Direct and Indirect Effects of Mandatory GMO Disclosure with Existing Voluntary Non-GMO Labeling*

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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). While this is a significant change to labeling requirements, voluntary non-GMO labels already exist to facilitate consumer choice. Past legislative and voter-initiated measures in several states have proposed mandatory GMO labeling, with Vermont being the only state to successfully pass and implement such a law. We leverage a novel dataset from the Non-GMO Project to examine the direct effect of mandatory GMO labeling and the indirect effect of the associated legislative process on demand for voluntarily-labeled non-GMO products. We show that the legislative process heightened consumer awareness of GMO topics and increased adoption of products with voluntary non-GMO labels, even absent actual implementation of mandatory GMO labeling: about one-third of new non-GMO product adoption is explained by the local information environment. We then utilize implementation of the mandatory GMO labeling law in Vermont as a quasi-experiment to show that in the presence of existing voluntary non-GMO labels, mandatory labeling did not have any additional effect on demand. Our findings suggest that voluntary non-GMO labels may already provide an efficient disclosure mechanism without mandatory GMO labels.

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

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1 Introduction

The labeling of genetically modified organisms (GMOs) has been the subject of political and public debates since commercialization of this technology in the 1990s.[1] According to the Pew Research Center (2018), 49% of US adults believe that foods containing GMO ingredients are less healthy than foods without them; and 88% of consumers have strong preferences for labeling this credence attribute (Annenberg Public Policy Center 2016).[2] 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 controversy over GMO labeling sparked numerous state-level mandatory labeling initiatives, most notably in California, Oregon, Washington, Maine, Connecticut, Colorado, and Vermont. Among this patchwork of proposed legislation, Vermont was the only state that successfully passed and implemented a mandatory GMO food labeling law. In the meantime, voluntary provision of *non*-GMO labels emerged to satisfy consumer preferences for this type of information, with products carrying a recognizable third-party verified non-GMO label and sales of such products exceeding $26 billion in 2019 (Food Business News 2019). The widespread market presence of this voluntary label, amid strong demand for labeling GMO products, raises questions about the role of mandatory GMO labeling.

In this paper, we examine the impact of mandatory GMO labeling on consumer preferences in a regime with established voluntary non-GMO labeling. A public policy initiative, such as mandatory disclosure of ingredient types, can impact consumer behavior *directly* through its implementation as well as *indirectly* through another mechanism: the legislative process itself can effect change by simply raising consumer awareness about a topic. We consider both the direct effect of mandatory GMO labels and the indirect effect of GMO labeling policy initiatives on demand for non-GMO products, and show that the indirect effect dominates. That is, we find that the legislative processes heightened consumer awareness about GMO topics and increased the adoption of products with voluntary non-GMO labels, even absent the actual implementation of mandatory GMO labeling. We further utilize the quasi-natural experiment provided by the Vermont GMO labeling law passage to show that the implementation of mandatory GMO labeling did not directly or additionally impact demand for GMO or non-GMO products in Vermont.

[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* (Darby and Karni 1973). Organic status or presence of GMO ingredients are examples of credence attributes.

It is often difficult to decompose the direct and indirect effects of any policy initiative, but we are able to disentangle these two effects by leveraging the institutional context. We carefully delineate the timeline when only voluntary non-GMO labels existed (i.e. no mandatory GMO labels existed), as well as the time period when both labels existed concurrently. We also take advantage of information environment differences, generated by mandatory GMO labeling legislative initiatives across several US states. Our empirical setting is 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 third-party verification for non-GMO products in the US.

We first examine the relationship between the adoption rate of newly introduced non-GMO products and the local information intensity on GMO-related topics at the time of product introduction. Fifty-five distinct products carrying voluntary NPGV labels were introduced in 9,590 grocery stores across the US during our sample period. We show that the heterogeneity in the adoption of new non-GMO products across different locations was predicted by consumers' interest in GMO topics—proxied by location-specific Google Trends Search Volume Indices (SVI)—at the time of entry in those locations. Controlling for product, store, and time fixed effects, we find that, on average, about one-third of the local adoption rate of new non-GMO product entrants can be explained by local information intensity. This proportion rises to 54% when we look at the time periods around peak legislative activity. Importantly, product entry and pricing were not correlated with the measured information environment, consistent with uniform pricing and assortment paradigms (DellaVigna and Gentzkow 2019, Clark et al. 2021). We then zoom into the specific time periods in states with notable information intensity peaks coinciding with GMO legislative activity in those states. We observe seventeen distinct non-GMO product entries during those months. We estimate that the average market share of those products would have been 29% lower (0.46% instead of 0.65%) without the heightened information environment due to legislative activity.

Next, to solidify our argument that changes in local information environment primarily explain the diverging levels of non-GMO product adoption, we focus on Vermont, the only state to pass and fully implement a GMO labeling law. Unlike other states, Vermont experienced a unique information environment that significantly diverged from its neighboring state, Maine, which also passed a GMO labeling law but failed to implement it.[3]

[3]The Maine law contained a conditional trigger clause, and at that time it was generally understood that implementation was highly unlikely.

Although Vermont and Maine both passed GMO labeling laws at nearly the same time, the implementation and rule-making process in Vermont resulted in a unique *local information treatment* characterized by a more intense and persistent GMO information environment in Vermont.[4] Accordingly, our information measure, Google SVI, shows initial similarity and subsequent divergence in the information environment between Vermont and Maine. We use the synthetic control (SC) method to construct a control (Synthetic Vermont) composed of a convex combination of counties in Maine that are most similar to Vermont in demand patterns prior to the passage of the law. We show that consumption of non-GMO products increased more in Vermont than Synthetic Vermont after the mandatory GMO labeling bill passed the Vermont House, an event signaling imminent passage of the law. We support our findings with a series of other tests comparing consumption patterns across bordering counties in Vermont. Together our results suggest that information campaigns *within* Vermont can explain differential consumption of non-GMO products in Vermont relative to neighboring areas. We corroborate this interpretation with interviews of campaign organizers whose actions generated the heightened information environment within Vermont.

Lastly, we formally explore whether any additional demand changes occurred after products began carrying mandatory GMO labels. We find no statistically discernible impact on demand in Vermont attributable to the implementation of mandatory GMO labels. This null result implies that many consumers receptive to altering their consumption to avoid GMO ingredients already made use of alternative labels such as "Non-GMO Project Verified" to facilitate those choices. The mandatory GMO label itself did not have any *direct* effect on demand, which suggests that voluntary non-GMO labels may already provide an efficient disclosure mechanism in the absence of mandatory GMO labels.

Our work contributes to our understanding of how public policy initiatives facilitate consumer choice. An extensive empirical literature has examined the role of policy-mandated information disclosure for credence attributes on market outcomes, e.g., public disclosure of restaurant hygiene inspection grades (Jin and Leslie 2003), soda taxes to discourage consumption of highly sweetened beverages (Kim et al. 2020, Rojas and Wang 2021, Seiler et al. 2021), and nutrition labels to facilitate more nutritious choices (Moorman 1998, Moorman et al. 2012, Hobin et al. 2017, Rao and Wang 2017, Bollinger et al. 2020). Our study focuses on the role of the information environment generated by the policy process in shifting consumer demand before policy implementation, much like Taylor et al. (2019) demonstrates in the context of soda taxes in Berkeley, California.

[4] In 2015, the official rule-making process necessary to implement the law enriched the information environment and heightened Vermonters' awareness of GMOs leading up to the law's implementation. Section 2 provides more detail about this process.

Most notably, our results sharply contrast with results from previous studies that suggest GMO labeling itself has a large direct negative effect on demand. Indeed, hundreds of studies have examined the effects of labels indicating the presence or absence of GMO ingredients on consumer demand. 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). The vast majority of these prior studies rely on stated preference (survey) or lab experiment data rather than actual market transactions and, thus, fail to capture the complexity of alternative information signals that exist in the marketplace.[5] A related concern regarding the usefulness and interpretability of stated preference results is the possibility of an intention-behavior gap (Smith 1991, Kahneman et al. 1999), whereby stated preferences may not map onto revealed preferences: actual purchase behavior might substantially diverge from perceived consumer attitudes (Sunstein 2020). Our study circumvents issues with stated preference or hypothetical scenarios 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 above and beyond GMO labeling that shape consumer demand response in differentiated product markets.

Nevertheless, as the food industry approaches the mandatory compliance date for a national mandatory labeling standard for GMO foods in the US,[6] food manufacturers, policymakers and researchers lack a clear understanding of how such credence labels will ultimately affect consumer choices. Our work highlights the importance of accounting for complex relationships between labeling laws, new and existing information signals, and firm strategies when analyzing policy effects. Labeling the GMO credence attribute alone may not change consumer behavior, even in markets with strong initial preferences for labeling. What matters more, potentially, is the availability of products with non-GMO labels and information surrounding them. Additionally, our results have important marketing and managerial implications for firms. Consumer movements and campaigns provide companies with opportunities and incentives to respond to rapidly changing consumers' preferences (Moorman et al. 2012, Alé-Chilet and Moshary 2021, Barahona et al. 2020). 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 and awareness are more pronounced.

[5] Dannenberg et al. (2009) analyzes over 114 valuations across 51 studies and concludes that the WTP elicitation method and the elicitation format are the key drivers in explaining the variation of the WTP estimates across studies.

[6] Congress passed the National Bioengineered Food Disclosure Standard (NBFDS) in 2016, which requires all foods for sale in the US to carry disclosure labels if they contain GMO ingredients beginning on January 1, 2022.

2 Background and Institutional Setting

In this section we explain (i) past state-level GMO labeling initiatives across seven US states and (ii) labeling initiatives specific to Vermont, the only state to successfully implement GMO labeling. These institutional details provide important background information relevant for our research design outlined in sections 4.1 and 4.2.

State-level mandatory GMO labeling initiatives. In the past decade, a patchwork of state-level legislation in several 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). Besides California, in 2013 and 2014, major GMO labeling legislative activities also emerged in Connecticut, Maine, Vermont, Washington, Colorado, and Oregon.

Beginning in mid-2013, a flurry of legislative activities took place on the East Coast. A mandatory GMO labeling bill passed the Vermont state House (H.112) in May 2013 and moved on to the Senate to be passed in its next session. A month later, both Maine (LD 718) and Connecticut (HB 6527) passed mandatory GMO labeling laws in both houses of their respective state legislatures; 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.[7] Later that same year, on the West Coast, Washington state residents narrowly voted down a ballot measure (Initiative 522) for mandatory GMO labeling in November 2013, followed by similar defeats of GMO labeling ballot initiatives a year later in November 2014 in Oregon (Measure 92) and Colorado (Proposition 105).

Of note, the labeling bills proposed in Washington, Colorado, and Oregon were put forth as public referenda, whereas those proposed in Vermont, Maine, and Connecticut were structured as legislative actions; but, nonetheless, the labeling law activity in each state resulted in temporary heightening of the local information environment surrounding GMO topics, as measured by Google Search Volume Index and illustrated in Figure 4. Moreover, these changes to the information environment happened regardless of whether the bill was passed or defeated, suggesting that the policy process itself affected the information environment more so than the bill's final outcome.

Vermont GMO labeling law and timeline. As previously noted, Vermont was the first and only state to successfully pass and implement a mandatory GMO labeling law: Vermont

[7] 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.

H.112 (Act 120) 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 unconditionally signed into law by the governor in May 2014 with a slated implementation date of July 1, 2016.[8] 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. 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 on April 27, 2015.

