states after Vermont (in green) and the three bottom ranking states (in orange), and we report the color-coded coefficients for these two groups of states in Figure 9. The estimated coefficient for the group of top three states (Connecticut, New Hampshire, and Maine) is statistically significantly negative, but only a third the magnitude of Vermont. These states are regional neighbors of Vermont, and they all considered or passed GMO labeling legislation, which may also explain why their Google Trends SVIs are higher.

Among the three top-ranking states, Maine and Connecticut both passed contingent GMO labeling laws that were never implemented (see discussion in the next subsection), and they also faced a heightened information environment surrounding GMOs due to their respective legislation (indicated by the Google Trends SVIs), albeit to a lesser extent than Vermont. We do observe a larger estimated gap for these two states than for most other states (the green lines in Figure 7). As for the group of bottom three states (Mississippi, Alabama, and Louisiana), the estimated coefficients of interest is not statistically significant, indicating that non-GMO product expansion did not change consumption patterns in those states.

Next, to systematically characterize the relationship between the change in consumption patterns and information intensity, we regress the coefficients from the state-level SC models (as in Figure 7) on the Google Trends indices reported in Figure 9. We use this approach to examine whether the GMO (or non-GMO) consumption pattern changes in each state are correlated with the online search activity. We find that there is a strong correlation between the two measures: the estimated coefficient is -0.0601^{***} (p-value = 0.000), indicating that states with higher Google Trends SVIs exhibited a greater decrease in GMO cereal consumption and a greater increase in non-GMO cereal consumption.[31]

Figure 9: Google Trends Search Volume Index for Keyword "GMO" by State



Contingent GMO Labeling Laws in Connecticut and Maine. While Vermont was the first and only US state to successfully implement a mandatory GMO labeling law, it was not the first state to *pass* a GMO labeling law. In fact, both Connecticut and Maine passed GMO labeling laws before Vermont in June 2013 and January 2014, respectively. Unlike Vermont, however, both of these laws, contained trigger provisions that were never met; that is, the implementation of the laws was contingent on the passage of similar labeling laws in other states.[32]

Therefore, we can exploit the fact that these laws were passed but never implemented in Connecticut and Maine to better understand the impact of the local information campaigns that accompanied implementation of the law in Vermont. As shown in Figure 9, Connecticut and Maine were two of the top three states, based on Google SVI, with consumer interest in

[31] The state-level SC coefficients are scaled by multiplying by 100 to reflect a percentage-point scale, so a one-unit change in SVI translates to a 0.0601 *percentage point* decrease in the DiD coefficient.

[32] In Connecticut, the law specified that it would not take effect unless similar legislation passed in four other states, at least one of them bordering Connecticut, and with the total population of those states exceeding 20 million. In Maine, the law would not take effect until four other contiguous states passed similar laws.

GMO and non-GMO topics. When we estimate the same SC model in Equation 1 separately for Maine and Connecticut, the estimated DiD coefficients are -0.01878^{***} and -0.02630^{***}, respectively. These treatment effects are about one third of the magnitude of those of Vermont, and therefore highlight the impact of the rule-making process and local information campaigns leading up to implementation of the law in Vermont.

DMA Border Areas. To further isolate the impact of the changing information environment in Vermont on GMO and non-GMO consumption patterns, we estimate more geographically localized DiD models that zero in on the treatment effect across and within media markets that span multiple states including Vermont. First, we focus on Vermont's largest media market (DMA), Burlington, which extends into New York and New Hampshire, as illustrated by the green shaded area in Figure 10. We compare treated stores in the Burlington DMA in Vermont (region A) to control stores in the Burlington DMA in New York and New Hampshire (regions E and D). Using the same DiD specification in Equation 2 with the same pre- and post- windows, we estimate the effect of the non-GMO supply expansion on differential quantity share for Burlington DMA stores located in Vermont. We find that the DMA region within Vermont still exhibits a larger effect than the bordering regions of the same DMA that lie outside of Vermont (Table 8). The estimated effect is more conservative than our main results; the DiD treatment coefficient is -0.0228^{***}, which is similar to the multi-state retailer effects described in Appendix C, and raises the question of whether any informational spillovers may have occurred across state lines through shared media channels in the Burlington DMA.

Figure 10: Vermont DMA Map

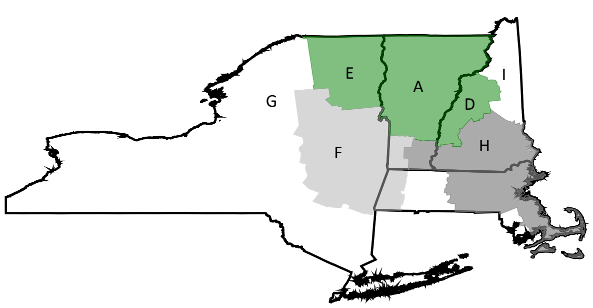


Table 8: DMA Test

	A vs. E & D	
DiD Coeff.	-0.0258***	
	(0.00665)	
	E vs. G	D vs. I
DiD Coeff.	-.0220	0.0209
	(0.0151)	(0.0162)

Notes: The green shaded area ($A + E + D$) is the Burlington DMA. A is within Vermont borders, whereas E and D are outside. Light gray is Albany-Schenectady-Troy DMA that also covers southwest Vermont. Dark Gray is Boston DMA that also covers southeast Vermont.