After the bill was signed into law, the rule-making process for Act 120 began, garnering significant local attention in Vermont. Rule-making, the legal process of developing specific requirements to implement the labeling law, involved additional state-sponsored campaigns and solicitation of considerable public input, all of which was also spurred on by local grass-roots initiatives.[9]

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 track, 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 2016). 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.

While the GMO labels were added nationally, the companies that chose to comply with Vermont law in this way chose not to widely publicize the addition of labels, possibly to

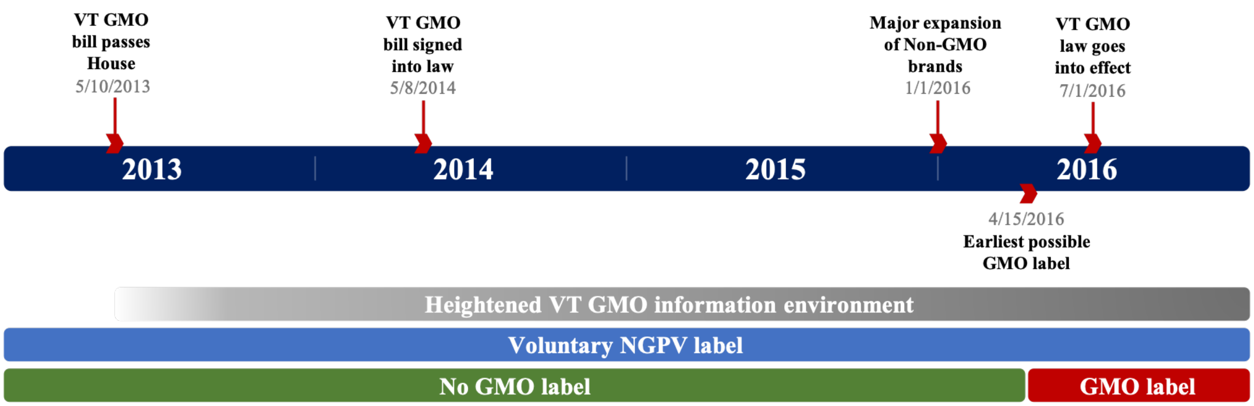
[8]Importantly, the initial passage in the House in May 2013 provided a definitive signal that the bill would ultimately become law, and, as such, this began to spur localized grassroots initiatives in Vermont as well as local media attention surrounding these events.

[9]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.1, which summarizes the rule-making process and the accompanying information campaigns.

mitigate expected negative consumer response. Furthermore, as illustrated in an example label from that time in Figure B1, the label was rather inconspicuous, and, thus, consumer awareness about the existence of the GMO label was very low nationwide, with the notable exception of Vermont.

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. 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; 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 less than a month (for more information on NBFDS, see Bovay and Alston 2018). For clarity, Figure 1 summarizes the timeline of key events that occurred during this period surrounding Vermont GMO legislation.

Figure 1: Vermont GMO Legislation Timeline



3 Data and Descriptive Statistics

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 five years, from 2012 to 2017, a period that includes the Vermont mandatory GMO labeling law implementation (July 2016). The RMS data records weekly quantities sold, revenue, and product information for 10,456 grocery stores, the focus of our study, across the 48 contiguous states in the US. Product information includes UPC (universal product code), product name, corporate name, package size (in ounces), and flavor variant.[10] We use these data to calculate quantity sold and to determine prices according to standard definitions used in the literature. Quantity is measured by the total volume sold, and is calculated by the number of units sold multiplied by the package size of each unit (in ounces). Price is measured on a per-ounce basis, and is calculated by multiplying the unit price by the number of units sold and dividing by the total quantity sold. To ensure that some products in smaller stores do not artificially enter and exit the sample over the sample period, we aggregate the data to the monthly level. Our final data set contains quantity and price information for products sold in month t at store s between January 2012 and December 2017.

Non-GMO Project Verified Data. The Nielsen data do not provide information about whether a given product contains GMO ingredients; 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 NGPV standard is the leading third-party verification program for GMO avoidance in North America, with over 60,000 verified products. 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. These NGPV data include UPC-level information[11] and the date when each product was certified for all products certified by the project.

Figure 2: Non-GMO Project Verified Label

[10] The analysis is conducted at the brand-flavor level, which we refer to interchangeably as "product" or "brand" throughout the paper.

[11] 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.

Figure 2 presents an example of the typical NPGV label. Panel (a) of Table 1 summarizes the quantity share, revenue share, prices, quantity, revenue and number of products for non-GMO products in our sample, separately for the seven states with GMO legislative activity (see section 2) and the rest of the states, between January 2012 and December 2017.

Table 1: Summary Statistics of non-GMO and GMO Products (Big-3)

	(a) All Non-GMO Products				**(b)** Big 3 GMO Products			
	Seven States		Other States		Seven States		Other States	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
Quantity Share	0.039	0.022	0.021	0.014	0.816	0.066	0.851	0.072
Revenue Share	0.038	0.022	0.018	0.013	0.823	0.05	0.861	0.054
Price	0.301	0.026	0.289	0.029	0.251	0.017	0.238	0.028
Quantity	0.343	0.209	0.195	0.194	9.047	3.031	10.796	6.806
Revenue	0.087	0.052	0.046	0.044	1.890	0.549	2.093	1.128
Number of Products	109		94		235		211	

Notes: Seven States refers to states with significant mandatory GMO labeling legislative activity—California, Colorado, Connecticut, Maine, Oregon, Washington and Vermont. Big-3 refers to Kellogg's, General Mills, and Post. Sample period is from January 2012 through December 2017. Quantity and revenue shares are overall quantity sold of all non-GMO or GMO products of a store divided by the category quantity sold in that store. 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.

Non-GMO Product Introductions. Table 2 reports the number of unique non-GMO product introductions as well as their respective average shares and average prices in the seven states with GMO legislative activity and the rest of the contiguous US states. Our sample period spans January 2013 through June 2016, which we use in our first empirical analysis in subsection 4.1 to examine the relationship between adoption of newly introduced non-GMO products and the local information intensity around GMO-related topics. We restrict our sample to this time frame for two reasons: new non-GMO product introductions before 2013 are very limited; and we want to focus on the period prior to implementation of mandatory GMO labeling in Vermont (July 2016). New product introduction is defined at the store-level based on whether or not a particular store sold a given product up to that point. Overall, we observe 55 different NPGV product introductions in 9,590 grocery stores across different locations in the US.[12] For each new product, we look at the short-term adoption rate (quantity share) at the product level around the time of its introduction. We separately report three-month and six-month averages that we use in estimations in section 4. For example, Table 2 reports that average monthly quantity share averaged across all new

[12] To ensure that we have representative regional variation in entry, we only include products that entered in both sets of states with and without legislative activity. Our results are virtually unchanged because of this restriction as we exclude products totalling 0.00095 by quantity share. Similarly, we also exclude two additional very small (by quantity share) products because their pricing patterns do not satisfy the identification assumption described below.

products and the first three months after entry was 0.308% in the seven states with legislative activity and 0.285% in the rest of the states. Six-month averages are also similar—0.316% and 0.287%, respectively.

Table 2: Product-Level Summary Statistics of Non-GMO Entrants

	(a) 3 months				**(b)** 6 months			
	Seven States		Other States		Seven States		Other States	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
Quantity Share (in %)	0.308	0.032	0.285	0.098	0.316	0.024	0.287	0.094
Revenue Share (in %)	0.145	0.016	0.160	0.054	0.151	0.019	0.161	0.056
Price	0.337	0.009	0.315	0.024	0.325	0.009	0.303	0.025
Quantity	0.013	0.005	0.014	0.008	0.014	0.006	0.015	0.009
Revenue	0.004	0.001	0.003	0.002	0.004	0.001	0.004	0.002
Number of Products	55		55		55		55	

Notes: Seven States refers to California, Colorado, Connecticut, Maine, Oregon, Washington and Vermont. Three months and six months refers to the number of months after the product entry. Seven States refers to California, Colorado, Connecticut, Maine, Oregon, Washington and Vermont. Sample period is from January 2013 through June 2016. The averages are weighted by store category quantity, the same weight that we use in estimations in section 4. Quantity and revenue shares are product-level quantity divided by the category quantity sold in that store. 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.

Figure 3: Timeline of Top-25 Largest Non-GMO Product Introductions

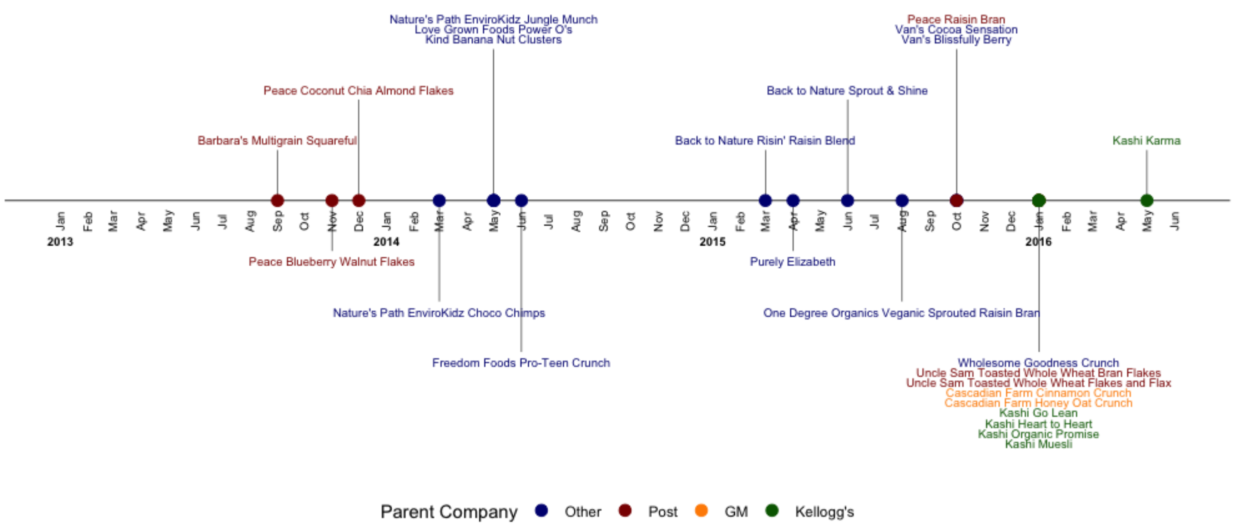


Figure 3 illustrates the entry timeline of the top-25 largest non-GMO brand introductions by sales in the US between 2013 and 2016. While we observe some consistent non-GMO brand introductions in the time period leading up to 2016, by far the largest non-GMO product expansion happened in January 2016 from the Big-3 RTE cereal firms (Kellogg's, General

Mills, and Post). At that time, the average number of non-GMO products per grocery store increased by 29.5% and the number of stores that carried at least one non-GMO product increased by 39%. 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. Notably, the timeline of this expansion is tied to annual distributional contract renewals and is not directly related to GMO labeling law activity. Appendix A.2 provides the details about the revitalization of Kashi product lines that lead to this product expansion. In section 4, we look at overall non-GMO product introductions during our entire sample period as well as introductions focusing specifically on January 2016 entry. In section 6 we also perform a simulation to predict what the average market share would have been for newly entering NGPV products without the heightened information environment relating to GMO legislative activity. In that exercise we look at NPGV product introductions during information peak periods in a subset of states.

Products Subject to VT Mandatory GMO Labeling Law. To track and verify the GMO status and labeling decisions with respect to the Vermont mandatory GMO labeling law, we need to restrict our analysis to the products and parent companies for which we have such verifiable information. Therefore, to analyze the effect of mandatory GMO labeling, we focus on the three largest parent companies in the RTE cereal category—General Mills, Kellogg's, and Post—whose combined market shares account for over 87% 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. We are able to accurately verify GMO labeling decisions and timelines for all of RTE cereal products under the umbrella of the Big-3 companies by reviewing official company announcements and press releases made in 2016 (section 2 provides a detailed recount of the GMO labeling timeline, and Figure 1 provides a visual summary). As previously noted, the Big-3 companies rolled out GMO labeling *nationally* in response to Vermont's law. We use this information to construct a temporal indicator of nationwide GMO labeling status for the Big-3 cereal firms in our empirical analysis. Panel (b) of Table 1 summarizes the number of products, quantity share, revenue share, prices, quantity and revenue for GMO products of Big-3 companies in our sample, separately for seven states with legislative activity and the rest of the states. We use this data in section 5 to understand the direct effects of GMO labeling in Vermont.[13]

[13]GMO and non-GMO quantity shares do not sum up to one in Table 1 because GMO products include only products from Big-3 manufacturers. The remaining quantity share corresponds to non Big-3 GMO products, which we exclude from our analysis due to our inability to verify their GMO labeling status.

Google Search Volume Index Data. One of the central questions our paper answers is whether, and to what extent, the magnitude of the adoption of newly introduced non-GMO products can be predicted by evolving consumer interest in GMO and non-GMO information. In the absence of more detailed data on consumer interests across states, we instead utilize data from Google Trends to measure varying levels of interest in GMO related topics across states and time, as captured by online searches.

To identify the most relevant keyword for this analysis, 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" were 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 search results after searching for these keywords were (1) the Wikipedia page on GMOs; (2) the Non-GMO Project Verified webpage on "What is a GMO?" and (3) the currently archived *Nature* webpage on the use of GMO technology.

Based on the results above, we opt to document Google Trends for the most common search term "GMO" across all states during the time period of our analysis. Google Trends analyzes the popularity of search queries in Google Search across various regions and time. We collect monthly state-specific Google Search Volume Index (Google SVI) measures for the period from January 2012 through December 2017 for all the contiguous US states in our sample (we use different subsets of this sample timeline for different empirical exercises in section 4).

Google Trends assigns an index value of 100 for the month and state in which the "relative search rate" is maximized. In our case, the maximized rate of 100 happens in the month of July 2016 in Vermont. Other index values are determined by the ratio of the search rate in a particular month/state to the maximum search rate. For example, a month when or a state where the relative search rate is half the maximum value would be assigned an index value of 50. Since Google SVI is normalized within each Google Trends query, we always include Vermont as one overlapping control state in each query. In doing so, we are able to construct a panel data of Google SVI for 48 states for every month that are directly comparable across time and locations.

Figure 4 shows the Google SVIs for our focal keyword for a sample of 12 different states between January 2013 and July 2016. Panel (a) shows the six states with significant GMO labeling law activities.[14] The grey vertical bars highlight the time periods where important

[14]The examples in Figure 4 illustrate Google SVI starting in 2013 because non-GMO product entry was practically non-existent prior to that. For this reason as well, we do not include California in Panel (a), since it experienced

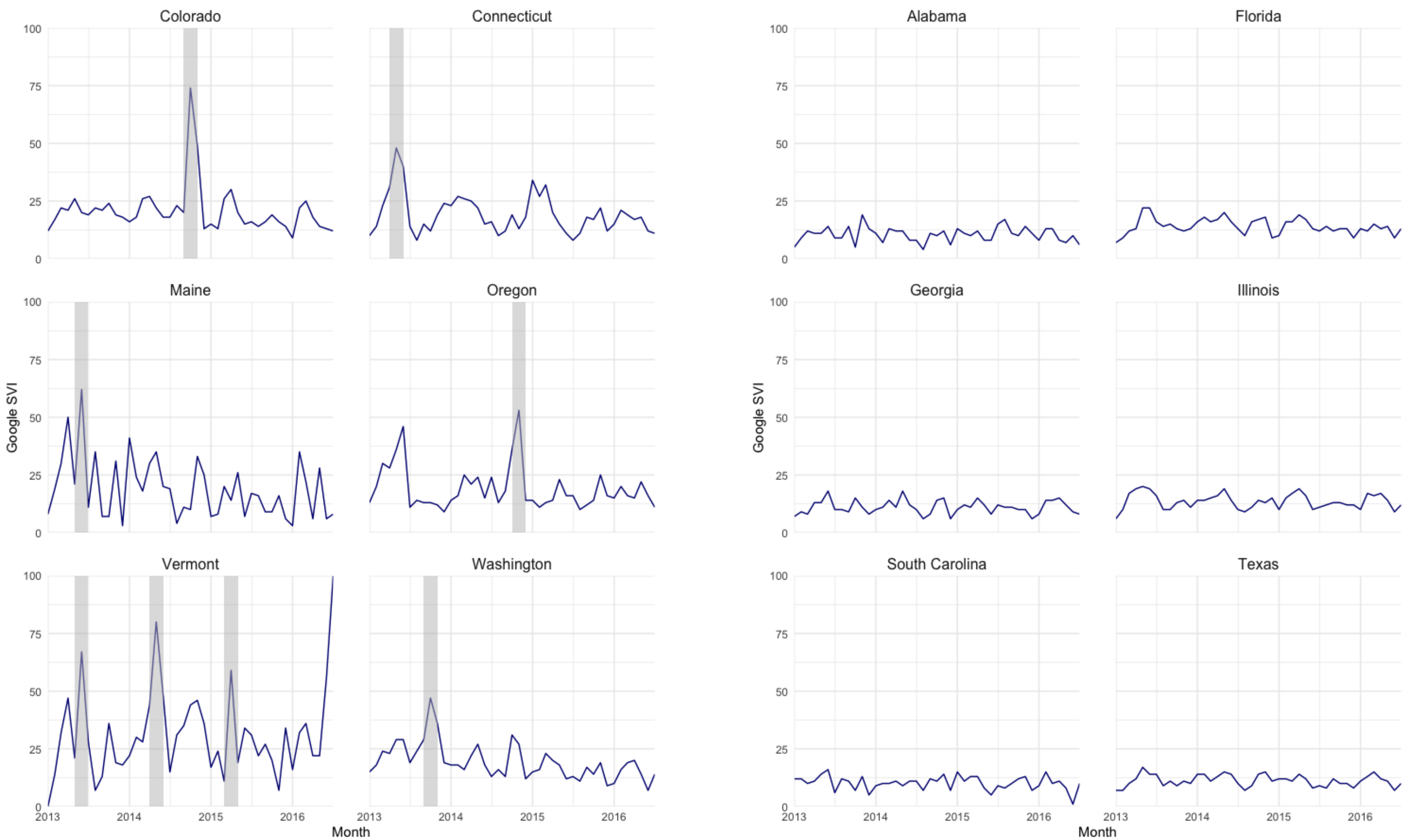
legislative activity for these labeling initiatives occurred in each of the states. For example, in Colorado the highlighted area represents the three-month time period centered around the 2014 statewide ballot election on which Proposition 105 was included. The highlighted areas for Connecticut, Maine, Oregon, and Washington are similarly defined. In Vermont, the highlighted areas reflect several important developments, in chronological order: passage of Act 120 in the House; passage of Act 120 in the Senate (and being signed into law); and rejection of the GMA federal lawsuit for a preliminary injunction, which was the only credible threat to implementation of the Vermont labeling law. On the other side, panel (b) presents a parallel time series of Google SVIs for a sample of states without any such legislative activity.

Overall, Figure 4 illustrates that the Google SVI peaks track the state-level legislative GMO labeling activity very closely. We therefore rely on the Google Trends indices as a measure of consumer interest in and information intensity about GMO-related issues at a specific time and in a particular state. At the same time, we acknowledge that this measure may capture not only information environment. In particular, the cross-sectional variation can capture pre-existing preferences independent from information environment. Data limitations prevent us from fully disentangling the factors that drive the changes in the Google SVI measure, thus we are agnostic towards fully explaining the full mechanism behind it. However, we provide consistent evidence in our analysis that information environment tied to legislative activities is one of the important drivers of the variation in this measure.

GMO legislative activity in 2012 before most non-GMO product entry.

Figure 4: Google Trends Search Volume Index for States with and without GMO Labeling Law Activity

(a) States with GMO labeling law activity **(b)** Sample of states without GMO labeling law activity



Notes: The grey vertical bars in Panel (a) highlight three-month periods centered around important legislative activity in each of the respective six states that had GMO labeling law activity between 2013 and 2016. In Colorado, Oregon, and Washington, these periods coincide with relevant statewide ballot elections (11/05/2013, 11/04/2014, and 11/04/2014, respectively). They coincide with final legislature votes in Connecticut (06/03/2013) and Maine (06/12/2013). In Vermont, they coincide with passage of Act 120 in the state House (05/10/2013) and Senate (05/08/2014), and failure of the GMA federal injunction attempt (04/27/2015).

4 Indirect Mandatory GMO Labeling Policy Effects

Our first empirical analysis looks at the relationship between the information environment surrounding GMO topics and the short-term adoption rate of non-GMO products, specifically, the newly introduced products carrying NPGV labels. In subsection 4.1, we examine this pattern using 55 distinct non-GMO product introductions across grocery stores in the entire US and demonstrate that the variation in information environment—proxied by Google SVI—predicts the adoption of these products shortly after their entry. Then, in subsection 4.2, we shift the focus to a more localized environment around Vermont and analyze how divergence of the information environment in Vermont relative to the neighboring areas affected non-GMO product demand. Both of these analyses illustrate the indirect effect of the legislative processes on demand for voluntarily-labeled non-GMO products.

4.1 Information Environment across the US

Empirical Specification. To examine the relationship between information intensity and non-GMO product demand, we exploit variation in the local GMO information environment and variation in introductions of non-GMO products across locations and time. Specifically, restricting our sample to observations that are within three or six months after entry (depending on the specification), we relate quantity shares of newly introduced non-GMO products to the average state-level Google Trends SVI for this same time period. The coefficient of interest, β, is captured in the following specification:

$$Y_{ist} = \beta \mathrm{SVI}_{ilt} + \gamma_i + \phi_s + \lambda_t + \varepsilon_{ist} \tag{1}$$

where the dependent variable Y_{ist} is the quantity share (in percentage terms) of the newly introduced non-GMO product i in store s, located in state l, during month t. We measure the local information environment by calculating the average Google Trends SVI over three- or six- months post entry for state l following product i's introduction at store s (located in state l) at time t. Please see section 3 for a description of the Google SVI construction procedure.[15] The specification in Equation 1 also controls for product (γ_i), store (ϕ_s), and time (λ_t) fixed effects. Therefore, β captures how the market share incrementally changes with Google SVI in the period immediately following product entry, above and beyond

[15] SVI_{ilt} is specific to product i, state l, and time t. For example, the same non-GMO product that entered into the same store in state l at two different time periods would have two different SVI_{ilt} measures. Likewise, the same non-GMO product that entered at the same time t but in different states would also have two different SVI_{ilt} measures. We average SVI over the three- or six- month post period because monthly SVI measures are highly volatile and our model performs better after smoothing the SVIs.

the systematic differences in adoption rate across stores and brands, after controlling for seasonality and overall time trends as well.