To test this possibility, we then compare the demand response in stores located in regions of New York and New Hampshire that belong to the Burlington DMA (regions E and D, respectively) to those in the immediately neighboring regions in each respective state that do *not* belong to Burlington DMA and, therefore, do not share media markets with Vermont (counties in regions G and I that border regions E and D, respectively). Again, we use the same DiD specification in Equation 2, and separately estimate the model in New York (E vs. G) and New Hampshire (D vs. I). As shown in Table 8, we do not find any statistically significant effects on differential quantity share for stores in the Burlington DMA located in New York or New Hampshire. These results suggest that 6 In light of this result, coupled with the Google Trends data presented in Figure 9, the somewhat attenuated *within-Vermont* Burlington DMA effect provides a lower-bound estimate, and can be explained by the fact that there also existed a heightened GMO information environment in the neighboring states not attributable to media coverage in Vermont.

Interviews with Campaigners. Finally, we take steps to gain additional context about the *on-the-ground* advocacy campaigns and rule-making process that took place in Vermont after passage of the GMO-labeling law and leading up to its implementation on July 1, 2016. We conducted two interviews with leaders from Vermont Right to Know, a coalition of several well-established organizations (Rural Vermont, Vermont Public Interest Research Group, and Northeast Organic Farming Association of Vermont) focused on food and agriculture in Vermont. This coalition was largely responsible for the anti-GMO movement in Vermont that paved the way for GMO-labeling legislation. These interviews helped corroborate several important factors regarding the heightened information environment surrounding GMOs in Vermont prior to implementation of the law. The interviews yielded two key insights: First, the coalition mounted a series of major advocacy and educational campaigns after the law was passed in 2014. The campaign tactics were localized in nature, targeting in-person interactions at local venues rather than broader media campaigns, and they took place across Vermont. Second, in 2015, the official rule-making process necessary to implement the law exposed Vermonters to a series of additional state-sponsored campaigns as well as solicitations for public input on details of the labeling rule, all of which served to enrich the information environment and heighten consumers' awareness of GMOs in Vermont leading up to the law's implementation.[33] Ultimately, these interviews provide the external context necessary to validate the finding we present in support of our argument that the information environment was the underlying mechanism that drove the differential consumer response in Vermont to the national expansion of the supply of non-GMO-containing foods.

The evidence presented here, coupled with the prior evidence of changing consumer attitudes over time, strongly suggests that it was the information environment that induced changes in consumption patterns in Vermont, rather than the actual GMO label itself. While

[33]For additional details on information campaigns and rule making, see Appendix A.

we cannot directly test the hypothesis that local consumer preferences independent of the information environment may have also contributed to the consumption changes, the mounting evidence presented thus far strengthens our argument.

8 Discussion

Our paper presents the first investigation on the impact of GMO and non-GMO labeling on consumer choices using real transaction data from different market environments with varying information density. Our results have timely implications on two fronts.

The first implication relates to how firms should respond to evolving demand, macroeconomic shocks, or changes in the legislative environment. Big food companies have spent millions of dollars in attempts to block state and federal agencies from passing mandatory GMO-labeling laws, out of fear of market share shrinkage. The top spenders were two of the Big 3 companies included in our analysis—General Mills and Kellogg's (Environmental Working Group 2016). However, our results uncover cases in which the consumption trends and legal initiatives that were thought to be detrimental have the potential to provide potential opportunities for revenue growth.

To explore this case, we implement a DiD regression similar to Equation 1 for Kellogg's total revenue in Vermont and Synthetic Vermont. The results indicate that Kellogg's average monthly revenue increased by 8% ($p = 0.003$) above and beyond the change in revenue of Synthetic Vermont; the boost occurred right after Kellogg's expansion of the Kashi products. This extra revenue is largely attributable to Vermonters' stronger preferences for the newly available Kashi non-GMO cereals. These preferences were in turn driven by consumer advocacy campaigns — the very activities that Kellogg's opposed.

Vermont, as one of the smallest states by population in the US, is unlikely to be the driving factor for Kellogg's major corporate decisions. Indeed, the timeline and the scale of Kashi's supply expansion (shown in subsection 3.2) suggest that its revitalization decision was coincidental with and *not* due to the implementation of Vermont's mandatory GMO-labeling law. We also provide evidence that Kellogg's did not engage in any local adjustment in pricing or assortment decisions.

Our findings offer important managerial implications for companies. Instead of expending resources to fight against consumer movements and campaigns such as GMO-labeling initiatives, firms should treat them as new market opportunities. Firms can potentially preempt adverse sales effects, and, as in the case with Kellogg's in Vermont, they may even grow revenue with agile reconfiguration of their product portfolio to cater to evolving consumer demand. This is particularly true for markets where such preferences are most intensified by information.

The second important insight that our results uncover is related to national mandatory GMO labeling. Beginning January 1, 2022, all foods for sale in the US will be required to carry disclosure labels if they contain GMO ingredients. Our results suggest that — absent extensive public information campaigns, and with the existing voluntary provision of *non*-GMO labels — the national GMO-labeling law is unlikely to have any significant effects on changing consumer behavior. Our results stand in stark contrast to some existing experimental studies that show sizable GMO-labeling effects. Using real transaction data and a quasi-experimental design, we are able to capture the complexity of alternative labels and the information environment to which consumers are exposed – factors that are nearly impossible to account for in experimental or survey-based settings. Thus, relative to prior studies, our findings have higher external validity in predicting national consumer response to the federal GMO-labeling mandate that will become binding in 2022.