The identification of β exploits variation in SVI across states and time. As discussed in section 3, all states and 92% of the stores in our sample experienced non-GMO product entry during the sample period (January 2013 through June 2016). Furthermore, entries of these non-GMO products happened both in states with substantial GMO labeling law activities that therefore experienced intensified information inflow and increased consumer awareness, and in states with no such activity (for background on these bills and their legislative processes, please see section 2 and Appendix A.1). The identifying assumption is that the entry and pricing of the newly introduced products are not correlated with the information environment, which we confirm below in marketing mix stability tests.

Baseline Results. As shown in Table 3, local information environment plays a significant role in the adoption of new non-GMO products. In both three- and six-month specifications, reported in columns (1) and (2) in Table 3, the parameter of interest β is positive and significant (0.00368*** and 0.0113***, respectively). The parameter estimates represent a substantial increase over the average adoption rate, which is 0.2899% and 0.2965%, respectively. Column (3) reports the estimation results restricting the sample to states with legislative activity only, with similar results.

In order to interpret the economic magnitude of the results, we focus on the six-month point estimate of β reported in column (2) in Table 3.[16] A one-unit increase in Google SVI is correlated with a 0.0113 percentage point increase above the average baseline quantity share of the new non-GMO products. This implies that, with a sample average Google SVI of 14, the average effect attributable to local information environment is 0.16% (0.0113×14). Thus, for any Google SVI score above the mean value, 35% or more of the variation in new non-GMO product adoption rate can be explained by variation in information intensity ($(0.0113 \times 14)/((0.0113 \times 14) + 0.2965)$). Zooming into the seven states with significant legislative activity, the peak Google SVI—corresponding to periods with heightened information intensity (as highlighted in grey in panel (a) of Figure 4)—averages to be about 31. Therefore, the effect attributable to the information environment is 0.35% (0.0113×31), suggesting that 54% of new non-GMO product adoption rate is explained by the information environment during these peak times ($(0.0113 \times 31)/((0.0113 \times 31) + 0.2965)$)).[17]

[16] Note that all columns except column (1) in Table 3 are based on six-month specifications.

[17] For robustness, we run the same specification and include measures for two additional related Google SVI terms: "Organic" and "Whole Grains." The reported baseline results are robust to these controls and are reported in Appendix C.8.

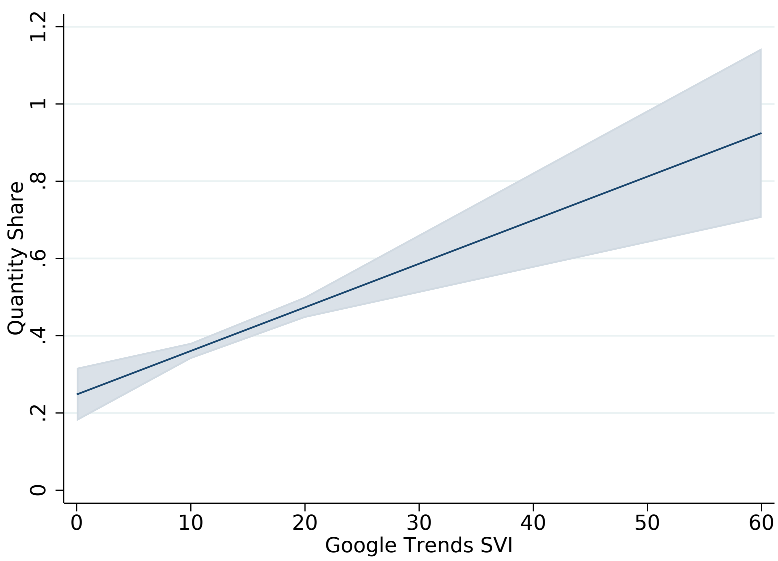
Table 3: Entry Regressions using Three Months and Six Months after Entry

	(1) Three months	(2) Six months	(3) Seven States	(4) 2016 Entry	(5) Placebo (Future)	(6) Placebo (Peaks)
SVI	0.00368***	0.01128***	0.01187**	0.01693***	-.004177	0.000134
	(0.0016)	(0.00244)	(0.0045)	(0.0010)	(0.00332)	(0.00090)
Store FE	Yes	Yes	Yes	No	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N of Obs.	70,698	133,579	35,341	89,799	133,579	35,341
R-squared	0.6753	0.6908	0.7409	0.3987	0.6770	0.7405

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses. Three months and six months refers to the number of months after the product entry. Seven States refers to California, Colorado, Connecticut, Maine, Oregon, Washington and Vermont. All columns except column (4) use panel-level SVI measures described in section 3 and for which a sample is depicted in Figure 4. Column (4) uses cross-sectional Google SVI measures explained in footnote 18.

Figure 5 plots the estimated SVI effect, $\hat{\beta}\text{SVI}_{ilt}$ along with the 95% confidence interval, as a function of Google SVI. Focusing on the six-month specification, this figure clearly shows a positive relationship between the Google SVI and the short term quantity share of the new non-GMO products.

Figure 5: Estimated Relationship between Google Trends SVI and Quantity Share of the Non-GMO Product Entrants



Notes: This figure plots the estimated marginal SVI effect ($\hat{\beta}\text{SVI}_{ilt}$) in Equation 1 with corresponding 95% confidence interval that reflects clustered standard errors. $\hat{\beta}$ is estimated using six months average Google SVI after entry (corresponding to Column (2) in Table 3).

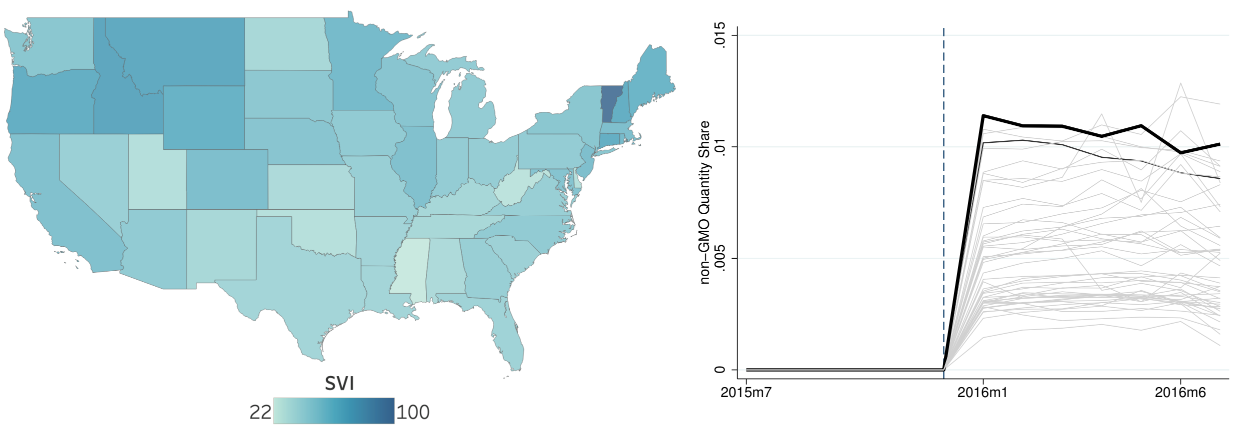
Results of January 2016 Entry. As discussed in section 3, the largest non-GMO product assortment expansion happened in January 2016. During this period, 30 distinct products were introduced in 48% of all the stores in our sample (accounting for 5,033 grocery stores). Panel (a) of Figure 6 provides a heatmap of a six-month cross-sectional measure of Google SVI scores during this time period across the contiguous states. As shown, Vermont is a visible outlier. In panel (b), we plot the adoption rate (average quantity share) of products introduced in January 2016 by state. Each line depicts one state, with Vermont in bold and Maine in dark grey.

We link the Google SVI and the quantity shares depicted in Figure 6 by estimating Equation 1, focusing only on the products that entered on January 2016. Results are reported in column (4) of Table 3.[18] Overall, we find a consistent, albeit slightly larger estimate of the marginal effect of Google SVI on non-GMO product adoption during this time period.

Figure 6: Vermont vs. All Other States in January 2016 Assortment Expansion

(a) Google SVI Intensity

(b) Entry Quantity Share



Notes: Panel (a) depicts a heatmap for the cross-sectional measure of Google SVI measuring the information environment during a six-month period starting in January 2016. Panel (b) illustrates the quantity share of newly introduced non-GMO brands in January 2016 across 48 states in our sample. Bolded line represents Vermont and dark grey line represents Maine.

Marketing Mix Stability Tests. Our main result can be consistent with alternative explanations, such as lower non-GMO prices in states and time periods with higher Google SVIs, or more frequent introductions of non-GMO products in markets and time periods with higher SVIs.[19] We formally test whether the disproportionate short-term non-GMO

[18] For this exercise we use a different set of Google SVIs—a cross-sectional measure that "takes the temperature" at a given time period of interest. Specifically, this measure indexes Google searches during the six-month period starting in January 2016. Since this is a cross-sectional measure that varies at the state level and does not vary over time, store fixed effects are collinear with SVI and thus excluded. The results reported in column (4) in Table 3 are robust to multiple other SVI measures, such as averages of the panel-level data pulled for the baseline analysis and SVI measures pulled for different time window widths.

[19] Another potential mechanism could be differential local advertising expenditure. This explanation is highly unlikely, though: Only a tiny fraction of advertising in the category is spent locally during our sample period. For example, total local advertising targeting Vermont DMAs comprised only 0.03% of national advertising expenditures. None of the advertised products during this time were non-GMO.

product adoption can be attributed to differences in product pricing or availability that are correlated with Google SVI. For these stability tests, we use the same right hand side specification as that in Equation 1.

As can be seen in Table 4, the results show that there is no significant correlation between prices or assortment and the information environment across all specifications.[20] We interpret these results as direct evidence that assortment and pricing are not strategically influenced by the information environment and that the main effect cannot be explained by these aforementioned marketing factors.

Interestingly, the results of the stability tests also suggest that retailers and manufacturers do not discriminate intertemporally based on local demand conditions. DellaVigna and Gentzkow (2019) and Clark et al. (2021) document related phenomena that multi-state retailers do not price discriminate or adjust assortment, 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 intertemporal discrimination in both prices and assortment.

Table 4: Marketing Mix Stability Tests

	Three months		Six months		Seven States		2016 Entry	
	# of Prod.	Prices	# of Prod.	Prices	# of Prod.	Prices	# of Prod.	Prices
SVI	-0.00117	-0.00074	-0.0028	-0.00115	-0.000451	0.00031	5.04e-06	-0.000069
	(0.00125)	(0.000604)	(0.00139)	(0.00081)	(0.00277)	(0.00133)	(3.25e-06)	(.00013)
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N of Obs.	71,650	71,650	135,336	135,336	35,341	35,341	89,799	89,799
R-squared	0.219	0.577	0.256	0.883	0.275	0.533	0.066	0.820

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses. Three months and six months refers to the number of months after the product entry. Seven States refers to California, Colorado, Connecticut, Maine, Oregon, Washington and Vermont.

Placebo Tests. We implement two placebo tests to make sure our results are not driven by spurious residual correlation in our data. In designing the placebo tests we look for scenarios where we do not expect the SVI term to be significant. In the first placebo test, reported in column (5) in Table 3, we replace contemporaneous SVI for state l at time t with the future SVI one year from a given month, i.e., $t + 12$. This placebo test is designed to check whether the contemporaneous adoption rate of non-GMO products can be explained by the information environment in the future. As expected, we find a null SVI effect.

In the second placebo test, we focus on the seven states with legislative labeling activities. We replace the SVI peaks related to legislative activities in those states (highlighted in grey

[20] In Appendix A.2 we provides additional evidence that the national 2016 product expansion is not driven by differential information environments across different localities.

in Figure 4) with the state-specific average SVIs outside those peaks. The result, reported in column (6) in Table 3, also shows a null effect and suggests that the identifying variation in our seven-state specification is driven by peaks in the information environment tied to GMO legislation activities in each state.

4.2 Information Environment in Vermont

Next, we look at the demand for non-GMO products in Vermont, the only state to successfully pass and implement a mandatory GMO labeling law. As we explain below, Vermont experienced an additional, localized influx of information that was specifically tied to the passage and implementation process of the law that other neighboring areas did not experience. For this analysis, we expand our sample to include all NGPV products—those previously existing and newly introduced—during our sample period.

Vermont vs. Maine. Here we examine how consumers in Vermont changed their consumption patterns relative to consumers in Maine. A mandatory GMO labeling law was unconditionally passed and implemented in Vermont, whereas in Maine a labeling law was passed but never implemented. Therefore, the major difference in the information environment between Vermont and Maine stems from the information environment generated *after* the successful law passage in Vermont, tied mostly to the rule-making process (detailed in section 2 and Appendix A.1). In our empirical analysis, we look for counties in Maine where consumption patterns are most similar to those in Vermont *prior* to the information environment divergence.

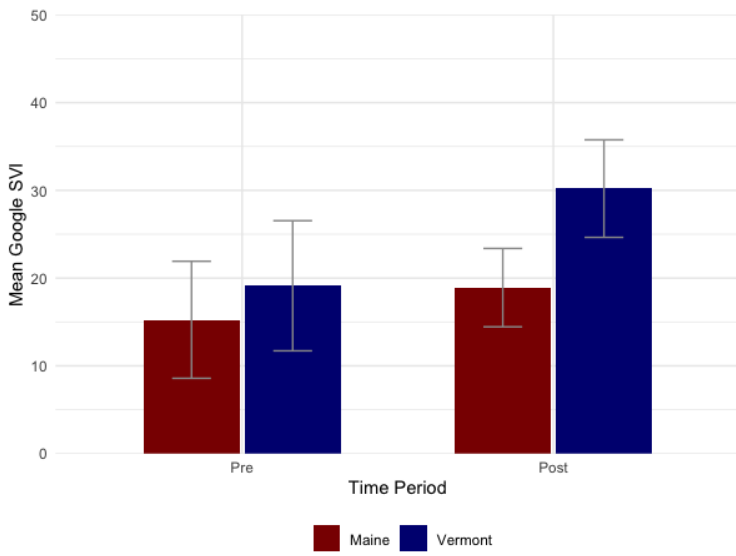
For the analysis that follows, we specify May 2013, the month when the Vermont mandatory GMO labeling law passed the House, as the treatment month. Prior to the passage of the Vermont law, the information environments in Maine and Vermont were comparable. Just a few weeks after the Vermont bill originated in the state House, Maine's mandatory GMO labeling bill *also* originated in its House. However, when Vermont Act 120 passed the House in May 2013, and it became clear that Vermont would be the first state to *unconditionally* pass and implement a mandatory GMO labeling law (and Maine would not), the information environment in Vermont surrounding GMO topics began to diverge from that in Maine.[21] As the final passage of Act 120 became imminent, grassroots information campaigns began to intensify in Vermont. Furthermore, once the Vermont bill was signed into law, the rule-making process for Act 120 began. This legal process developed explicit

[21] Vermont's law contained no conditional trigger clause, unlike Maine that relied on legislation being passed in other states. For this reason, the May 2013 House passage provides a critical information signal in Vermont.

rules and requirements to implement the law, and entailed several key features that intensified the information environment: state-sponsored information campaigns, public comment solicitation during the rule-drafting process, and advocacy efforts by local consumer groups to raise awareness (see Appendix A.1 for more details).

The designation of May 2013 as a pre/post division point is also supported by Google SVI data. Figure 7 illustrates that prior to May 2013, the mean Google SVI scores in Maine and Vermont were statistically indiscernible, indicating that both states were exposed to similar average information environments. In the period after that, however, while the mean score in Maine remained the same statistically, the mean in Vermont diverged appreciably, resulting in a statistically significantly higher mean Google SVI score in Vermont.[22]

Figure 7: Maine vs. Vermont Mean Google SVI Scores Pre vs. Post



Notes: Pre-treatment period is from January 2012 to April 2013. Post-treatment period is from May 2013 to March 2016; Error bars are 95% confidence intervals.

Next, we explain how we use different counties in Maine to construct a control location. We look for a set of counties where the non-GMO consumption patterns were very similar to those in Vermont prior to May 2013. To do so, we use a synthetic control (SC) method to construct such a composite location.

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

[22]Our designation of May 2013 does not necessarily reflect a sharp or discrete cutoff point in the information trends between Maine and Vermont. This date represents the point at which, institutionally, the information environment *started to* reasonably diverge in Vermont, which we corroborate with Google SVI data. Our results are robust to minor adjustments to this pre/post division point.

(2017) refer to SC 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 (Tirunillai and Tellis 2017, Pattabhiramaiah et al. 2019, Ada et al. 2020, 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 made up of different control counties in Maine and what we hereafter refer to as the Synthetic 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 in the pre-treatment period. Thus, any deviation that happens in the post-treatment period is attributable to the treatment effect. In our setting, this is the difference in the information environment surrounding GMO related topics generated by the the local efforts related to legislative process and law implementation. Our main outcome of interest is the quantity share of non-GMO products. Thus, the measured treatment effect is the differential non-GMO quantity share between locations due to variation in information intensity around GMO topics. As noted above, we specify the starting point of the treatment period to be May 2013, when the bill passes the house in Vermont and the local information environment in Vermont starts diverging from that in Maine. Therefore, our pre-period extends from January 2012 to April 2013, and the post-period spans May 2013 to March 2016 (March 2016 is the latest month for which we can confirm that no GMO labels existed in Vermont).

The SC method performs better with less volatile data. Therefore, we aggregate Vermont's store-month level data to state-month level using store RTE cereal category sales as weights. We do the same weighted aggregation for each county in Maine to construct county-month level data. Vermont state-month level data is the treated unit, and Maine counties become a donor pool of control units for the synthetic match procedure. In an additional analysis reported in Appendix C.4, we also implement a synthetic match procedure with multiple treated units, whereby we match each county in Vermont to a donor pool of Maine counties (with replacement).

In constructing Synthetic Vermont, we use a number of predictive variables to capture pre-period non-GMO product consumption trends, prices, and assortments. Specifically, we include three types of predictive variables: (i) pre-treatment GMO and non-GMO consumption patterns; (ii) pre-treatment trends in assortment (to ensure that the scope of new product introductions is similar); and (iii) pre-treatment prices (to ensure that changes in demand in the post-period are not attributable to divergence in prices).[23]

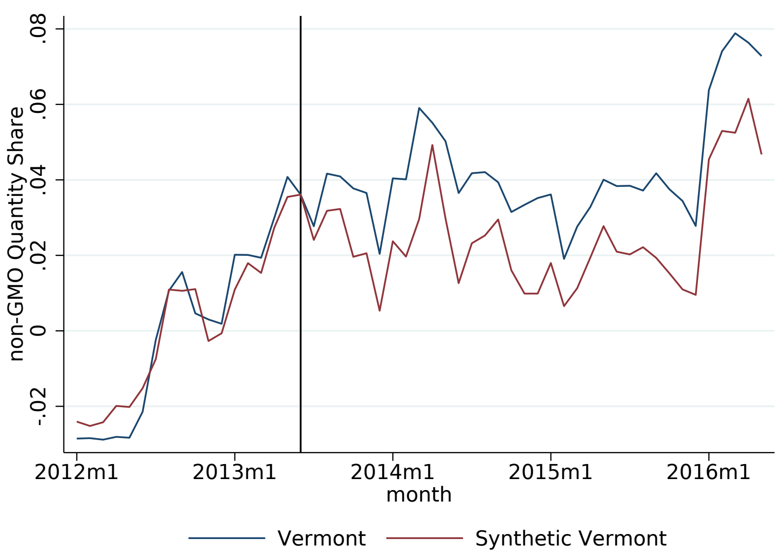
[23]The complete list of the controls is as follows. We use pre-treatment differences between: GMO quantity share

We conduct the synthetic match procedure using demeaned time trend variables by subtracting the pre-treatment location-specific average from all the time trend variables, thereby removing any level differences specific to geographic locations. 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 demeaning results in better matching (root mean squared prediction error (RMSPE) is 0.0032 with demeaning and 0.0129 without demeaning).

The resulting Synthetic Vermont is constructed as a weighted average of select Maine counties from the donor pool that minimizes RMSPE, effectively creating state-month level observations for the treated and control units. Table C1 in Appendix C presents the counties selected by this procedure and the resulting optimal weights.

Our SC procedure does a good job constructing a measurably reliant control for Vermont out of different counties in Maine. Figure 8 depicts demeaned time series of non-GMO consumption trends in Vermont and Synthetic Vermont.[24]

Figure 8: Demeaned non-GMO Quantity Shares
in Vermont vs. Synthetic Vermont



Notes: This figure depicts demeaned non-GMO quantity shares in Vermont and Synthetic Vermont. The black vertical line indicates May 2013, the time when mandatory GMO legislation successfully passed the House vote in Vermont.

Visual inspection of the time trends in Figure 8 highlights the fact that consumption

and non-GMO quantity share, GMO revenue share and non-GMO revenue share, number of GMO and non-GMO UPCs, number of GMO and non-GMO products, and prices of GMO and non-GMO products. We also use pre-treatment averages for: GMO and non-GMO quantity share, GMO and non-GMO revenue share, number of GMO and non-GMO products, number of GMO and non-GMO UPCs, and prices of GMO and non-GMO products.

[24] The respective time trends prior to demeaning are presented in Figure C1 of Appendix C. Table C2 summarizes non-GMO quantity shares in pre-treatment and post-treatment periods across different sets of locations in Maine and Vermont. For a robustness test focusing on a context where pre-period quantity share levels are the same in Vermont and Maine, please see the results reported in Appendix C.3.

trends are very similar in the pre-period, but they diverge substantially in the post-period. To quantify the difference in consumption between Vermont and Synthetic Vermont after the treatment, we specify and estimate the following baseline regression, which is similar in spirit to the Synthetic Control DiD (SDID) approach discussed in Arkhangelsky et al. (2019):

$$Y_{lt} = \delta[I_l \times Post_t] + I_l + \lambda_t + \varepsilon_{lt} \tag{2}$$

where l denotes location (Vermont or Synthetic Vermont), and t denotes month. Y_{lt} is non-GMO quantity share, I_l is an indicator variable that takes a value of one for Vermont and zero otherwise, $Post_t$ is a post-treatment indicator that equals one for months on or after May 2013, and λ_t is month fixed effects.[25] The main coefficient of interest, δ, measures the difference in non-GMO product demand between Vermont and Synthetic Vermont in the post period.[26]

Table 5: Results for Quantity Shares, Assortment, and Prices

	(1) Quantity Share	(2) # of Products	(3) Prices
Post × Vermont (δ)	0.0155***	0.1160	-0.003
	(0.0014)	(0.0655)	(0.0043)
Vermont (I_l)	0.0147***	0.1037*	0.0229***
	(0.0010)	(0.0575)	(0.0034)
Month FE	Yes	Yes	Yes
Observations	102	102	102
R-squared	0.985	0.977	0.922

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses.