To provide a more concrete preview of what compliance with the national legislation will look like for the RTE cereal industry, the NBFDS states that "the disclosure must be of a sufficient size and clarity to appear prominently and conspicuously on the label, making it likely to be read and understood by the consumer." There are four options provided by the USDA that are available for manufacturers to meet the labeling requirements: (1) on-package text, e.g., *"Contains a bioengineered food ingredient"*; (2) USDA-approved symbols (see an example in Figure B4 in Appendix B); (3) electronic or digital links that include instructions to scan for more information; or (4) text-message disclosure (USDA Agricultural Marketing Service 2018). During the current voluntary compliance period, several cereal companies have opted to implement option (1) to comply with the upcoming law. An example of this option is presented in Figure B3 in Appendix B. The text is very similar to the label that was applied by the Big 3 in 2016 to comply with the Vermont mandatory GMO-labeling law (see Figure B2 in Appendix B). Our findings in subsection 6.5 suggest that there was no additional information effect after the arrival of those GMO labels, even in the market with the most elevated information environment in the US. Therefore, we conjecture that the visually similar labels that will become mandatory in 2022 will not lead to significant changes in consumption patterns either, especially if no additional anti-GMO informational campaigns are launched.

9 Concluding Remarks

Using novel non-GMO ingredient-verification data and a revealed preference approach, our paper provides evidence that the information environment surrounding the Vermont GMO-labeling law impacted consumer behavior in both a statistically and economically significant way. We take advantage of a *nationwide* large-scale non-GMO supply expansion that took place before the labeling law implementation but coincided with the heightened information environment. We apply synthetic control methods to show that right after the supply expansion, consumers in Vermont increased consumption of non-GMO cereal, and decreased consumption of GMO cereal significantly more than comparable regions of the US. This estimated, outsized demand response in Vermont is robust to different specifications and models. Across all the robustness checks, our overall finding is qualitatively the same.

To understand the mechanism behind this finding, we further conduct a series of empirical analyses. Our results suggest that the most likely reason for this change in consumer behavior is heightened anti-GMO information environment triggered by law-related campaigns and the rule-making process, rather than the GMO labeling itself. Using the Google Search Volume Index to proxy for public concerns about GMOs across states, we find that the non-GMO product consumption increase (and corresponding decrease in GMO consumption) is positively correlated with the Search Volume Index. We also find that states that passed similar labeling laws (but failed to implement them) saw similar demand changes, albeit much smaller in scale. Furthermore, a series of surveys conducted by Kolodinsky and Lusk (2018) shows that Vermonters' concern over the presence of GMOs in foods reached its peak in March 2016, while such concerns in the rest of the US remained flat. Our discussions and interviews with grassroots campaigners in Vermont also confirm the importance of information environment in shaping consumer behaviors.

References

Abadie A, Diamond A, Hainmueller J (2010) Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association* 105(490):493–505.

Abadie A, Diamond A, Hainmueller J (2015) Comparative politics and the synthetic control method. *American Journal of Political Science* 59(2):495–510.

Annenberg Public Policy Center (2016) Americans support gmo food labels but don't know much about safety of gm foods. Technical report, Philadelphia, PA.

Athey S, Imbens GW (2017) The state of applied econometrics: Causality and policy evaluation. *Journal of Economic Perspectives* 31(2):3–32.

Autor DH (2003) Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of labor economics* 21(1):1–42.

Bollinger B, Leslie P, Sorensen A (2011) Calorie posting in chain restaurants. *American Economic Journal: Economic Policy* 3(1):91–128.

Bollinger B, Liebman E, Hammond D, Hobin E, Sacco J (2020) EXPRESS: Educational Campaigns for Product Labels: Evidence from On-Shelf Nutritional Labeling. *Journal of Marketing Research* 0022243720981975, ISSN 0022-2437.

Bovay J, Alston JM (2016) Gm labeling regulation by plebiscite: analysis of voting on proposition 37 in california. *Journal of Agricultural and Resource Economics* 161–188.

Bovay J, Alston JM (2018) Gmo food labels in the united states: Economic implications of the new law. *Food Policy* 78:14–25.

Brasher P (2016a) General mills to start labeling biotech products. *Agri-Pulse* URL https://www.agri-pulse.com/articles/6728-general-mills-to-start-labeling.-biotech-products.

Brasher P (2016b) Kellogg's, Mars to start labeling GMOs amid Senate deadlock. *Agri-Pulse* URL https://www.agri-pulse.com/articles/6731-kellogg-s-mars-to-start.-labeling-gmos-amid-senate-deadlock.

Carter CA, Schaefer KA (2019) Impacts of mandatory ge food labeling: a quasi-natural experiment. *American Journal of Agricultural Economics* 101(1):58–73.

Clark R, Houde J, Zhu X (2020) Morphology of product assortment in us retail Working Paper.

Dannenberg A, et al. (2009) The dispersion and development of consumer preferences for genetically modified food–a meta-analysis. *Ecological Economics* 68(8-9):2182–2192.

Darby MR, Karni E (1973) Free competition and the optimal amount of fraud. *Journal of law and economics* 16(1):67–88.

DellaVigna S, Gentzkow M (2019) Uniform pricing in us retail chains. *The Quarterly Journal of Economics* 134(4):2011–2084.

Dranove D, Jin GZ (2010) Quality disclosure and certification: Theory and practice. *Journal of Economic Literature* 48(4):935–963.

Environmental Working Group (2016) Big Food Companies Spend Millions to Defeat GMO Labeling. URL https://www.ewg.org/research/big-food-companies-spend.-millions-defeat-gmo-labeling.

European Green Capital (2020) Several European countries move to rule out GMOs. URL https://ec.europa.eu/environment/europeangreencapital/countriesruleoutgmos/.

Ferman B, Pinto C (2021) Synthetic controls with imperfect pre-treatment fit. *arXiv:1911.08521 [econ]* URL http://arxiv.org/abs/1911.08521, arXiv: 1911.08521.

Grocery Manufacturers Association (2014) GROCERY MANUFACTURERS ASSOCIATION POSITION ON GMOS. URL https://www.ohiomfg.com/wp-content/uploads/2014-02-28_lb_lead_GMA_on_GMO.pdf.

Guo T, Sriram S, Manchanda P (2020) "Let the Sunshine In": The impact of industry payment disclosure on physician prescription behavior. *Marketing Science* 39(3):516–539.

Harmening J (2016) We need a national solution for GMO labeling. URL https://blog.generalmills.com/2016/03/we-need-a-national-solution-for-gmo-labeling/.

Hobin E, Bollinger B, Sacco J, Liebman E, Vanderlee L, Zuo F, Rosella L, L'ABBE M, Manson H, Hammond D (2017) Consumers' response to an on-shelf nutrition labelling system in supermarkets: Evidence to inform policy and practice. *The Milbank Quarterly* 95(3):494–534.

Jin GZ, Leslie P (2003) The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics* 118(2):409–451.

Kahneman D, Ritov I, Schkade D, Sherman SJ, Varian HR (1999) Economic preferences or attitude expressions?: an analysis of dollar responses to public issues. *Elicitation of preferences*, 203–242 (Springer).

Kellogg Annual Report (2015) Kellogg Company 2015 Annual Report. URL https://s1.q4cdn.com/243145854/files/doc_financials/2015/ar/2015-Annual.pdf.

Kellogg Annual Report (2016) Kellogg Company 2016 Annual Report. https://s1.q4cdn.com/243145854/files/doc_financials/2016/ar/2016-Annual.pdf.

Kesmodel D, Gasparro A (2015) Inside Kellogg's Effort to Cash In on the Health-Food Craze. *WSJ* URL https://www.wsj.com/articles/inside-kelloggs-effort-to-cash-in-on-the-.health-food-craze-1441073082.

Kim S, Lee C, Gupta S (2020) Bayesian synthetic control methods. *Journal of Marketing Research* 57(5):831–852.

Kolodinsky J, Lusk JL (2018) Mandatory labels can improve attitudes toward genetically engineered food. *Science advances* 4(6):eaaq1413.

Lusk JL, Jamal M, Kurlander L, Roucan M, Taulman L (2005) A meta-analysis of genetically modified food valuation studies. *Journal of Agricultural and Resource Economics* 30(1):28–44.

Moorman C (1998) Market-level effects of information: Competitive responses and consumer dynamics. *Journal of Marketing Research* 35:82 – 98.

Moorman C, Ferraro R, Huber J (2012) Unintended Nutrition Consequences: Firm Responses to the Nutrition Labeling and Education Act. *Marketing Science* 22.

Narang U, Shankar V (2019) Mobile app introduction and online and offline purchases and product returns. *Marketing Science* 38(5):756–772.

National Academies of Sciences (2016) *Genetically Engineered Crops: Experiences and Prospects*. ISBN 978-0-309-43738-7, URL http://dx.doi.org/10.17226/23395.

Nevo A (2001) Measuring market power in the ready-to-eat cereal industry. *Econometrica* 69(2):307–342.

Nevo A, Wolfram C (2002) Why do manufacturers issue coupons? an empirical analysis of breakfast cereals. *RAND Journal of Economics* 319–339.

Nunes K (2020) Kellogg getting Kashi back on track URL https://www.foodbusinessnews.net/articles/5330-kellogg-getting-kashi-back-on-track.

Pattabhiramaiah A, Sriram S, Manchanda P (2019) Paywalls: Monetizing online content. *Journal of Marketing* 83(2):19–36.

Pew Research Center (2018) What do americans think about food additives and gmos?

Rao A, Wang E (2017) Demand for "healthy" products: False claims and ftc regulation. *Journal of Marketing Research* 54(6):968–989.

Rojas C, Wang EY (2017) Do taxes for soda and sugary drinks work? scanner data evidence from berkeley and washington. *Scanner Data Evidence from Berkeley and Washington (September 23, 2017)* .

Scherer FM (1979) The welfare economics of product variety: an application to the ready-to-eat cereals industry. *The Journal of Industrial Economics* 113–134.

Schmalensee R (1978) Entry Deterrence in the Ready-to-Eat Breakfast Cereal Industry. *The Bell Journal of Economics* 9(2):305–327.

Seiler S, Tuchman A, Yao S (2020) The impact of soda taxes: Pass-through, tax avoidance, and nutritional effects. *Journal of Marketing Research, forthcoming. First published online on October* 12(2020):19–12.

Smith VL (1991) Rational choice: The contrast between economics and psychology. *Journal of Political Economy* 99(4):877–897.

Sunstein CR (2020) Are food labels good? *Food Policy* 101984.

Thomas LA (1999) Incumbent firms' response to entry: Price, advertising, and new product introduction. *International Journal of Industrial Organization* 17(4):527–555.

USDA Agricultural Marketing Service (2018) National Bioengineered Food Disclosure Standard. URL https://www.federalregister.gov/documents/2018/12/21/2018-27283/national-bioengineered-food-disclosure-standard#p-88.

Wert CV (2017) Kashi: Growing the supply chain for organic food. Technical report, New York NY.