The baseline specification results reported in Table 5 quantify the general patterns discussed above. The results in column (1) indicate an economically and statistically significant increase in the non-GMO quantity share in Vermont compared to Synthetic Vermont.[27]

Next, similar to the stability analysis reported in section 4.1, we formally test whether the outsized differential demand response in Vermont can be attributed to differential changes

[25] Equivalently, one can include a dummy for post period ($Post_t$), a dummy for treatment (I_l), and the interaction term ($I_l \times Post_t$). We choose to include month fixed effects instead of the $Post_t$ dummy because they capture more granular seasonal variation.

[26] Using the same specification, we also examine the quantity share changes of organic products (products with USDA organic label, but no NPGV label) and GMO products. Results are reported in Table C6 in Appendix C.

[27] Standard errors reported in Table 5 are DiD regression-based clustered standard errors. In Appendix C.5 we report bootstrapped standard errors following Arkhangelsky et al. (2019) and placebo-based standard errors following Abadie et al. (2010). The results remain unchanged.

in marketing mix variables. The results, reported in columns (2) and (3) in Table 5, show no statistically significant divergence in assortment composition or pricing after treatment in Vermont compared to Synthetic Vermont. If any pricing or assortment adjustments occurred, they were parallel in Vermont and Synthetic Vermont, and therefore were differenced out.

DMA Border Areas. A complementary test to understand the effects of diverging local information environment is to compare adjacent areas: the areas that border Vermont to the areas within Vermont borders. We estimate a geographically localized DiD model that zeroes in on the treatment effect for media markets that span multiple states including Vermont. We focus on the three media markets (DMAs) within Vermont's borders: (i) Burlington DMA, (ii) Albany-Schenectady-Troy DMA, and (iii) Boston DMA. Each of the three DMAs extends beyond the Vermont border into neighboring states. As shown in Figure 9, the largest DMA, Burlington, extends into New York and New Hampshire; Albany-Schenectady-Troy DMA extends into New York; and Boston DMA extends into New Hampshire.

In our empirical exercise we consider all stores within a given DMA in Vermont as treated stores, and all stores outside the Vermont border but within the same DMA as control stores. As shown in Figure 9, we compare consumption patterns in regions A to E and D; B to F; and C to G. We employ the following DiD specification on the month-store level data:

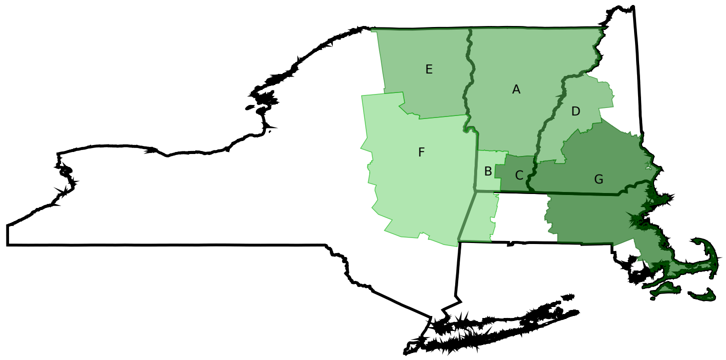
$$Y_{slt} = \delta[I_l \times Post_t] + I_l + \lambda_t + \mu_s + \varepsilon_{slt} \tag{3}$$

where I_l is an indicator that takes a value of one if store s is located in Vermont, and zero otherwise; λ_t and μ_s are month and store fixed effects; and $Post_t$ is an indicator equal to one for months on or after May 2013.

Figure 9 reports the estimation results. We find that the DMA regions that lie within Vermont exhibit a larger increase in non-GMO consumption than the bordering regions of the same DMA that lie outside Vermont.

Interviews with Campaigners. Finally, we take steps to gain external context about *on-the-ground* advocacy campaigns and the rule-making process that took place in Vermont leading up to implementation of Act 120 on July 1, 2016, to support our argument that the information environment drove differential consumer response in Vermont relative to other areas in the US. 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

Figure 9: Vermont DMA Map and Non-GMO Quantity Share Estimates



DiD Non-GMO Quantity Share		
A vs. E & D	B vs. F	C vs. G
0.0030***	0.0167***	0.0223***
(0.0010)	(0.0020)	(0.00171)

Notes: The top green shaded area ($A + E + D$) is the Burlington DMA. A is within Vermont borders, whereas E and D are outside. Light green is Albany-Schenectady-Troy DMA that also covers southwest Vermont (B). Dark green is Boston DMA that also covers southeast Vermont (C). The regression results on the right represent estimates of δ from three sets of estimations of the specification in Equation 3. *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses.

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 during our sample period and yielded two key insights. First, the coalition mounted a series of major advocacy and educational campaigns after the law was passed. 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.[28]

The cumulative evidence presented in this section strongly suggests that it was the information environment and resulting consumer awareness generated within Vermont that induced changes in consumption patterns in Vermont. While we cannot directly test the hypothesis that local consumer preferences independent of the information environment may have also contributed to consumption changes, the combined evidence presented thus far strengthens our argument. In the next section we formally test if mandatory GMO labeling had any additional effect on consumption above and beyond the information effect discussed here.

[28]For additional details on information campaigns and rule making, see Appendix A.1.

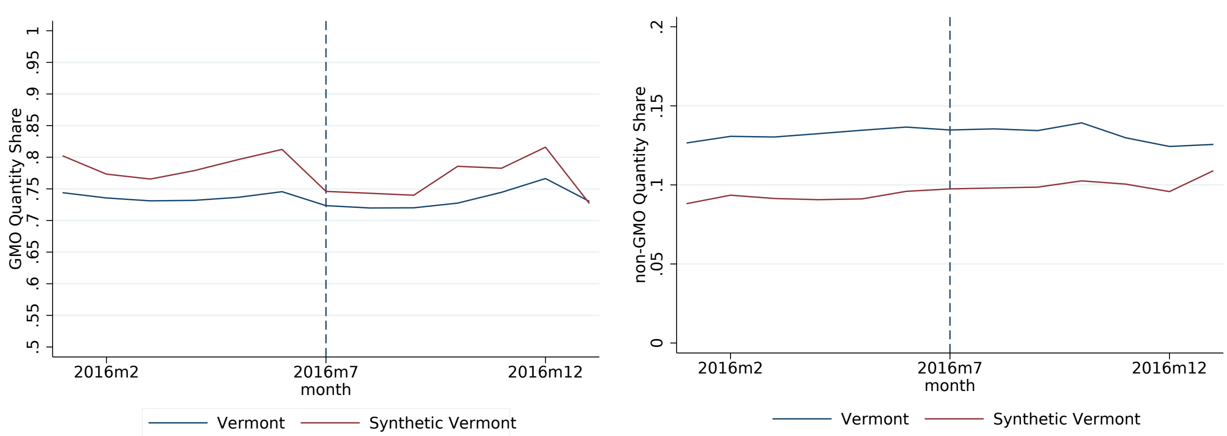
5 Direct Mandatory GMO Labeling Effects

Figure 10 depicts GMO and non-GMO product quantity shares six months before and after the mandatory GMO law implementation in July 2016 (indicated with a dashed line). Visual inspection of this figure suggests that there were no apparent changes in GMO or non-GMO consumption patterns in Vermont or Synthetic Vermont. In this section, we explore this relationship formally. We test whether the implementation of the Vermont labeling law had any *direct* impact on GMO and non-GMO product consumption.

Figure 10: Quantity Shares and Mandatory GMO Labeling Law Implementation

(a) GMO Quantity Share

(b) Non-GMO Quantity Share



Notes: This figure depicts GMO and non-GMO quantity shares in Vermont and Synthetic Vermont from January 2016 to December 2016. The quantity shares are moving averages over three month intervals. The dashed line indicates the month when GMO labeling law was implemented.

As a reminder, GMO labels were added by Big-3 cereal companies nationwide and appeared on the shelves across the US around the same time. We hypothesize that if the 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, then after July 2016 we would find (i) further changes in GMO product quantity share in Vermont; and (ii) a larger divergence in the gap in GMO quantity share between Vermont and Synthetic Vermont.

The first test we run addresses the first hypothesis—whether there are any significant consumption changes *within* Vermont. We look at the first difference in GMO and non-GMO quantity shares within Vermont (post- vs. pre-treatment). For this exercise, the treatment is the implementation of the mandatory GMO labeling law (starting in July 2016). To isolate the direct GMO labeling effect, we specify the pre-treatment period as February 2016 to June 2016, and the post-treatment period as July 2016 to December 2016. Using a t-test, we compare post-treatment GMO quantity share in Vermont to the respective pre-treatment quantity shares in Vermont. The p-value is 0.9532; thus, we fail to reject the null hypothesis of no differences in consumption patterns for GMO products after implementation of the law. We also run the same test on the non-GMO quantity share. The p-value is 0.7111, which indicates no significant changes in non-GMO consumption patterns after the law implementation as well. 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.[29]

The second test addresses whether the consumption patterns after the law's implementation further diverge between Vermont and Synthetic Vermont. To implement this test, we use the GMO and non-GMO quantity share time series, previously constructed for Vermont and Synthetic Vermont, and estimate Equation 2 with the same pre- and post- treatment periods as the above test. For both GMO and non-GMO quantity shares, the results show that the estimated coefficient for δ is not statistically significantly different from zero: $p = 0.397$ and $p = 0.133$, respectively. Thus, we find no evidence of an additional effect on the consumption of GMO or non-GMO products attributed to the mandatory GMO label information or to consumers' awareness of the mandatory GMO label.

Table 6: Direct Effects of Mandatory GMO Labeling Policy

	GMO products		Non-GMO products	
	Three months	Six months	Three months	Six months
Post × Vermont (δ)	0.0245	0.0171	-0.00449	-0.00568
	(0.0382)	(0.0194)	(0.00610)	(0.00350)
Vermont (I_l)	-0.0470	-0.0526***	0.0417***	0.0401***
	(0.0245)	(0.0127)	(0.00575)	(0.00290)
Month FE	Yes	Yes	Yes	Yes
Observations	12	24	12	24
R-squared	0.847	0.877	0.977	0.980

Notes: Three months and six months refers to the number of months before and after July 2016. *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses.

In both tests, the null effect is robust to different lengths of pre- and post-treatment periods. These two tests suggest that the implementation of GMO labeling did not have any direct impact on consumer choices in Vermont. Coupled with the main results, these results imply that consumers who were receptive to altering their purchasing behavior to avoid GMO ingredients had already encountered alternative labels such as "Non-GMO Project

[29] In a follow up robustness test, we specify the treatment window as April 2016, the earliest possible month when GMO labels could have appeared in the stores (three months before and three months after). We get similar results, and we cannot reject our null hypothesis.

Verified" to facilitate those choices. Furthermore, our results demonstrate that voluntary non-GMO labels may be an efficient disclosure mechanism in this market even in the absence of mandatory GMO labels.