Appendices

A Information Campaigns and Rule-Making Prior to Implementation

The successful passage of the Vermont labeling law can be attributed to a combination factors including a well-organized group effort that brought lawyers, campaigners and experts together, extensive use of social media that changed the speed with which information spread, and a rule-making process overseen by the legislation. In passing Act 120, the Vermont Legislature tasked the State Attorney General with developing rules to implement the law. This rule-making process took place from April 2014 to April 2015, during which time the Vermont Attorney General's Office developed rules clarify to the scope and reach of the law, providing the specific requirements for the labeling of food, including size and placement of the required disclosures. They also solicited and accepted considerable public input, which improved transparency of the labeling requirements. The resulting Consumer Protection Rule CP 121 was adopted by the Vermont Attorney General's Office on April 17, 2015. In addition, the Attorney General's Office published an annotated version of the rule as additional guidance and as a memo regarding enforcement priorities. The Vermont Attorney General also provided further explanation and information for manufacturers, producers, retailers, and consumers.[34]

Meanwhile, the GMO labeling law was supported and advocated for by a powerful Vermont Right to Know GMOs coalition, a partnership among Rural Vermont, Vermont Public Interest Research Group (VPIRG) and the Northeast Organic Farming Association of Vermont (NOFA-VT). The coalition spearheaded a four-year grassroots campaign to successfully pass the Vermont GMO food labeling law, during which they engaged over 10,000 citizens, many of whom testified before legislative committees and/or at the numerous public hearings that were held by the Vermont Legislature.[35] For example, VPIRG launched the organization's biggest summer campaign ever in 2014, sending teams of young activists to knock on doors in every Vermont town and to sign people up as supporters of GMO labeling. Because of the numerous targeted campaigns, Vermonters were exposed to significantly more informational and educational efforts about GMOs than residents of other states.

The informational and educational efforts resulted in higher awareness or concerns for GMO food in Vermont. Kolodinsky and Lusk (2018) presents two surveys conducted in Vermont and in the nation (excluding Vermont) about concerns for GMO food, at three time periods before mandatory labels appeared on grocery shelves (March 2014, March 2015, and March 2016) and two time periods after mandatory labels appeared (November 2016 and March 2017). **??** reproduces their survey results. In March 2016, the concerns in Vermont reached its peak, which is a period when the campaigns were most active.

[34] See https://ago.vermont.gov/ge-food-labeling-rule/ and https://vtdigger.org/2015/04/21/attorney-general-adopts-gmo-labeling-rules-for-vermont-food-retailers/ for more details.

[35] https://www.ruralvermont.org/news/2018/7/2/submit-your-comments-on-gmo-labeling-rules-now

B Nationwide non-GMO Product Expansion and Examples of Labels

Figure B1 presents average number of non-GMO products in Vermont and in other states. The jump in January 2016 is parallel between Vermont and other states.