6 Discussion

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

First, our main findings offer important managerial implications for companies. "Big Food" companies have spent millions of dollars in attempts to block state and federal agencies from passing mandatory GMO labeling laws. The top spenders were two of the Big-3 companies included in our analysis—General Mills and Kellogg's (Environmental Working Group 2016). This behavior was primarily based on concerns of market share shrinkage for existing GMO products. To that end, if firms see costly product reformulation to avoid GMOs as the only viable product strategy to mitigate these concerns over negative demand response, then incurring these short-term lobbying costs might be reasonable.[30] Our results suggest, however, that consumer movements and campaigns such as GMO labeling initiatives offer firms an opportunity to exploit changes in consumer preferences by developing new products differentiated by the non-GMO attribute. Historically, this resonates with the observed long-run industry response to the establishment of the National Organic Program (albeit, a voluntary certification) in 2000, which for many firms meant establishing an expanded product portfolio with both conventional and Organic products. Analogously, with the impending roll out of the NBFDS, a similar strategy in the nascent non-GMO product market may not only preempt adverse sales effects in the short term, but also drive long term growth by catering to evolving consumer preferences, particularly in markets where such preferences are most pronounced. More generally, our results uncover a case in which the consumption trends and legal initiatives that were perceived by industry as detrimental have the potential to provide revenue growth opportunities.

To explore this scenario, we conduct a simulation using the six states in panel (a) of Figure 4 to predict what the average market share would have been for newly entering NGPV products *without* the information environment peaks coinciding with GMO legislative activity in those states. To do this, we replace the peak SVIs with the observed mean SVI

[30] We do not observe cost in our data, which may be higher for non-GMO products due to ingredient sourcing and certification, thereby reducing margins. It may also take considerable time, perhaps beyond the planning horizon of these firms, to build out and develop the supply chain relationships and realize the scale economies necessary for such an option to be considered feasible.

outside those peaks (mean SVI across the six states is 14 outside the peaks vs. 31 during the peaks) and focus on the specific time periods coinciding with legislative activity in each state. We observe seventeen distinct non-GMO product entries during those months and estimate that the average market share of those products would have been 29% lower (0.46% instead of 0.65%) without the heightened information environment due to legislative activity.[31] Beyond just Vermont, our result provides a broader estimate of how much non-GMO brands gained from the heightened information environment in the states with major GMO legislative activity.

The second important insight that our results uncover pertains directly 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 effect on consumer behavior in the short run. 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. Relative to prior studies, our findings therefore have greater external validity in predicting national consumer response to the federal GMO labeling mandate that becomes 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 B3 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 RTE cereal companies have opted to implement option (1) to comply with the upcoming law. An example of this option is presented in Figure B2 in Appendix B. The text size and placement is very similar to the label that was used by the Big-3 in 2016 to comply with the Vermont mandatory GMO-labeling law (see Figure B1 in Appendix B). Our findings in section 5 indicate that there was no additional treatment effect after the arrival of those GMO labels,

[31] In this simulation we hold everything else constant, so it should be regarded as illustrative rather than a full-equilibrium counterfactual.

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.

It is important to qualify our findings in the context of short term and long term effects, though. Our results do not account for the possibility that consumer preferences around the GMO attribute may continue to evolve over time, particularly as consumers learn more about GMOs under the mandatory disclosure regime. Indeed, over the last two decades we observe a similar evolution in the market for Organic products over time. That said, we would expect most of this change to occur through the proliferation of voluntary non-GMO product labeling, rather than through mandatory GMO labeling, for two main reasons. First, as it stands, the mandatory text label adopted by most firms to date is rather inconspicuous; and if it is further hidden behind a QR code, many consumers may never actually observe the label. Moreover, it is unclear whether or not consumers will connect the mandatory NBFDS label with the voluntary non-GMO label or to GMOs more generally; in fact, the mandatory label avoids using the term "GMO" altogether. This differs from other government-based food labeling programs such as the Organic label, which features a prominent and recognizable seal, typically on the front of the product package. Second, firms producing non-GMO products have an incentive to invest in advertising and other forms of information disclosure to grow this niche segment, so we would expect to see more consumer adoption of non-GMO products in the long term. Once again, though, we expect this impact to be driven by the non-GMO market (and NGPV labeling) rather than through mandatory GMO labeling.

7 Concluding Remarks

In this paper, we combine retail scanner data with novel non-GMO product verification data and Google SVI data to study the impact of mandatory GMO labeling on consumer preferences in a regime with established voluntary non-GMO labeling, with consideration given to both the *direct* effect of mandatory GMO labels as well as the *indirect* effect of GMO labeling policy initiatives on demand for non-GMO products. Using a revealed preference approach, our paper provides evidence that the information environment surrounding GMO legislative activity across multiple states in the US induced statistically and economically significant changes in consumer behavior. We show that adoption of products with voluntary non-GMO labels increased in these states, even without actual implementation of mandatory GMO labeling. To establish our first main result, we use a time-varying state-specific Google SVI to proxy GMO information environment, coupled with a monthly sales data for 55 newly introduced non-GMO products across 9,590 stores in the US. We show that about one-third of the local adoption rate for new non-GMO products is predicted by variation in the GMO information environment.

We then exploit a quasi-natural experiment in Vermont, the only state to implement mandatory GMO labeling in the US, to further show that local changes in the information environment explain diverging levels of demand for non-GMO products. We leverage institutional details of the roll out of mandatory GMO labeling in Vermont and use a synthetic control framework to show that uptake of non-GMO products increased more in Vermont due to its uniquely intense and persistent GMO information environment. To understand the underlying mechanism that drives this finding, we conduct a series of further empirical analyses. Our results suggest that the heightened anti-GMO information environment triggered by law-related educational campaigns and the rule-making process prior to implementation, rather than GMO labeling itself, most plausibly explain this change in consumer behavior. We find that DMA regions in Vermont that also span other states still exhibit a larger demand change within Vermont than the bordering regions of the same DMA that lie outside of Vermont. Additionally, our discussions and interviews with grassroots campaigners in Vermont also corroborate the importance of the local information environment in shaping consumer preferences. Lastly, we formally test whether the actual implementation of mandatory GMO labeling had any additional effect on demand for GMO products in Vermont and find no statistically discernible impact.

Our direct effect null result, taken together with the intricate timeline of the natural experiment that underpins our analysis, underscore the need for a nuanced empirical approach to disentangle related changes that occur in close sequence. While previous stated preference and lab experiment studies effectively disregard such real-world complexities by construction, our revealed preference findings provide a more complete and realistic picture of the market implications of a complicated labeling policy that interacts with information signals that are new or already in existence. In this context, the fact that we find no short term *direct* effect of mandatory GMO labeling on consumer demand, a result that significantly departs from prior literature, is perhaps neither surprising nor concerning—well-established voluntary disclosure mechanisms already exist in the marketplace to facilitate consumer choice. This result, however, should not be construed to suggest that the mandatory GMO labeling law had no *overall* effect. Indeed, the underlying information mechanism we uncover at the core of our findings is due to GMO legislative activities and the local lawmaking process, thereby emphasizing the importance of understanding the *indirect* market effects of policy initiatives as well.

As with every study, there are several limitations that present opportunities for future research. First, our data does not permit direct measurement of changes in consumer preferences, and therefore we cannot capture the effect of preferences on demand for GMO and non-GMO products beyond that which is correlated with our information measure (Google SVI). Nonetheless, the totality of the evidence we present shows that variation in the information environment does predict a significant portion of non-GMO adoption. On a related note, we must acknowledge endogeneity of variation in the information environment itself, given the influence of underlying consumer preferences; however, this poses no issue for identification as long it is uncorrelated with product pricing and availability. Lastly, to reiterate our discussion point, the effects we measure capture short term changes in consumer purchase behavior due to mandatory GMO labeling and do not reflect changes in consumer preferences that may occur over time as consumers become more informed about the label.

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Appendices

A Additional Background Information

A.1 Information Campaigns and Rule-Making Prior to Vermont GMO Labeling Law Implementation

The successful passage of the Vermont labeling law can be attributed to a combination of 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 an extensive 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 prior to the law implementation, during which time the Vermont Attorney General's Office developed rules to clarify 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.[32]

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 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.[33] Because of the numerous targeted campaigns, Vermonters were exposed to significantly more informational and educational efforts about GMOs than residents of other states.

These efforts resulted in higher awareness of or concerns for GMO food in Vermont. Kolodinsky and Lusk (2018) present two surveys conducted in Vermont and nationally 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). During the March 2016 survey wave, the recorded concerns in Vermont reached their peak, which reflected the recent period with the most active informational campaigns.

[32]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.

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

A.2 2016 Kashi Expansion

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.[34] The brand converted its entire product line to contain only non-GMO ingredients by renovating the line of existing products, adding some new ones, and creating a supply chain of over 500 Non-GMO Project Verified ingredients (Wert 2017).

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 they face, reveals that their decision to revitalize the Kashi brand was driven by consumer trends in the RTE cereal category. We found no mention of increased risks due to a potentially changing GMO labeling legislation environment (Kellogg Annual Report 2015, 2016).

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 annual distributional contract renewals.

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

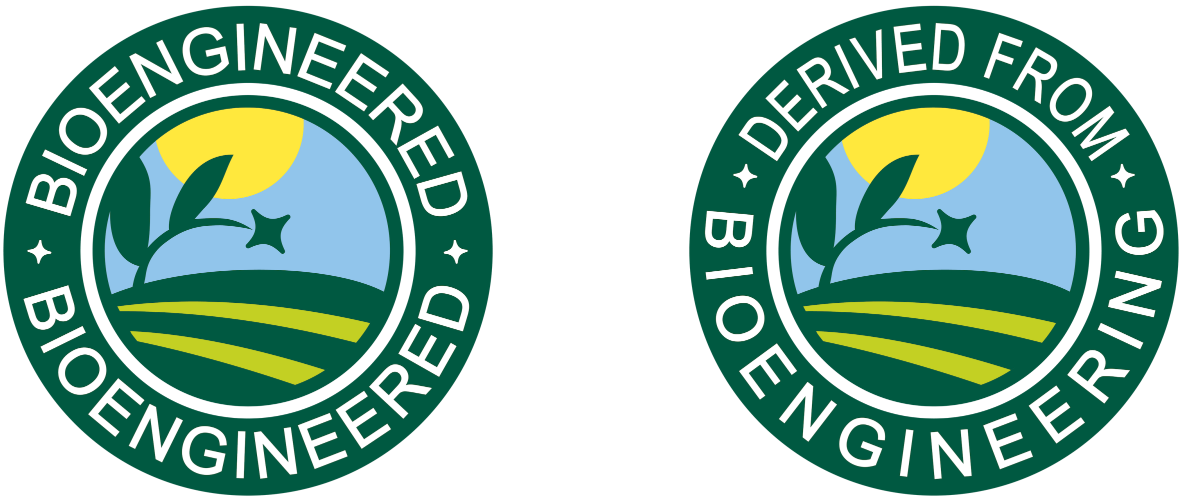
B Examples of Labels

Figure B1: A General Mills Product with the GMO Label During the Sample Period

Figure B2: Examples of Voluntary Compliance with Impending NFBDS Law

Figure B3: Two of the USDA Approved Options for GMO Disclosure

(a) (b)



C Robustness Tests and Additional Results

C.1 Synthetic Control Weights for Matched Counties in Maine

Table C1 presents counties in Maine that are matched to Vermont by the synthetic control method and their respective weights.