Figure B1: Number of non-GMO Products
Vermont and other states

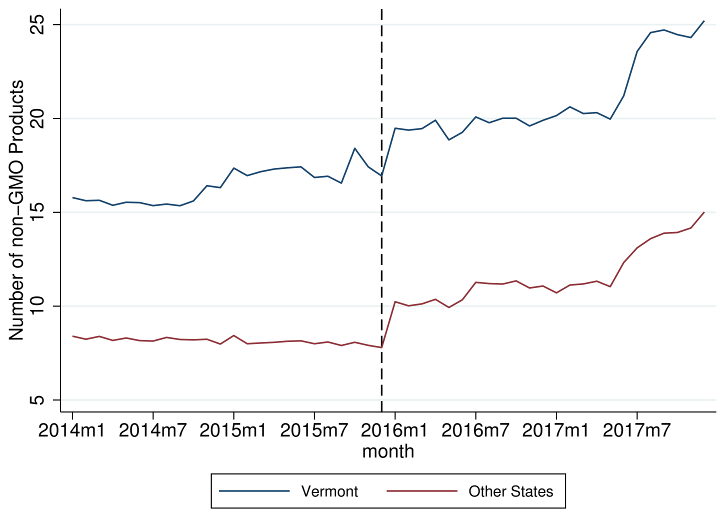


Figure B2: A General Mills Product with the GMO Label During the Sample Period

Figure B3: Examples of Voluntary Compliance with Impending NFBS Law

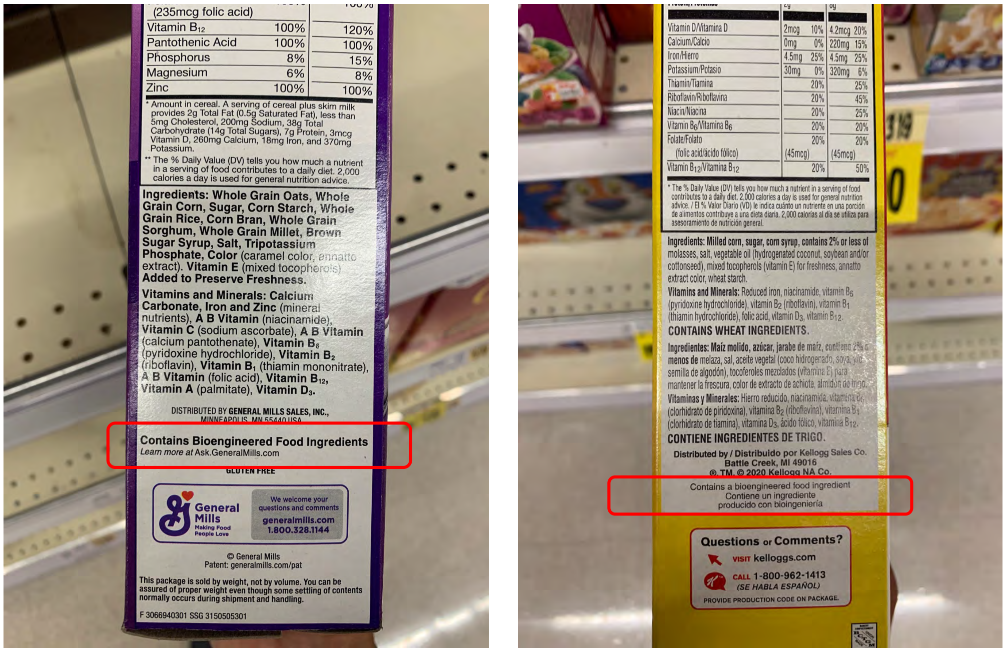
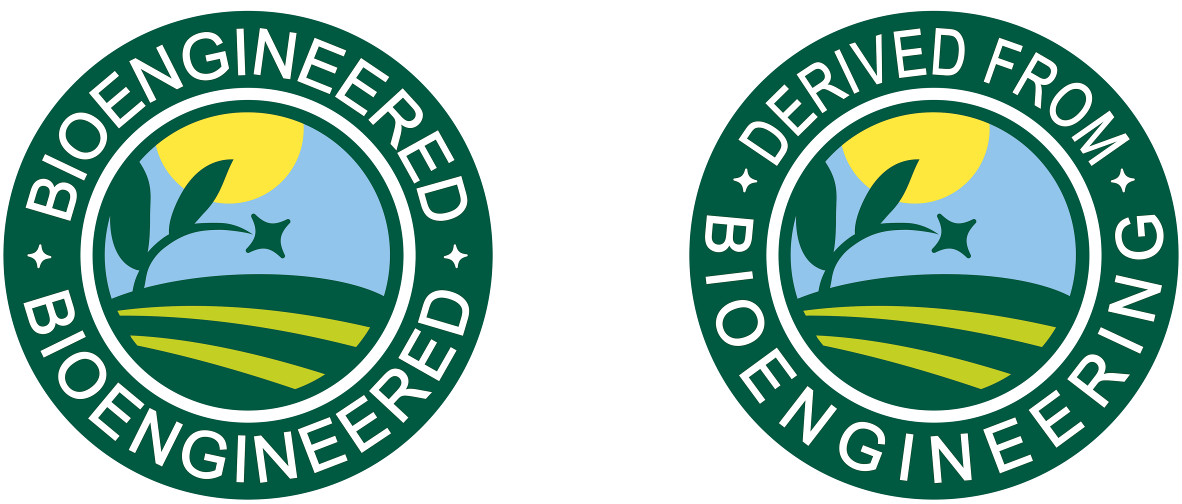


Figure B4: Two of the USDA Approved Options for GMO Disclosure

(a) (b)



C Multi-State Retailer Test

Here we conduct a robustness test where we focus only on multi-state retailers that operate in Vermont. We track differential demand responses within the same retailer across different states. Our sample for this exercise includes one national drug store (retailer 4901) and two regional grocery store chains (retailer 843 and 34) that operate in Vermont and in neighboring states.[36] Specifically, for each of the three multi-state retailers (r) that operates in Vermont we estimate:

$$Y^r_{ilt} = \delta I^r_{VT} I_t + I^r_{VT} + \lambda_t + \varepsilon^r_{ilt} \tag{3}$$

where Y^r_{ilt} is our outcome of interest—differential quantity share in store i in location l (Vermont vs. Outside Vermont) and month t. I^r_{VT} is an indicator variable for retailer r's stores based in Vermont; I_t is a post-treatment indicator that is equal to one for months on or after January 2016; λ_t is month fixed effects; and the main parameter of interest is δ.

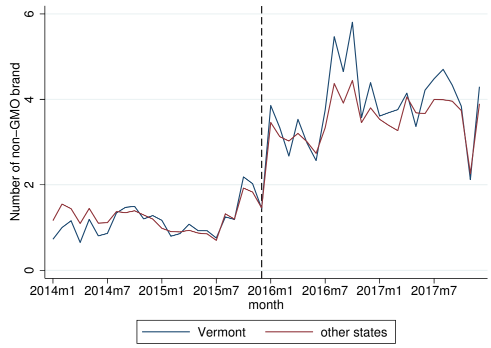
We regard this exercise as a conservative robustness test that is likely to generate a lower bound of the treatment effect for the following reasons. First, examining demand variation within the same retailer places a strict restriction on the similarity of supply due to distributional contracts negotiated at the retailer level. Indeed, the existence of within-chain uniformity in distribution patterns is closely linked to the concepts of uniform assortment and uniform prices due to managerial costs, inertia, and brand image concerns discussed in DellaVigna and Gentzkow (2019) and Clark et al. (2020). We also confirm that the supply changes within any given chain retailer are very similar across locations inside and outside of Vermont (see Figure C1). Second, while drug store retailer 4901 operates nationally, the Vermont locations of these drug store retailers sell a very small share of the total cereal consumed in Vermont (in our sample, only 2.82% of cereal purchased in Vermont comes from this retailer), and shopping at drug stores does not represent a typical grocery shopping environment for buying RTE cereal. Third, while the regional grocery retailers 843 and 34 sell most of the cereal in Vermont in our sample, their non-Vermont locations are all in neighboring states, which, as discussed in section 3, also tend to have a heightened information environment surrounding GMO labeling. These last two reasons are the primary factors that explain the expected attenuation of the treatment effect in this robustness exercise.

The multi-state retailer estimation results are presented in Table C1. The results qualitatively corroborate our findings from the main specification, although quantitatively the estimated effects are smaller as a result of the above-mentioned reasons. Consistent with the main results, we find that even within the same retailer, Vermonters increase their consumption of non-GMO cereal and decrease their consumption of GMO cereal relatively more compared to consumers outside Vermont who buy from the same retailer. The stability test results reported in the same table also confirm that these changes are not driven by supply or price imbalances. One small exception is a slight imbalance in assortment change within the national drug store retailer 4901; regional retailers do not have such imbalances.

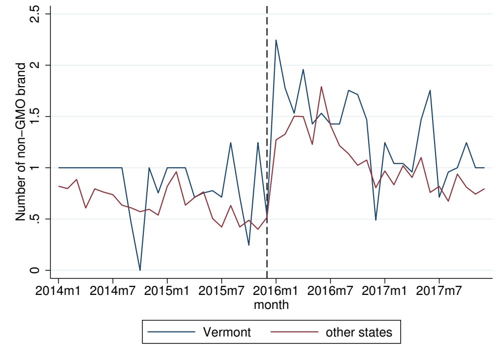
[36] We exclude two multi-state retailers—the mass merchandiser (retailer 6904) and drug store (retailer 4904), which have only 2 and 3 outlets in Vermont, respectively. Their overall combined cereal market share in Vermont is a negligible 0.6%.

Figure C1: Non-GMO Supply Expansion at Each Multi-State Retailer

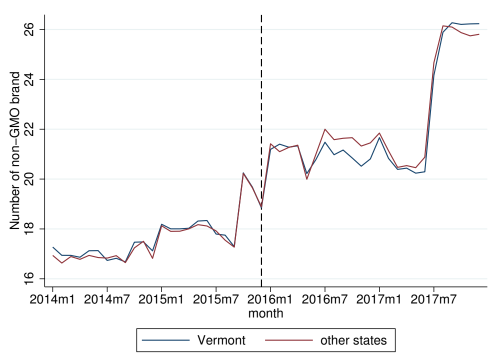
(i) Retailer 4901 ($p = 0.6906$)



(ii) Retailer 4904 ($p = 0.3091$)



(iii) Retailer 843 ($p = 0.9981$)



(iv) Retailer 34 ($p = 0.0860$)

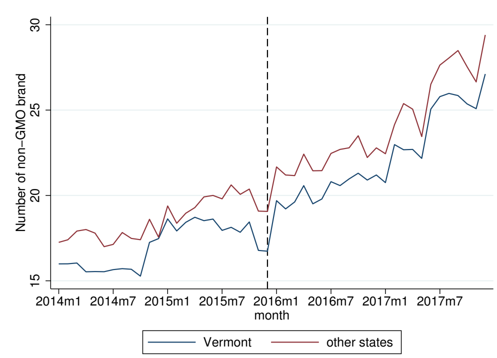


Table C1: Retailer-Specific Demand Effects

Retailer Identifier	4901	843	34
DiD Differential Quantity Share	-0.0242***	-0.00782*	-0.0187***
	(0.00376)	(0.00429)	(0.0043)
Assortment Stability	-0.346**	0.183	0.519
	(0.0913)	(0.534)	(0.517)
Price Stability	-0.00942	-0.00288	0.00175
	(0.00694)	(0.0035)	(0.00425)
Observations	329,284	12,802	10,272
Operating Region	32 STATES	MA,ME,NH,NY,VT	MA,ME,NH,RI,VT
# of stores in VT	36	17	19
# of stores outside of VT	4423	157	124
% of Cereal Sales in Vermont	2.82	53.65	41.02

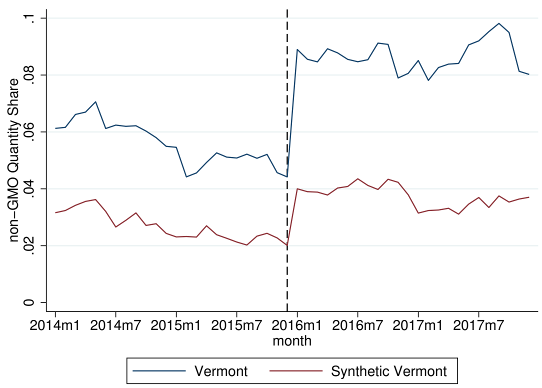
Notes: Each row represents a separate DiD regression. We report δ. Assortment and price stability refer to difference between GMO and non-GMO in assortment and price. *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at store and month level in parentheses.

D Additional Results

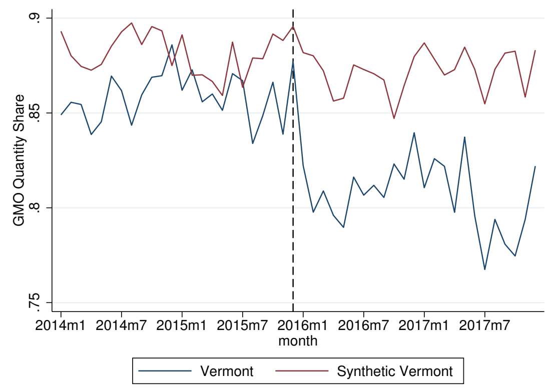
D.1 Synthetic Control Graphs without Demeaning

Figure D1: GMO and non-GMO Quantity Shares in Vermont vs. Synthetic Vermont without Demeaning

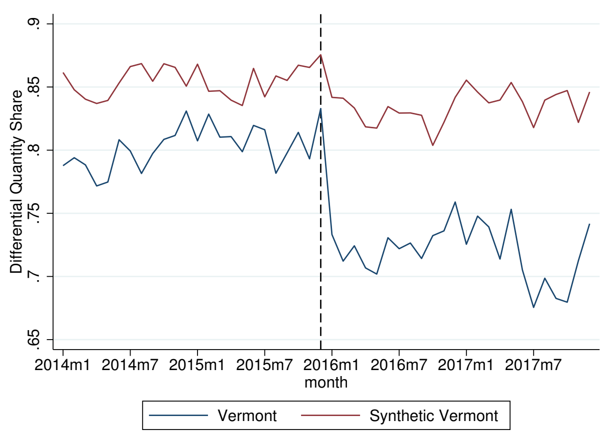
(a) non-GMO Quantity Share



(b) GMO Quantity Share



(c) Differential Quantity Share



D.2 Results with Three Months Post Period

Table D1: DiD Estimates for Quantity Shares
(3 Months Post-Treatment)