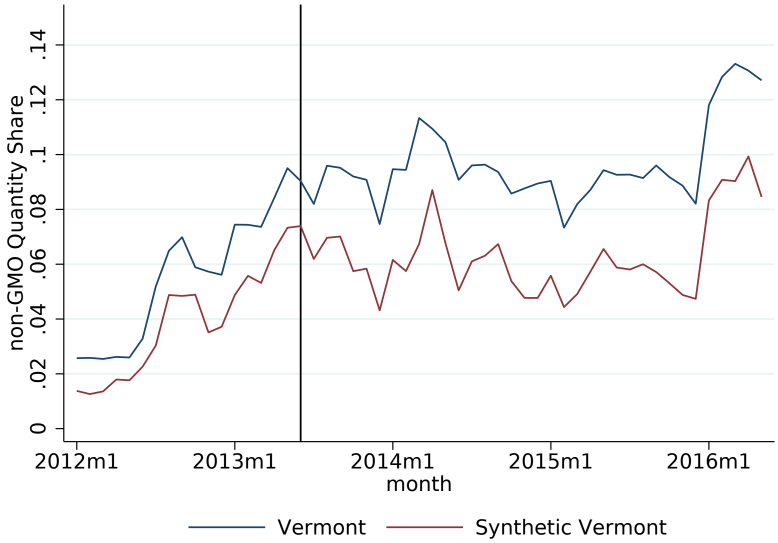
Table C1: Synthetic Control Weights for Matched Counties in Maine

County Name	Weight
Cumberland	0.277
Lincoln	0.077
Piscataquis	0.538
Sagadahoc	0.080
Waldo	0.028

C.2 Synthetic Control and Pre-Period Level differences

Figure C1 shows time trends of non-GMO quantity share in Vermont and Synthetic Vermont without demeaning.

Figure C1: Non-GMO Quantity Shares in Vermont vs. Synthetic Vermont without Demeaning



Notes: This figure depicts non-GMO quantity shares of RTE Cereal in Vermont and Synthetic Vermont without demeaning. The black vertical line indicates May 2013, the time when mandatory GMO legislation successfully passed the House vote in Vermont.

Table C2 summarizes non-GMO quantity shares in pre-treatment and post-treatment periods, for five sets of locations: Vermont, Maine, Synthetic Vermont, and subsets of stores in Vermont and Maine where the pre-treatment average quantity shares are statistically the same (see Appendix C.3 below).

Table C2: Quantity Share of Non-GMO Products for Pre- and Post-Treatment Periods

	Before	*After*
Vermont	0.0337	0.0676
	(0.0087)	(0.0129)
Maine	0.0190	0.0422
	(0.0061)	(0.0158)
Synthetic Vermont	0.0189	0.0373
	(0.0055)	(0.0095)
Subset of Stores in Vermont	0.0377	0.0841
	(0.0075)	(0.0207)
Subset of Stores in Maine	0.0392	0.0791
	(0.0068)	(0.0212)

Notes: Standard deviation in parentheses. *Before* refers to time periods from January 2012 to April 2013. *After* refers to time periods from May 2013 to March 2016.

C.3 Robustness: Difference-in-Differences with the same Pre-Period Quantity Share

For this robustness test, we look for stores in Maine and Vermont that have statistically indistinguishable non-GMO quantity shares in the pre-period. Specifically, we zoom into a subset of stores that belong to the same chain operating in both Vermont and Maine. We estimate the specification outlined in Equation 3 that we also use for the DMA border test:

$$Y_{slt} = \delta[I_l \times Post_t] + I_l + \lambda_t + \mu_s + \varepsilon_{st}$$

where I_l is an indicator that takes a value of one if store s is located in Vermont, and zero otherwise; λ_t and μ_s are month and store fixed effects; and $Post_t$ is an indicator equals one for months after May 2013.

As reported in Table C2, in this subset of stores, the pre-quantity share in Vermont is 0.0376 and in Maine it is 0.0392 ($p = 0.261$). The fact that the pre-levels are statistically the same is also captured by the insignificant coefficient for Vermont (I_l). We report the results in Table C3. We still find a strong and significant coefficient estimate for δ, suggesting that our results are robust in situations when pre-treatment period consumption levels are the same.

Table C3: DiD with Similar Pre-Treatment Quantity Shares

	Non-GMO Quantity Share
Post × Vermont (δ)	0.00509***
	(0.00132)
Vermont (I_l)	-0.000582
	(0.00117)
Month FE	Yes
Store FE	Yes
Observations	324
R-squared	0.947

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses.

C.4 Synthetic Control Results with Multiple Treated Units

In our main synthetic control analysis, we match Vermont as a state to specific counties in Maine. Here we also implement an alternative synthetic match procedure where we match each county in Vermont to counties in Maine, using the same synthetic control specification. After these individual county-level synthetic matches, we pool the Vermont counties and their matched synthetic counties, and estimate the aggregated treatment effect using the DiD specification outlined in Equation 2. Table C4 presents the results.

Table C4: Estimates for Quantity Shares, Assortment, and Prices—Multiple Treated Units

	(1) Quantity Share	(2) # of Products	(3) Prices
Post × Vermont (δ)	0.00514***	0.142	-0.00223
	(0.000754)	(0.137)	(0.00205)
Vermont (I_l)	0.00448***	-0.614***	-0.00776***
	(0.000331)	(0.0761)	(0.00126)
Month FE	Yes	Yes	Yes
Observations	663	663	663
R-squared	0.676	0.642	0.545

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses. Matches with RMSPE higher than 0.003 (the RMSPE from our main synthetic control result) are removed to ensure similar match quality as the main analysis.

C.5 Alternative Calculation of Standard Errors

As suggested in Arkhangelsky et al. (2019), bootstrapping presents a natural approach for inference with panel data. We follow the bootstrap variance estimation algorithm proposed by Arkhangelsky et al. (2019) and calculate bootstraped standard errors as an alternative to the regression-based clustered standard errors reported in the manuscript. We independently and repeatedly resample datasets with treated and control units for 1,000 iterations. For each bootstrap sample b, we compute the SDID estimator $\hat{\delta}^b$ following the procedure in subsection 4.2. The bootstrap variance is given by $\hat{V}_{\delta}^{b} = \frac{1}{B}\sum_{b=1}^{B}(\hat{\delta}^{(b)} - \frac{1}{B}\sum_{b=1}^{B}\hat{\delta}^{(b)})^2$.

Table C5: Bootstrap Treatment Effect and Standard Errors

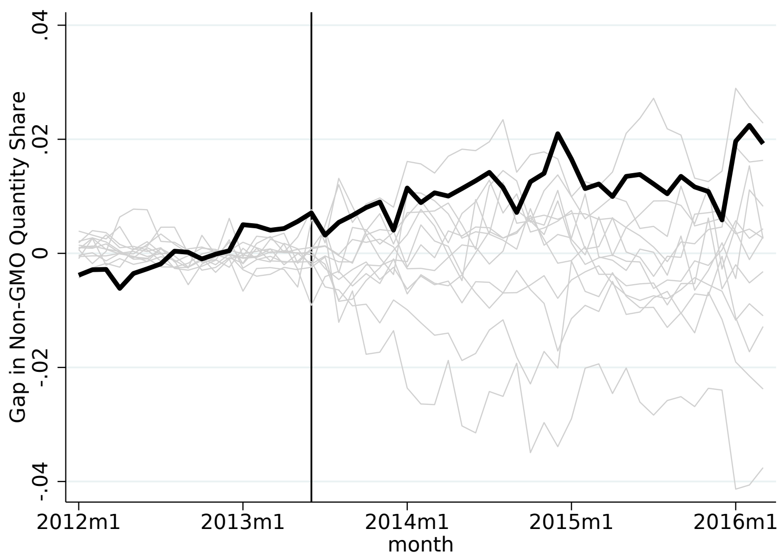
	(1) Quantity Share	(2) # of Products	(3) Prices
Post × Vermont (δ)	0.0152***	-0.0107	-0.0010
	(0.0048)	(0.1492)	(0.0041)
p-value	0.006	0.720	0.710

Notes: This table presents the bootstrap mean, standard error (in parentheses) and p-value of the treatment effect.

C.6 Synthetic Control Placebo Test

To assess the statistical significance of the synthetic control results, we conduct a series of placebo tests (Abadie and Gardeazabal 2003, Abadie et al. 2010, Tirunillai and Tellis 2017) by applying the synthetic control method to the control counties in Maine, which did not experience significant divergence in its information environment. From the tests, we produce a distribution of estimated gaps in non-GMO quantity share between each county and its synthetic control. Figure C2 visualizes the gaps for placebo counties and Vermont (denoted by the bolded black line). The observed effect for Vermont is large relative to the effect estimated for a randomly chosen county in Maine (that did not experience changes in information intensity). The quality of fit of the synthetic control can be evaluated using the ratio of the post-treatment root mean squared prediction error (RMSPE) to the pre-treatment RMSPE. This ratio is highest for Vermont when compared to most of the placebo counties in Maine, suggesting that the treatment effect is strong for Vermont. Given the small number of control counties in our sample (15 counties), as suggested by Xu (2017), we also implement this placebo test procedure using bootstrap for 1,000 iterations: for each iteration, we sample with replacement a set of control counties and apply the synthetic control method to the control counties. We find that on average the ratio is the highest for Vermont across all the iterations.

Figure C2: Non-GMO Quantity Share Gap for Vermont and Placebo Gaps for Control Counties in Maine



Notes: This figure depicts non-GMO quantity share gap for Vermont (bolded black line) and for control counties in Maine (thin grey lines).

C.7 Synthetic Control Results for Organic and GMO Products

We estimate the same SC model and DiD specification in Equation 2 for GMO products and organic products without NGPV certification. We find a significant decrease for GMO quantity share in Vermont relative to Synthetic Vermont. We also find a very small and marginally significant decrease in Organic share (products that are certified USDA Organic, but do not carry the otherwise redundant NPGV label). These results suggest that it is precisely the Non-GMO aspect of the label that matters the most in explaining the divergence in consumption in Vermont relative to Synthetic Vermont. We do not analyze the entry of organic products without NPGV labels because most newly introduced organic products received both NPGV and USDA Organic certification, making it impossible to separately identify NPGV vs. USDA Organic labeling effects for new entrants. Table C6 presents these results, with our main results from Table 5 included in column (1) for convenience.

Table C6: DiD Estimates for Quantity Shares of Non-GMO, Organic, and GMO Products

	(1) Non-GMO Quantity Share	(2) Organic Quantity Share	(3) GMO Quantity Share
Post × Vermont (δ)	0.0155***	-0.0003*	-0.01525***
	(0.0014)	(0.0002)	(0.00305)
Vermont (I_l)	0.0147***	0.0016***	-0.00444
	(0.0010)	(0.0001)	(0.0028)
Month FE	Yes	Yes	Yes
Observations	102	102	102
R-squared	0.985	0.9118	0.997

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses. Organic products are products with organic labels but which are not certified Non-GMO.

C.8 Robustness: Controlling for the Information Environment related to "Whole grains" and "Organic"

Table C7 reports the results of the specification in Equation 1 with the addition of two measures for related Google SVI terms: "Organic" and "Whole grains." The reported baseline results for "GMO" are robust to these controls.

Table C7: Information Environment about "Whole grains" and "Organic"

	Three months	Six months
"Whole grains" SVI	0.00288***	0.00680***
	(0.000731)	(0.00125)
"Organic" SVI	-2.98e-06	0.00975**
	(0.00344)	(0.00449)
"GMO" SVI	0.00413**	0.00628*
	(0.00168)	(0.00359)
Store FE	Yes	Yes
Brand FE	Yes	Yes
Month FE	Yes	Yes
Observations	70,698	133,579
R-squared	0.676	0.692

Notes: *** p<0.01, ** p<0.05, * p<0.1; Clustered standard errors in parentheses.