VARIABLES	(1) non-GMO Quantity Share	(2) GMO Quantity Share	(3) Differential Quantity Share
After × Vermont (δ)	0.0191***	-0.0432***	-0.0624***
	(0.00207)	(0.00855)	(0.00937)
Vermont (I_{VT})	0.0291***	-0.0232***	-0.0522***
	(0.000783)	(0.00323)	(0.00354)
Constant	0.0285***	0.880***	0.852***
	(0.000512)	(0.00212)	(0.00232)
Observations	56	56	56
R-squared	0.990	0.890	0.956
Month FE	YES	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

Table D2: Stability Tests for Assortment, Prices and Advertising Levels
(3 Months Post-Treatment)

VARIABLES	(1) non-GMO Product	(2) GMO Product	(3) non-GMO Price	(4) GMO Price	(5) Total Ad	(6) GMO Ad
After × Vermont (δ)	0.105	-0.324	-0.00947	0.00128	8613.152*	7659.72*
	(0.490)	(0.738)	(0.00699)	(0.00405)	(3376.658)	(3183.358)
Vermont (I_{VT})	6.058***	2.455***	0.0350***	0.00222	7557.537***	8510.969***
	(0.185)	(0.279)	(0.00264)	(0.00153)	(1212.572)	(1203.196)
Constant	10.82***	46.70***	0.276***	0.251***	5052.508***	5586.357***
	(0.121)	(0.183)	(0.00173)	(0.00100)	(800.191)	(787.6769)
Observations	56	56	56	56	56	56
R-squared	0.982	0.852	0.912	0.705	0.845	0.871

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

D.3 Results with 24 Post Period

Table D3: DiD Estimates for Quantity Shares
(24 Months Post-Treatment)

	(1) non-GMO Quantity Share	(2) GMO Quantity Share	(3) Differential Quantity Share
After × Vermont (δ)	0.0202***	-0.0423***	-0.0625***
	(0.00153)	(0.00506)	(0.00600)
Vermont (I_{VT})	0.0291***	-0.0232***	-0.0522***
	(0.00108)	(0.00358)	(0.00424)
Constant	0.0321***	0.877***	0.845***
	(0.000540)	(0.00179)	(0.00212)
Month FE	Yes	Yes	Yes
Observations	96	96	96
R-squared	0.988	0.928	0.965

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

Table D4: Stability Tests for Assortment, Prices and Advertising Levels
(24 Months Post-Treatment)

	(1) non-GMO Product	(2) GMO Product	(3) non-GMO Price	(4) GMO Price	(5) Total Ad	(6) GMO Ad
After × Vermont (δ)	3.096***	2.727***	-0.00779*	0.000208	-3055.905	-4009.337*
	(0.727)	(0.841)	(0.00463)	(0.00197)	(1824.302)	(1821.703)
Vermont (I_{VT})	6.058***	2.455***	0.0350***	0.00222	7557.537***	8510.969***
	(0.514)	(0.595)	(0.00327)	(0.00139)	(1251.461)	(1288.138)
Constant	11.14***	44.55***	0.261***	0.255***	17742.38***	18829.43***
	(0.257)	(0.297)	(0.00164)	(0.000697)	(1053.413)	(1031.829)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96	96	96	96	96	96
R-squared	0.923	0.889	0.932	0.784	0.860	0.882

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

D.4 Revenue Share Results

In this section we present synthetic control and DiD results for revenue share, using the same specification as the main analysis for quantity share.

The results shown in Table D5 suggest that revenue share difference also decreased more in Vermont than in synthetic Vermont. Similar to quantity share, this discrepancy in revenue share difference are both driven by a significant increase in non-GMO revenue share in Vermont (larger than synthetic Vermont by 0.0174), and a significant decrease in GMO revenue share in Vermont (bigger than synthetic Vermont by 0.0315). As Table 6 shows, there is no significant differences in prices in Vermont relative to synthetic Vermont, so the changes in quantity shares is the main force behind these changes in revenue shares.

Table D5: Revenue Share Change
(6 Months Post-Treatment)

	(1)	(2)	(3)
VARIABLES	non-GMO Revenue Share	GMO Revenue Share	Combined Revenue Share
After$\times$ Vermont (δ)	0.0153***	-0.0300***	-0.0453***
	(0.00180)	(0.00426)	(0.00498)
Vermont (I_{VT})	0.0351***	-0.0378***	-0.0729***
	(0.000806)	(0.00190)	(0.00223)
Constant	0.0314***	0.876***	0.844***
	(0.000510)	(0.00120)	(0.00141)
Observations	60	60	60
R-squared	0.992	0.972	0.988
Month FE	YES	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at month level in parentheses.

D.5 States as Donor Pool

In this section we present additional synthetic control results using a donor pool consisting of 42 states that are not adjacent to Vermont, instead of 192 DMAs in the main analysis. We again exclude Washington D.C.. The DiD coefficient is estimated to be -0.0625***, very similar to results from our baseline specification with DMAs (-0.0607***). States that are matched and their weights are: Minnesota (0.811), Rhode Island (0.079), California (0.073), and Indiana (0.037).

Figure D2: Synthetic Control Estimate at State Level